Welcome Remarks: Robert Cook and Gerri Walsh
Friday, October 22
10:00 a.m. – 10:05 a.m.

Speakers: Robert Cook
President and CEO
FINRA

Gerri Walsh
President, FINRA Investor Education Foundation and Senior Vice President, Investor Education
FINRA and FINRA Investor Education Foundation

Welcome Remarks Speaker Bios:

Speakers:

Robert W. Cook is President and CEO of FINRA, and Chairman of the FINRA Investor Education Foundation. From 2010 to 2013, Mr. Cook served as the Director of the Division of Trading and Markets of the U.S. Securities and Exchange Commission. Under his direction, the Division's professionals were responsible for regulatory policy and oversight with respect to broker-dealers, securities exchanges and markets, clearing agencies and FINRA. In addition, the Division reviewed and acted on over 2,000 rule filings and new product listings each year from self-regulatory organizations, including the securities exchanges and FINRA, and was responsible for implementing more than 30 major rulemaking actions and studies generated by the Dodd-Frank and JOBS Acts. He also directed the staff's review of equity market structure. Immediately prior to joining FINRA, and before his service at the SEC, Mr. Cook was a partner based in the Washington, DC, office of an international law firm. His practice focused on the regulation of securities markets and market intermediaries, including securities firms, exchanges, alternative trading systems and clearing agencies. During his years of private practice, Mr. Cook worked extensively on broker-dealer regulation, advising large and small firms on a wide range of compliance matters. Mr. Cook earned his J.D. from Harvard Law School in 1992, a Master of Science in Industrial Relations and Personnel Management from the London School of Economics in 1989, and an A.B. in Social Studies from Harvard College in 1988.

Gerri Walsh is Senior Vice President of Investor Education at the Financial Industry Regulatory Authority (FINRA). In this capacity, she is responsible for the development and operations of FINRA's investor education program. She is also President of the FINRA Investor Education Foundation, where she manages the Foundation's strategic initiatives to educate and protect investors and to benchmark and foster financial capability for all Americans, especially underserved audiences. Ms. Walsh was the founding executive sponsor of FINRA's Military Community Employee Resource Group. She serves on the Advisory Council to the Stanford Center on Longevity and represents FINRA on IOSCO's standing policy committee on retail investor education, the Jump$tart Coalition for Personal Financial Literacy, NASAA's Senior Investor Advisory Council and the Wharton Pension Research Council. Prior to joining FINRA in May 2006, Ms. Walsh was Deputy Director of the Securities and Exchange Commission's Office of Investor Education and Assistance

(OIEA) and, before that, Special Counsel to the Director of OIEA. She also served as a senior attorney in the SEC's Division of Enforcement, investigating and prosecuting violators of the federal securities laws. Before that, she practiced law as an associate with Hogan Lovells in Washington, D.C. Ms. Walsh received her J.D. from N.Y.U. School of Law and her B.A., *magna cum laude*, from Amherst College. She is a member of the New York and District of Columbia bars.

Welcome Remarks: Robert Cook and Gerri Walsh

Speakers

- Speakers
  - Robert Cook, President and CEO, FINRA
  - Gerri Walsh, President, FINRA Investor Education Foundation and Senior Vice President, Investor Education, FINRA and FINRA Investor Education Foundation

Keynote Conversation: Expanding Capital Markets Access in Diverse Communities
Friday, October 22
10:05 a.m. – 10:45 a.m.

Moderator: Ritta McLaughlin
Director, Investor Education Community Outreach
FINRA Investor Education Foundation

Panelists: Camille Busette
Senior Fellow - Economic Studies, Governance Studies, Metropolitan Policy Program; Director - Race, Prosperity, and Inclusion Initiative
Brookings Institution and FINRA Board Member and FINRA Foundation Board Member

Noel Andrés Poyo
Deputy Assistant Secretary for Community Economic Development, Office of Domestic Finance
United States Department of the Treasury

Gerri Walsh
President, FINRA Investor Education Foundation and Senior Vice President, Investor Education
FINRA and FINRA Investor Education Foundation

Keynote Conversation: Expanding Capital Markets Access in Diverse Communities Panelist Bios:

Moderator:

Ritta McLaughlin is the director of investor education community outreach at the Financial Industry Regulatory Authority (FINRA) Investor Education Foundation. In this capacity, she serves as an expert on various personal finance and investor education topics, emphasizing communities of diverse cultures and socio-economic backgrounds. Ms. McLaughlin is responsible for cultivating and managing strategic partnerships with national and local organizations to enable and deliver innovative financial capability programming and foster engagement with diverse communities. She serves as an advocate for informing and educating diverse communities about saving and investing. In this role, Ms. McLaughlin enhances FINRA's efforts to educate and empower diverse communities and increase engagement by delivering innovative financial capability programming. She also collaborates with researchers on studies to advance the understanding of diverse communities' financial capabilities, circumstances, and well-being. Prior to joining the FINRA Investor Education Foundation, Ms. McLaughlin was the Chief Education Officer for the Municipal Securities Rulemaking Board (MSRB). She oversaw the education and outreach activities of the MSRB and facilitated discussion and problem-solving among stakeholders to address challenges in the municipal market, advocate solutions where appropriate, and influence positive market practices. Ms. McLaughlin was responsible for the development and oversight of operations MSRB Podcast and the MSRB's MuniEdPro®. MuniEdPro®, launched in 2016, is a suite of interactive, online courses about municipal market activities and regulations that provide real-world simulations that allow the learner to understand municipal securities transactions and the related market and regulatory considerations. MuniEdPro® was awarded the 2018 Bronze Brandon Hall Award for Excellence in Technology for MuniEdPro®. Prior to joining the MSRB, Ms. McLaughlin was associate treasurer for the District of Columbia, where she handled the District's multi-billion-dollar debt management program. During her career, Ms. McLaughlin was also a public finance investment banker at J.P. Morgan, Bear Stearns and RBC serving as a senior banker for several states and municipalities. She is the President of the Board of the National Women in Public Finance and serves as a member of the Race, Equity and Bond Markets Advisory Group of the Robert Wood Johnson Foundation and Advisory Board Member of the District of Columbia Other Post-Employment Benefits Trust Fund. Also, she is a Founding Member of the Board of Governors for the Association for Public Finance Professionals of the District of Columbia, Maryland, and Virginia (APFP). Most recently she served as an Advisory Board Member for the State of California COVID-19 Taskforce for CEFA and CHFFA. She received a bachelor's degree in urban policy from Vassar College and a master's degree in urban policy and management from The New School for Social Research.

Panelists:

Camille Busette is director of the Brookings Race, Prosperity, and Inclusion Initiative and a senior fellow in Governance Studies, with affiliated appointments in Economic Studies and Metropolitan Policy. Ms. Busette has dedicated her career to expanding financial opportunities for low-income populations. She came to Brookings from the Consultative Group to Assist the Poor (CGAP), where she served as the organization’s lead financial sector specialist. Previously, she worked with the Consumer Financial Protection Bureau (CFPB), a U.S. Government financial services regulator, where she served as the agency’s inaugural head of the Office of Financial Education. Prior to her tenure at the CFPB, Ms. Busette held executive positions in the private and NGO sector. She previously served as a Senior Economics Policy Fellow at the Center for American Progress, a Washington D.C. based think tank, where she focused on financial opportunities for low income populations.

Noel Andrés Poyo is the U.S. Department of Treasury's Deputy Assistant Secretary for Community Economic Development. He most recently served for 14 years as Executive Director of the National Association for Latino Community Assets Builders (NALCAB), a nonprofit membership organization serving as the hub of a network of more than 120 community and economic development organizations that serve geographically and ethnically diverse Latino communities. Beginning in 2015, he also served as chief executive officer of *Escalera* Community Investments, NALCAB's subsidiary asset management company that controls social investment funds designed to capitalize affordable housing projects and small businesses. Mr. Poyo's 22-year career has focused on integrating immigrants and people with low incomes into the mainstream financial services and real estate sectors of our economy and on improving the livability and economic resilience of low-income neighborhoods and affordable housing communities. He has played diverse roles in the implementation of community development projects valued at more than $1 billion. From 2015 to 2017, Mr. Poyo served as 1 of 15 members of the Community Advisory Council for the Board of Governors of the Federal Reserve System. He has extensive experience advising the executive leadership of some of the nation's largest banks and numerous nonprofit lenders and social investors. Mr. Poyo is a graduate of Yale University.

Gerri Walsh is Senior Vice President of Investor Education at the Financial Industry Regulatory Authority (FINRA). In this capacity, she is responsible for the development and operations of FINRA's investor education program. She is also President of the FINRA Investor Education Foundation, where she manages the Foundation's strategic initiatives to educate and protect investors and to benchmark and foster financial capability for all Americans, especially underserved audiences. Ms. Walsh was the founding executive sponsor of FINRA's Military Community Employee Resource Group. She serves on the Advisory Council to the Stanford Center on Longevity and represents FINRA on IOSCO's standing policy committee on retail investor education, the Jump$tart Coalition for Personal Financial Literacy, NASAA's Senior Investor Advisory Council and the Wharton Pension Research Council. Prior to joining FINRA in May 2006, Ms. Walsh was Deputy Director of the Securities and Exchange Commission's Office of Investor Education and Assistance (OIEA) and, before that, Special Counsel to the Director of OIEA. She also served as a senior attorney in the SEC's Division of Enforcement, investigating and prosecuting violators of the federal securities laws. Before that, she practiced law as an associate with Hogan Lovells in Washington, D.C. Ms. Walsh received her J.D. from N.Y.U. School of Law and her B.A., *magna cum laude*, from Amherst College. She is a member of the New York and District of Columbia bars.

Keynote Conversation: Expanding Capital Markets Access in Diverse Communities

Panelists

- **Moderator**
  - Ritta McLaughlin, Director, Investor Education Community Outreach, FINRA Investor Education Foundation
- **Panelists**
  - Camille Busette, Senior Fellow – Economic Studies, Governance Studies, Metropolitan Policy Program; Director – Race, Prosperity, and Inclusion Initiative, Brookings Institution and FINRA Board Member and FINRA Foundation Board Member
  - Noel Andrés Poyo, Deputy Assistant Secretary for Community Economic Development, Office of Domestic Finance, United States Department of the Treasury
  - Gerri Walsh, President, FINRA Investor Education Foundation and Senior Vice President, Investor Education, FINRA and FINRA Investor Education Foundation

Gaps and Consequences
Friday, October 22
11:00 a.m. – 12:15 p.m.

In this session, researchers discuss some of the most critical gaps and consequences of inclusion, or the lack thereof, in capital markets. Topics include racial and ethnic demographic trends for investors, entrepreneurship, fintech, use of alternative financial services and socialization.

Moderator:

Gary Mottola
Director of Research
FINRA Investor Education Foundation

Panelists:

Chris Brummer
Agnes N. Williams Research Professor; Faculty Director, Institute of International Economic Law; Professor of Law
Georgetown Law

Kyoung Tae (KT) Kim
Associate Professor and Graduate Program Coordinator
University of Alabama

Kyung Min Lee
Affiliated Faculty at the Schar School of Policy and Government Global Practice
George Mason University

Olivia Valdes
Associate Principal Research Analyst
FINRA Investor Education Foundation

Kenneth White
Assistant Professor Department of Financial Planning, Housing and Consumer Economics
University of Georgia

Gaps and Consequences Panelist Bios:

Moderator:

Gary R. Mottola is the research director for the FINRA Investor Education Foundation and a social psychologist with more than 25 years of research experience. In his role at the FINRA Foundation, he oversees and conducts research projects aimed at better understanding financial capability in America, protecting investors from financial fraud, and improving financial disclosure statements. Dr. Mottola received his B.A. from the University at Albany, M.A. from Brooklyn College, and Ph.D. from the University of Delaware. He was a visiting scholar at Wharton in 2006 and is an adjunct professor of statistics in Villanova University's MBA program.

Panelists:

Chris Brummer is a Georgetown law professor and author. He also lectures widely on financial inclusion and equity, financial regulation and global governance. His views regularly inform a wide array of conversations, from diversity in regulatory agencies and corporate boards to cutting edge issues in financial technology and international regulatory and monetary diplomacy. His work has been featured in *The New York Times*, *CNN*, *Marketwatch*, *Fast Company*, *The Wall Street Journal*, *Bloomberg*, *Yahoo Money*, *Roll Call*, *Cointelegraph*, and *Coin Desk*, among others. Mr. Brummer started his career at Cravath Swaine and Moore LLP, and now serves as the Faculty Director of the Institute of International Economic Law. For more than a decade, he has lent his expertise to industry leaders, nonprofits and policymakers, and offered his insights as to how firms and governments can best understand and react to new developments and challenges in the financial system. Aside from working as a professor, he also served as both a member of the Commodity Futures Trading Commission's Subcommittee on Virtual Currencies and the Consultative Working Group for the European Securities and Markets Authority's Financial Innovation Standing Committee. Mr. Brummer also concluded a three-year term as a member of the National Adjudicatory Council of FINRA. Mr. Brummer served most recently as a member of the Biden-Harris Transition team, assisting in leading work streams relating to financial technology, racial equity and systemic risk for the Treasury ART.

Dr. KT Kim is an Associate Professor and Graduate Program Coordinator in the Department of Consumer Sciences at University of Alabama where he teaches in the CFP Board registered undergraduate and master programs. He is currently also a Director of Family Financial Planning and Counseling Graduate Program. Dr. Kim enjoys doing applied research related to various household financial decisions throughout the life course and the effect financial literacy and financial education on household decisions. Dr. Kim has published over 50 peer reviewed research articles that are currently published or in press including *Applied Economics Letters, Economics Letters, Economic Modelling, Financial Research Letters, International Journal of Consumer Studies, Journal of Consumer Affairs, Journal of Economic Psychology, Journal of Family and Economic Issues, Journal of Financial Counseling and Planning, Journal of Financial Research, Journal of Poverty,* and *Review of Quantitative Finance and Accounting*. Dr. Kim has been an associate editor for *Family and Consumer Sciences Research Journal* and a member of the editorial board for *Journal of Consumer Affairs*, *Journal of Financial Counseling and Planning* and *Journal of Financial Planning.*

Kyung Min Lee is an economist (JPO) at Finance, Competitiveness, and Innovation Global Practice of the World Bank Group. He is also an affiliated faculty at the Schar School of Policy and Government at George Mason University. His research area is applied microeconomics, labor economics, health economics, and entrepreneurship. For his research, he analyzes large individual- or firm-level surveys and administrative databases. He also conducts firm-level surveys for cross-country studies. His work has appeared in peer-reviewed journals such as *Industrial and Corporate Change*, *Journal of Pension Economics and Finance*, *International Journal of Health Economics and Management*, and *American Journal of Preventive Medicine*. He holds a Ph.D. in Public Policy from George Mason University. Dr. Lee received the Kauffman Dissertation Fellowship from the Ewing Marion Kauffman Foundation in 2018. He was also awarded the Joseph L. Fisher Public Policy Doctoral Student Award from the Schar School at George Mason University in 2019.

Olivia M. Valdes, Ph.D. is an associate principal research analyst for the FINRA Investor Education Foundation. Her role includes leading and conducting research projects that pertain to the promotion and understanding of financial capability in America, the protection of consumers against financial fraud and exploitation, and the improvement of financial disclosure statements. Dr. Valdes obtained her B.A from University of South Florida and her Ph.D. in Experimental Psychology from Florida Atlantic University.

Kenneth J. White Jr. earned his Ph.D. in Consumer Sciences with a focus on Family Resource Management from The Ohio State University (in August 2016) and joined the faculty at the University of Georgia as an Assistant Professor in the Department of Financial Planning, Housing and Consumer Economics. Dr. White's research interests involve financial literacy, education, socialization, and wellbeing of historically marginalized populations. His work can be seen in core financial planning journals such as *Journal of Financial Planning, Journal of Financial Therapy, Journal of Family and Economic Issues, Family and Consumer Sciences Research Journal,* and *Financial Services Review*. He has also published work in international journals such as, *Contemporary Family Therapy* and *Sport, Business, and Management*. Dr. White regularly collaborates across disciplines, with colleagues at universities and colleges nationwide, and often conducts research with current and former graduate and undergraduate students. Dr. White teaches undergraduate and graduate students in UGA's CFP® Board Registered Programs. His primary areas of instruction are retirement planning and income tax planning.

Gaps and Consequences

Panelists

- **Moderator**
  - Gary Mottola, Director of Research, FINRA Investor Education Foundation
- **Panelists**
  - Chris Brummer, Agnes N. Williams Research Professor; Faculty Director, Institute of International Economic Law; Professor of Law, Georgetown Law
  - Kyoung Tae (KT) Kim, Associate Professor and Graduate Program Coordinator, University of Alabama
  - Kyung Min Lee, Affiliated Faculty at the Schar School of Policy and Government Global Practice, George Mason University
  - Olivia Valdes, Associate Principal Research Analyst, FINRA Investor Education Foundation
  - Kenneth White, Assistant Professor Department of Financial Planning, Housing and Consumer Economics, University of Georgia

Gauging the Participation of Diverse Communities in the Capital Markets

2021 ACCESS & IMPACT CONFERENCE

FINRA Investor Education FOUNDATION | FINRA | NORC

Bridging the Divide

The Racial and Ethnic Composition of Investor Households

Olivia Valdes, FINRA Investor Education Foundation

Methods

- 2018 NFCS Data
- N = 25,197
- Likelihood of owning non-retirement investments
  - By Race/Ethnicity
  - When factoring out other sociodemographic factors
  - Looking at combined roles of gender & race/ethnicity

Findings

Likelihood of Owning Investment Account

(Before and after adding controls)

	Before	After
African American	26%	34%
Hispanic/Latino	23%	31%
White	35%	33%

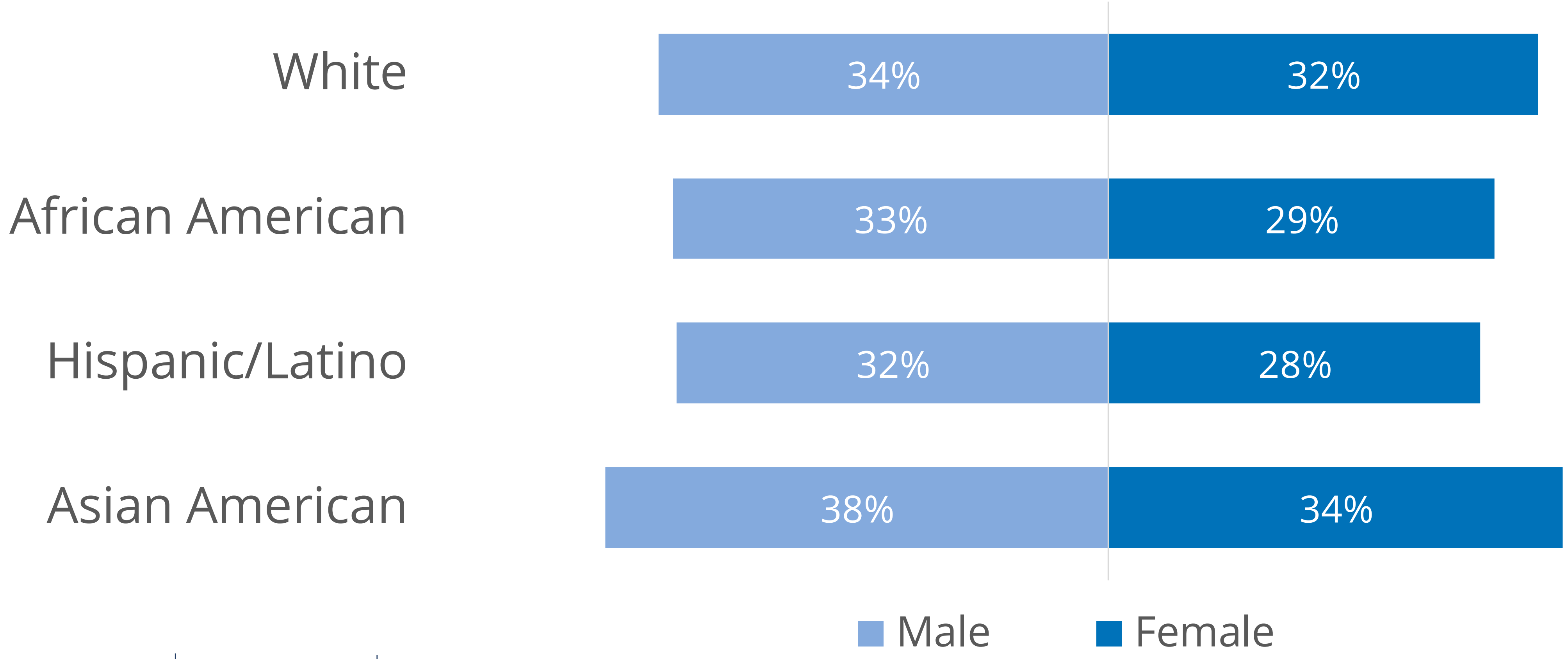
When hypothetically 'equaling the playing field', the gaps between people of color and white adults substantially close

Factors Tied to Owning Non-Retirement Investments

- Emergency Savings
- Income
- Risk Tolerance
- Financial Literacy
- Owning Home
- College Degree
- Age
- Marital Status
- Gender
- Employment Status

Findings

Even after factoring out sociodemographic factors, large disparities remained for **women of color**



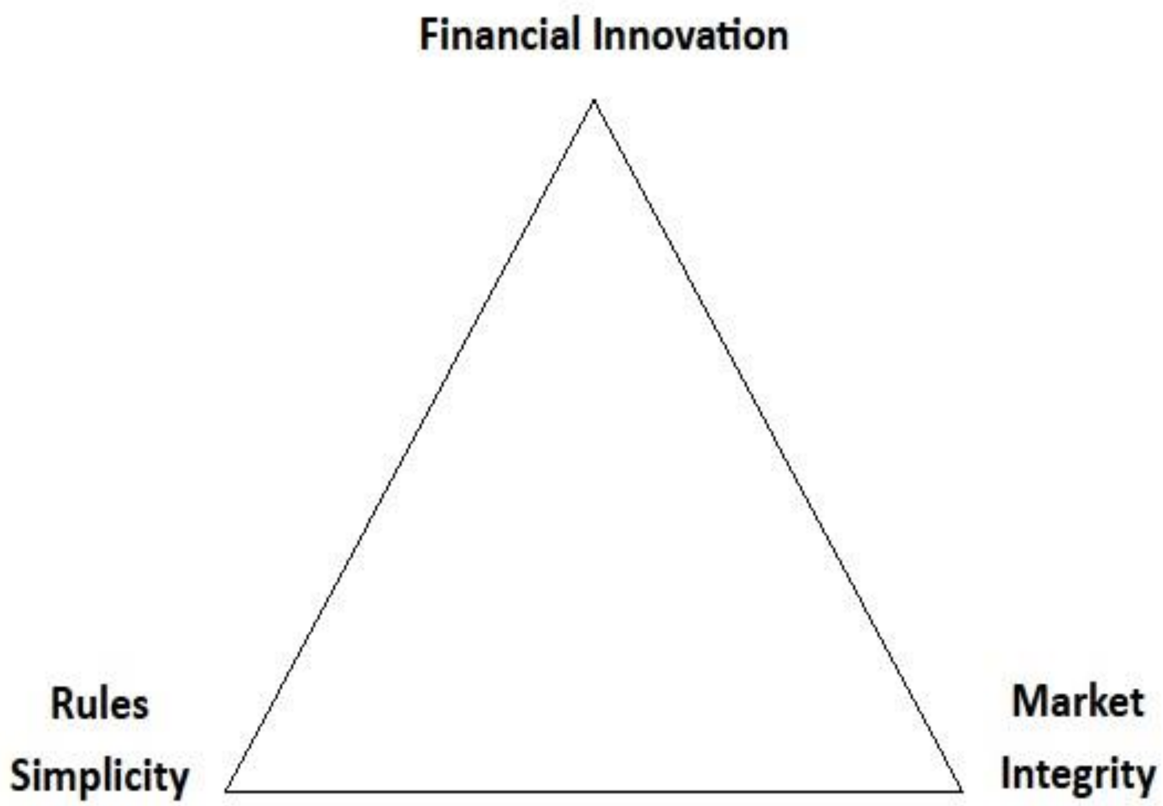
Implications

- Hispanic/Latino and African American adults remain underrepresented in investor ranks
- Sociodemographic differences, largely stemming from systemic racism, may explain some discrepancies
- Women of color at greater disadvantage, even when factoring out sociodemographic factors
- Increased access to financial products and quality education may help bridge divide and aid new investors

Fintech and the Innovation Trilemma

Chris Brummer, Georgetown Law

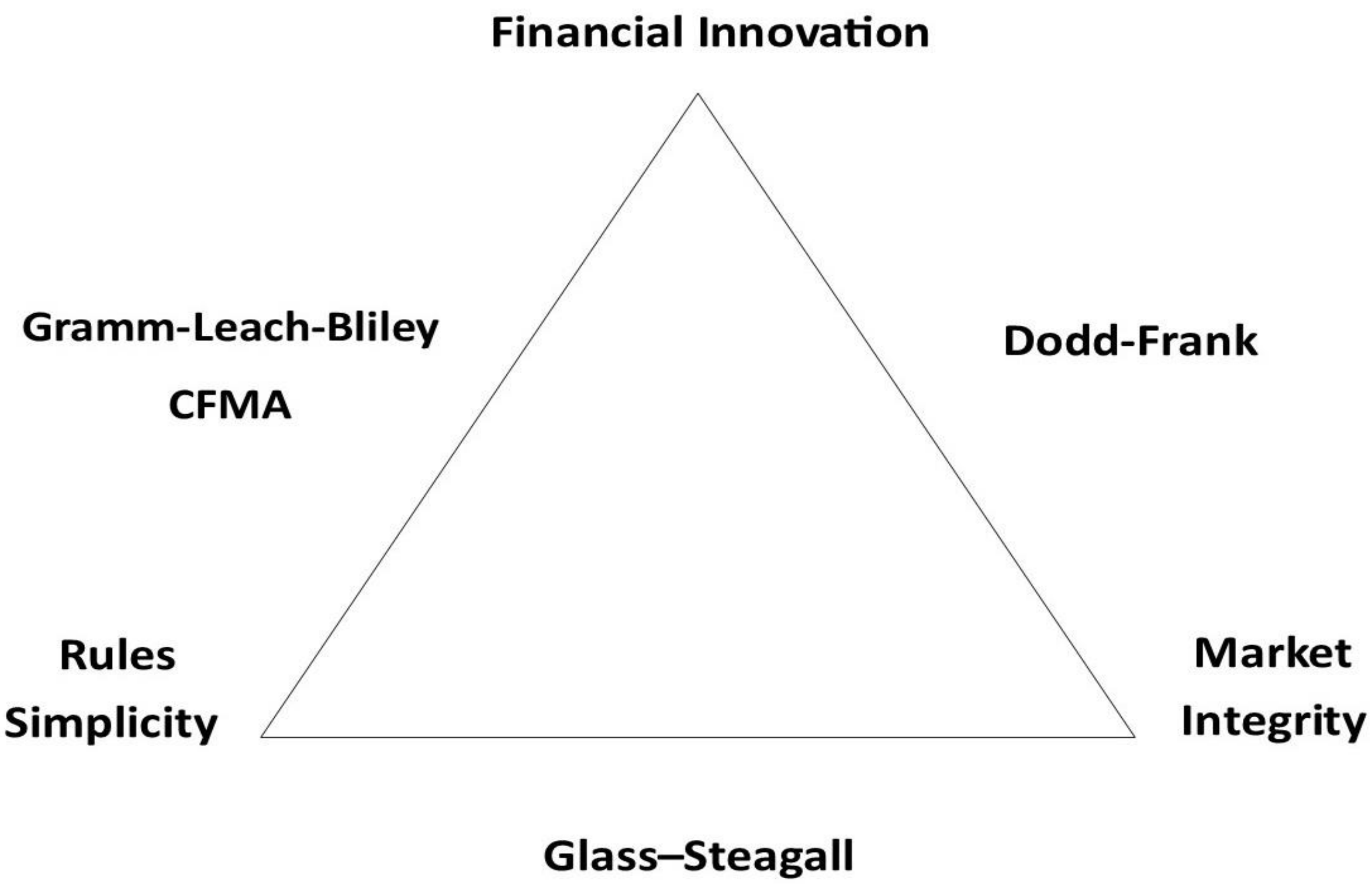
The Theory
(As in Life, Rules are about Choices)



The Theory (Cont'd)

- When regulators prioritize market integrity and clear rulemaking, they must do so through broad prohibitions, likely inhibiting financial innovation
- Alternatively, if regulators wish to encourage innovation and provide rules clarity, they must do so in ways that provide simple, low intensity regulatory frameworks. This increases risks to market integrity
- Finally, if regulators look to promote innovation and market integrity, they will have to do so through a complex matrix of rules and exemptions, heightening the difficulties of compliance, international coordination and enforcement

Historical Examples (USA)



Fintech Exacerbates the Trilemma
(This Time, It Is Different)

- Big Data
- Automation
- Decomposition of component parts of in the provision of financial services
- Gatekeeper Disintermediation
- Gamification

Inequality Exacerbates Tradeoffs Too (A new trilemma?)

- Maximize Opportunity
- Minimize risk
- Avoid exacerbating wealth inequality

Black Entrepreneurs, Job Creation, and Financial Constraints

Mee Jung Kim, Kyung Min Lee, David Brown, John S. Earle

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and not those of the National Science Foundation, Small Business Administration, U.S. Census Bureau, or World Bank. All results have been reviewed to ensure that no confidential information is disclosed. Disclosure Review Board bypass numbers: CBDRB-FY20-CES009-001 and CBDRB-FY20-CES009-002.

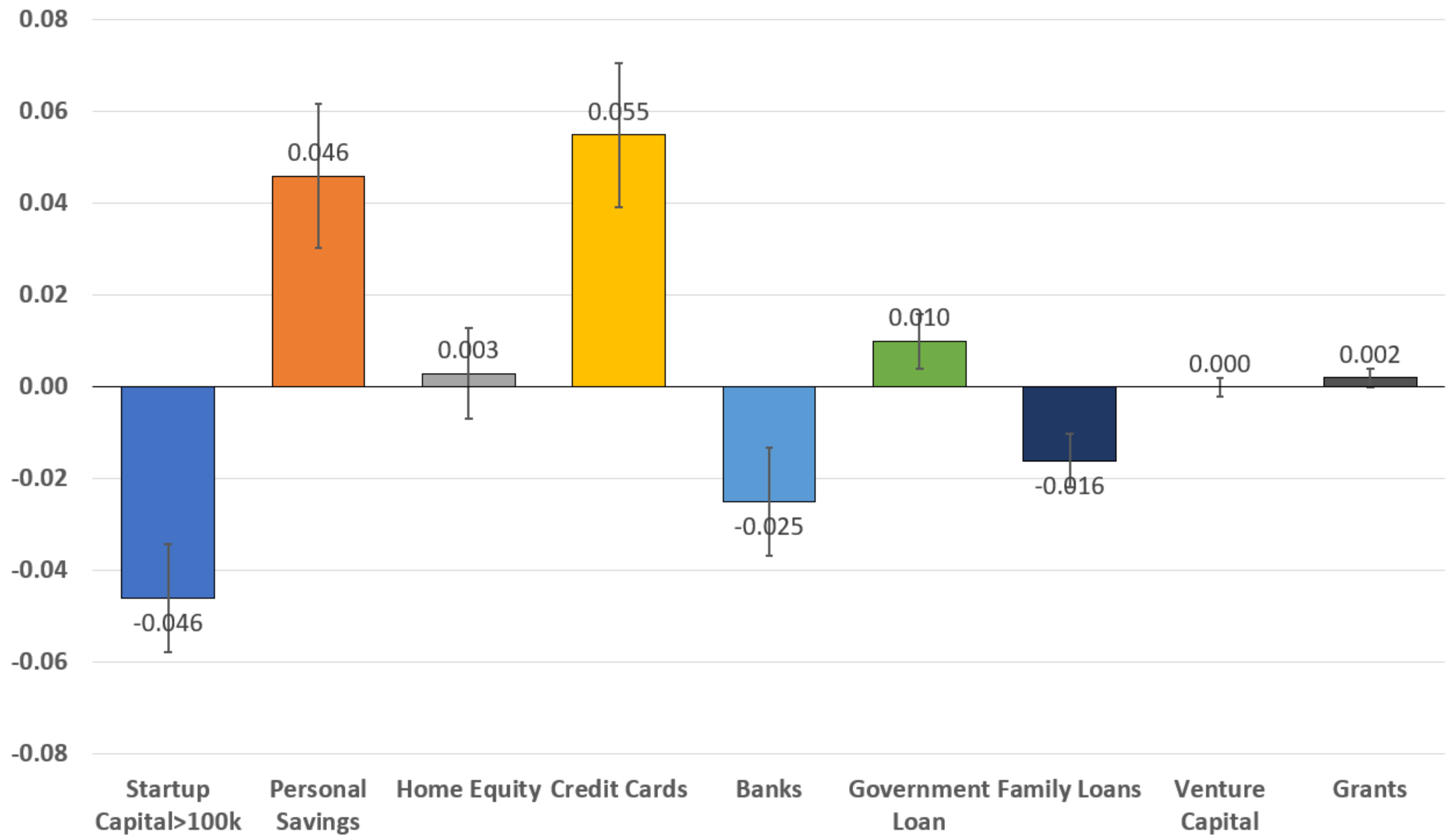
Research Motivation and Question

- **Black-owned firms have fewer employees**
  - Results in lower Black employment, incomes
  - Less wealth accumulation by Black entrepreneurs
- **Is lack of financial access the cause?**
  - Other possibility: different demand for capital
  - Characteristics and motivations of entrepreneurs by race
- **Does the Community Reinvestment Act (CRA) help?**
  - Change in CRA eligibility in 2012
  - Do Black-owned firms benefit more?

Methodology

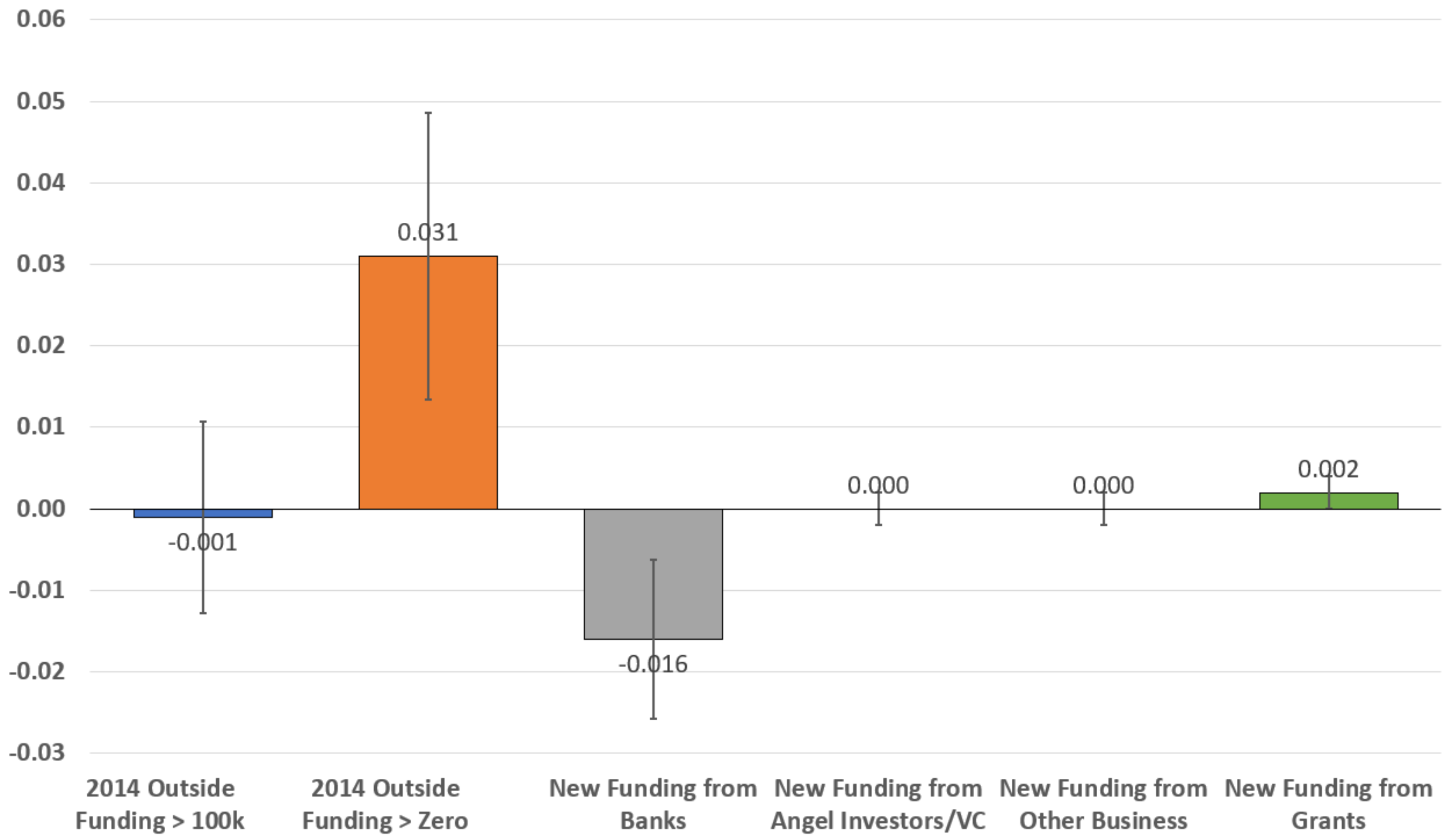
- Data: firm-level from Census Bureau
  - Annual Survey of Entrepreneurs (ASE)
  - Survey of Business Owners (SBO)
  - Longitudinal Business Database (LBD)
- Analysis: comparing Black- and White-Owned Firms
  - Regression
    - characteristics of entrepreneurs
    - use of finance
    - number of employees
  - Regression Discontinuity in Panel Regression Framework
    - effect of CRA on employment

Findings: Racial Gap in Start-up Finance



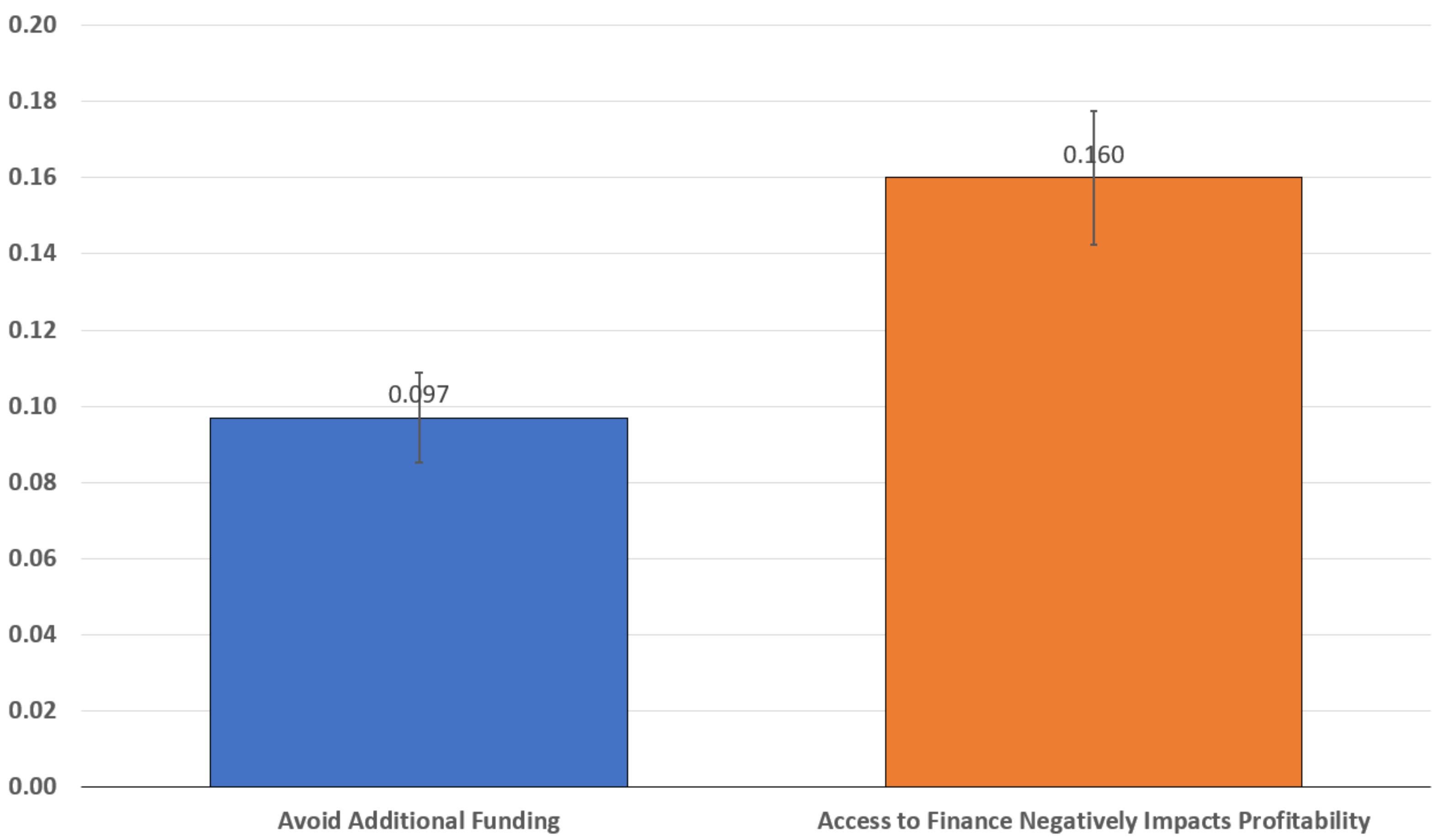
Disclosure Review Board bypass numbers: CBDRB-FY20-CES009-001 and CBDRB-FY20-CES009-002

Findings: Racial Gap in 2014 Finance



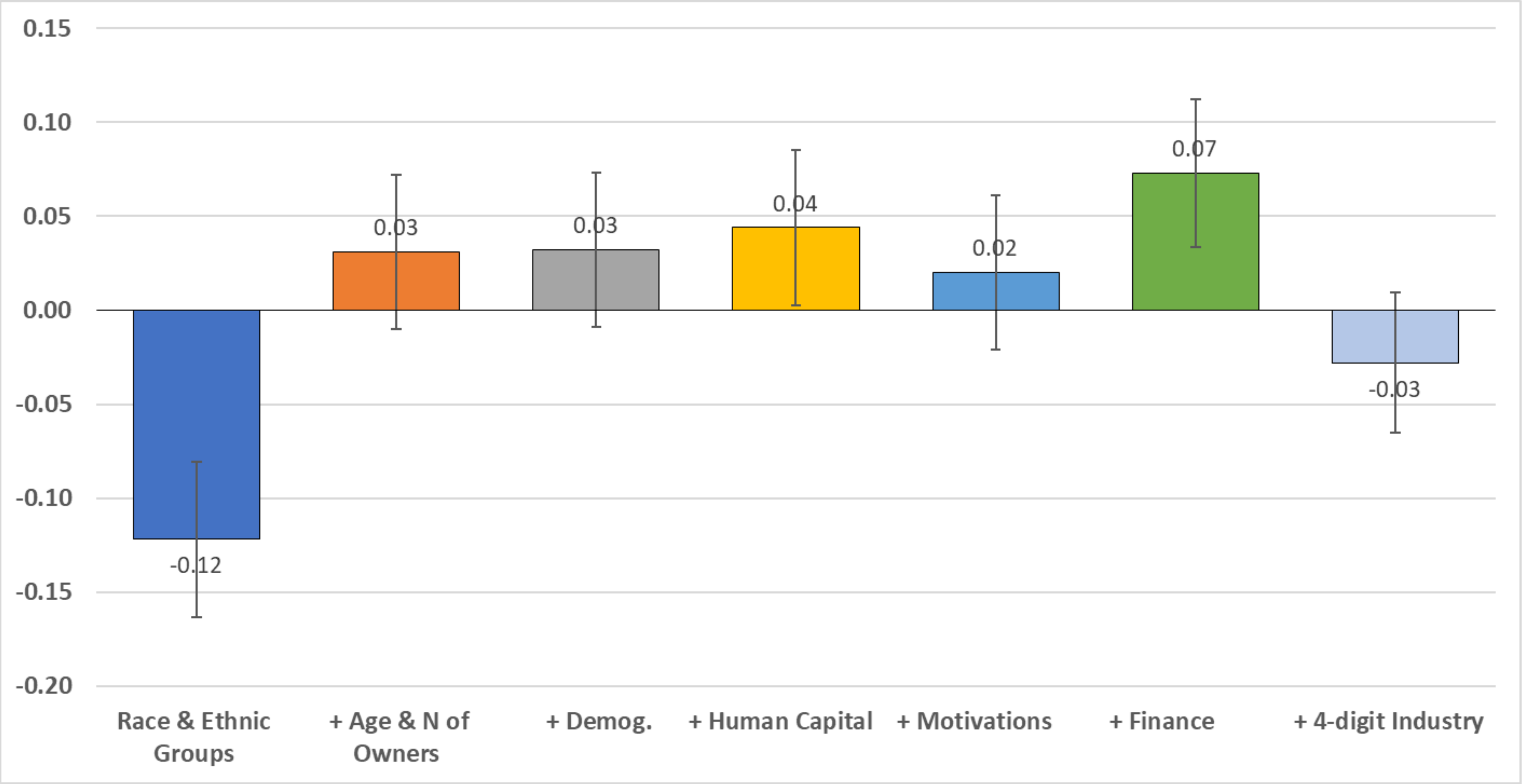
Disclosure Review Board bypass numbers: CBDRB-FY20-CES009-001 and CBDRB-FY20-CES009-002

Findings: Racial Gap in Financial Constraints



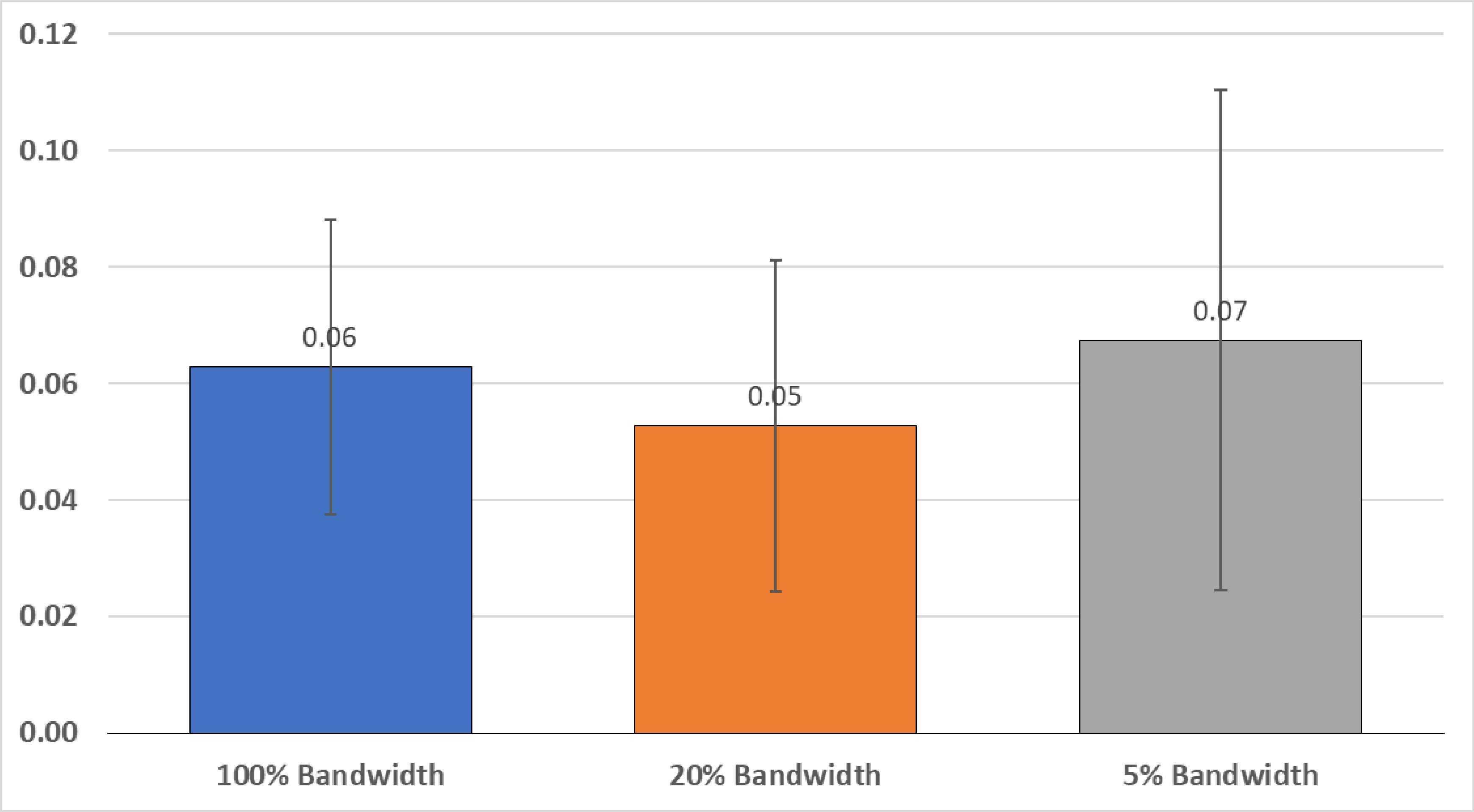
Disclosure Review Board bypass numbers: CBDRB-FY20-CES009-001 and CBDRB-FY20-CES009-002

Findings: Racial Gap in Employment



Disclosure Review Board bypass numbers: CBDRB-FY20-CES009-001 and CBDRB-FY20-CES009-002

Findings: Effects of CRA on Employment



Disclosure Review Board bypass numbers: CBDRB-FY20-CES009-001 and CBDRB-FY20-CES009-002

Main Takeaways

- Black entrepreneurs use less finance (especially bank credit) and have fewer employees
- But they have characteristics (graduate education, motivations, aspirations, hours of work) associated with stronger demand for finance
- Controlling for measured finance raises the relative size of Black-owned firms
- CRA raises employment 5-7% more at Black-owned firms
- Consistent with discrimination or worse asymmetric information problems faced by Black entrepreneurs

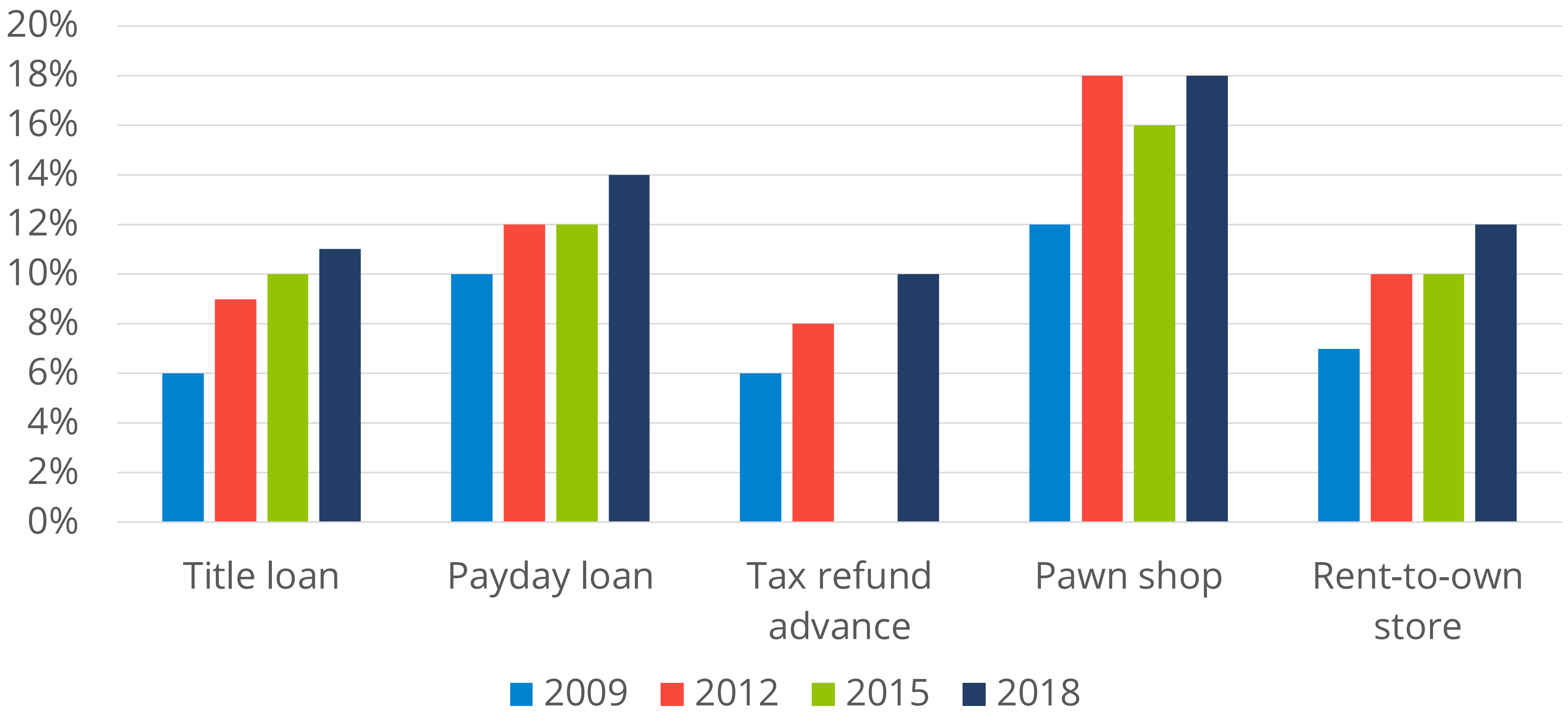
Implications

- Research estimates the causal effect of tougher financial constraints (faced by Blacks) on firm employment
- CRA, although a weak policy, helps relax constraints for Blacks
- Should CRA be strengthened?

Decomposition of Racial/Ethnic Differences in the Alternative Financial Services Market Participation

Kyoung Tae (KT) Kim, University of Alabama

Time Trends in AFS Usage, 2009-2018 NFCS



Purpose of this Study

- This study investigated racial/ethnic disparities in the Alternative Financial Services Usage and its contributing factors where such gap stems.
- Using a decomposition analysis, we identified the relative contribution of various factors attributable to the racial/ethnic gaps.
- This study focused on the role of financial literacy measured in two forms: objective and subjective literacy to explain the racial/ethnic disparities.

Methodology

- Data
- ✓ 2018 National Financial Capability Study (NFCS) dataset
- ✓ Analytic sample: 22,968 respondents

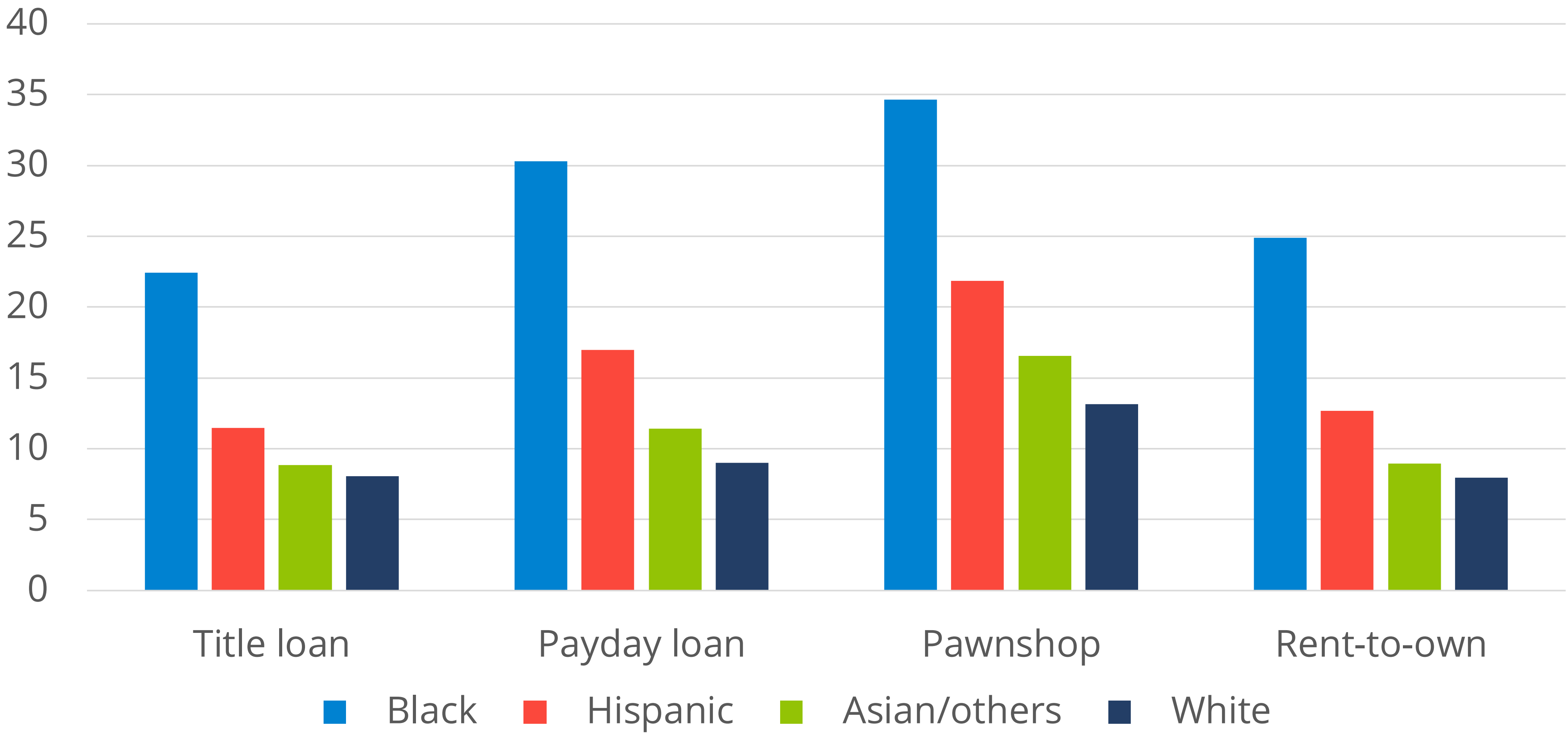
- Dependent variables
- ✓ Alternative financial services usage
- ✓ (a) Auto title, (b) payday loans, (c) pawnshops, and (d) RTO stores.

Methodology (Cont.)

- Independent variable
  - ✓ Race/ethnicity: whites, blacks, Hispanics, and Asians/others
  - ✓ Financial literacy: objective and subjective literacy
  - ✓ Various control variables

- Empirical Analysis
  - ✓ Logistic Regression Model
  - ✓ Decomposition Analysis: Fairlie decomposition technique

AFS Usage Across Race/Ethnicity, 2018 NFCS



Multivariate Results from Logistic Regression Models

- Blacks were more likely to use title loan, payday loans, pawnshops, and RTO than were whites.
- Hispanics and Asian/others were less likely to use title loans, but Hispanics were more likely to use payday loans compared to whites.
- Objective financial literacy was negatively related while subjective financial literacy was positively associated with the likelihood of AFS use across four different types consistently.

Results from Decomposition Analyses

- Both objective and subjective financial literacy are contributing factors to explain the racial/ethnic gaps in AFS use, but patterns are different across three pair-wise comparisons.
- Among various sociodemographic factors, transitory income shock, age, risk tolerance, and having a dependent child were identified as strong factors attributable to the racial/ethnic gaps.

Implications

- Educators should note differences in the use of AFS among racial/ethnic groups and related factors when designing and implementing education programs.

- Even though there have been high rate of formal financial market participation, e.g., banking system, AFS market fills a supplementary niche in the consumer financial marketplace, especially for minority groups.

- Policymakers and formal financial institutions need to monitor the use of AFS and develop policy to help financially vulnerable groups.

Implications (Cont.)

- Given the significant role of financial literacy to explain the racial/ethnic gaps in AFS use, fostering collaborative efforts between social service organizations and financial educators are needed.

- This could assist minority groups to improve their level of financial literacy, leading to discouraging AFS market participation in the future.

- Future research will revisit and extend the current study focusing on "During the COVID-19 pandemic" using the 2021 NFCS dataset once available.

How Financial Socialization Messages Relate to Financial Management, Optimism and Stress

Variations by Race

Kenneth White, Kimberly Watkins, Megan McCoy, Bertranna Muruthi & Jamie Lynn Byram

Methodology

- **2014 Study on Collegiate Financial Wellness, collected at The Ohio State University.**

- **Data were analyzed in two parts:**
  1) We tested how the three types of parental financial messages (messaging about savings, banking, and investing) varied by race.
  2) We tested how the association of these three messages with three financial outcomes (financial management, financial stress, and financial optimism) varied by race.

Main Takeaways

- African American students received the least saving and banking messages compared to other racial/ethnic groups. Hispanic students reported receiving the investing message the least of all groups

- Students who received the message to invest demonstrated higher average financial management, lower average financial stress, and higher average financial optimism.

- African American students that received the message to invest their money had a greater average increase in their financial management scores than both Asian students and Other students that were encouraged to invest their money.

Implications

- Legislators could support the efforts of personal finance professionals by passing legislation that would increase funding for financial education interventions for parents and children.

- Financial professionals and educators can engage parents on how to have conversations with their children to decrease racial and ethnic disparities in the type of messaging being discussed in the home.

- Realize that teaching children *investing* concepts involving more comprehensive lessons with discussions on risk, time value of money, and financial goal setting may have a positive spillover effect on other financial behaviors.

FINRA Investor Education FOUNDATION

Insights: Financial Capability

October 2021

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FINRA Investor Education Foundation
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What's Inside

Stata code used for analyses conducted for this issue brief is available for download at FINRAFoundation.org. The data can be found at USFinancialCapability.org.

Regression output can be obtained by contacting the authors

Bridging the Divide: A Closer Look at Changes in the Racial and Ethnic Composition of Investor Households

Background and Objective

In the year following the death of George Floyd and others, a social reckoning in the United States has unfolded, prompting large-scale efforts to advance racial equity and inclusiveness across the country. Historically, people of color have been under-represented in the investor ranks. Increasing representation of these groups may serve as an avenue to narrow a significant racial and ethnic wealth gap, enabling people of color to benefit from market returns. This study leverages a rich data source to examine the racial and ethnic composition of investors across a six-year period and explores the socio-demographic and psychographic characteristics that are tied to investment account ownership. The insights from this study can inform initiatives aimed at encouraging market participation.

Summary

Nearly two-thirds of American households have some form of investment, typically through taxable accounts[1], IRAs or employer-sponsored retirement funds.[2] Although a sizeable number of households report owning investment accounts, people of color, particularly those who identify as African American or Hispanic/Latino, are underrepresented as investment account holders. While African American and Hispanic/Latino adults make up 12 and 16 percent of the U.S. adult population, respectively, they comprise only 10 and 11 percent of households with taxable investment accounts.

Using data from three waves of the FINRA Foundation's National Financial Capability Study, we examined investment account ownership over a six-year period across households of differing racial and ethnic backgrounds.[3] Our findings confirmed the presence of a persistent investment racial and ethnic divide: African American and Hispanic/Latino respondents were largely

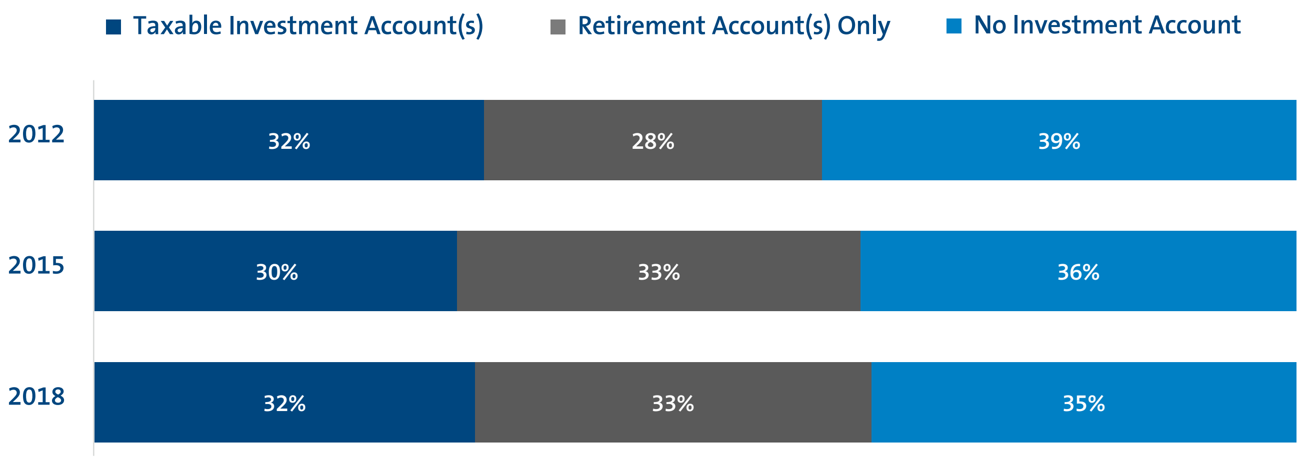
underrepresented as taxable investors and overrepresented in households without any investment accounts. That is, few had investments outside of a retirement account and many had no investment accounts whatsoever. However, after controlling for sociodemographic variables, the gap in the likelihood of owning a taxable investment account between white and African American and Hispanic/Latino adults closed substantially, particularly in 2018. For Asian American adults, we saw a somewhat different pattern in that the rate of taxable account ownership surpassed that of white Americans. However, upon controlling for sociodemographic variables, the differences between the two race/ethnicities were minimized, though the likelihood of owning a taxable investment account remained higher for Asian American adults than for their white counterparts.

One encouraging trend was that the proportion of those owning a taxable investment account increased by 18 percent for African Americans over the six-year period. However, gender differences, particularly among respondents of color, were more troubling, even when controlling for demographic differences. While the gap between white women and white men was relatively minor, with white women 6 percent less likely to own a taxable account than white men, across the six-year period, African American women and Hispanic/Latina women were 14 percent less likely than their male counterparts to own a taxable investment account. Similar gender gaps were identified among Asian American respondents.

Investment Account Ownership (of Any Kind)

The proportion of all households reporting owning or not owning investment accounts remained largely stable throughout the six-year span (*see* Figure 1). A substantial portion of households reported owning no investment accounts of any kind, although the overall proportion declined over time. In 2012, 39 percent reported no investment accounts, falling to 36 percent in 2015 and ultimately 35 percent in 2018. By contrast, 28 percent of households reported owning only retirement accounts in 2012. The proportion rose to 33 percent in 2015, remaining stable in 2018. Given that many are automatically enrolled in retirement accounts through an employer, the relative stability in retirement account ownership is not surprising. The proportion of households reporting taxable investment accounts remained relatively flat across the six-year period (note that the vast majority of households owning taxable investment accounts also owned retirement accounts). In 2012, 32 percent of respondents reported having a taxable account, 30 percent in 2015 and 32 percent in 2018.

Figure 1. Households by Investor Status, 2012 to 2018

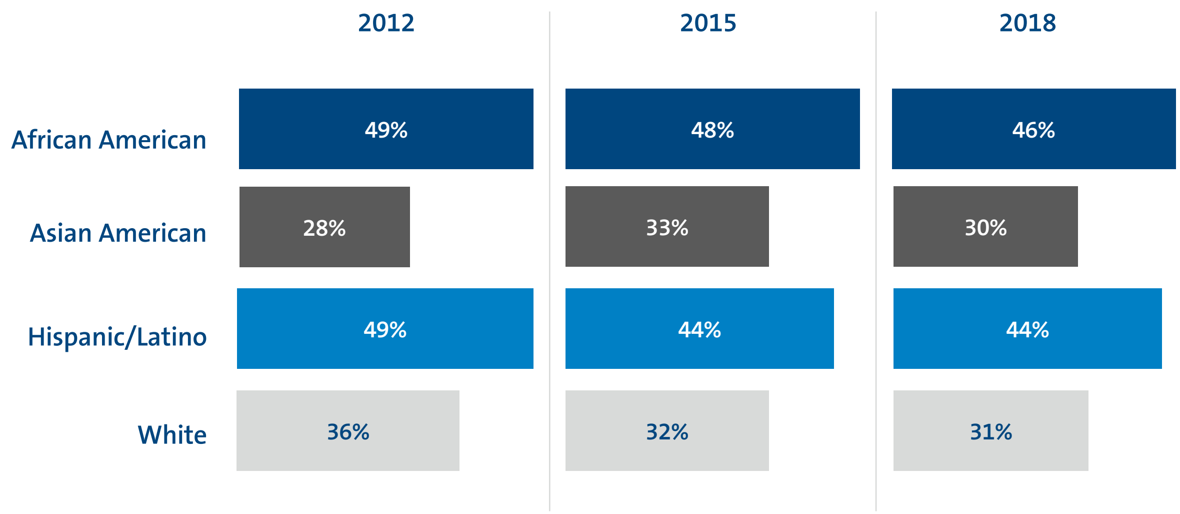


A Look at Account Ownership Across Different Races and Ethnicities

Households Owning No Taxable or Retirement Investment Accounts

Nearly half of African American and Hispanic/Latino respondents reported having neither a taxable investment account nor a retirement account (Figure 2). However, encouragingly for these groups, from 2012 to 2018, the portion of African Americans reporting no investment accounts fell from 49 to 46 percent. Among Hispanics/Latinos, this number fell from 49 to 44 percent. The share of white respondents who reported not having an investment account was 36 percent in 2012 and fell to 31 percent in 2018. For white respondents, changes over time were particularly encouraging; the proportion of those reporting no investment accounts fell by 14 percent from 2012 to 2018. Fewer than a third of Asian American respondents (28 percent) reported lacking any investment account in 2012. However, this proportion increased to 30 percent by 2018.

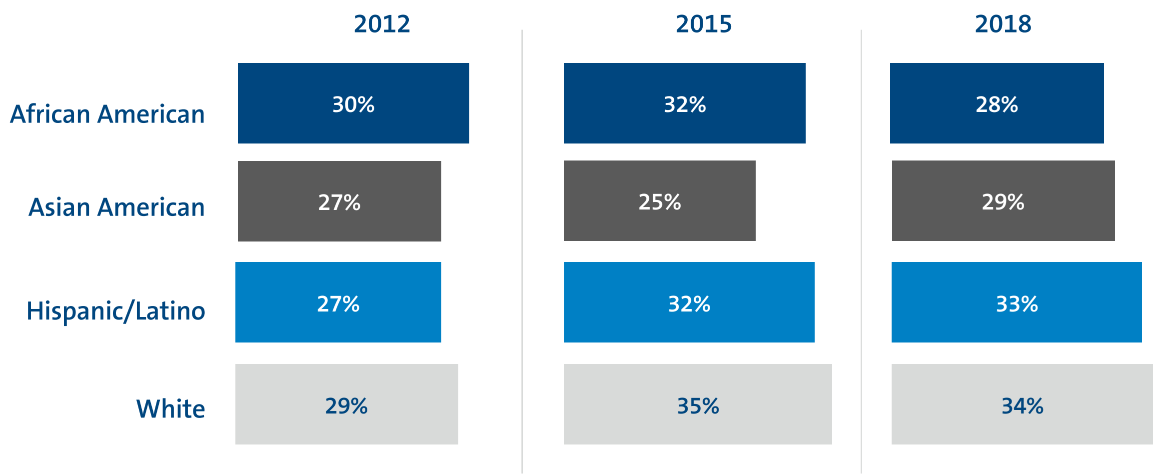
Figure 2. Proportion of Respondents Owning No Taxable or Retirement Investment Accounts, By Race and Ethnicity



Households Owning Only Retirement Investment Accounts

Across the different races and ethnicities studied, about 3 in 10 respondents reported owning only retirement accounts (Figure 3). While the proportion fell slightly for African Americans, from 30 to 28 percent from 2012 to 2018, it rose steadily for Hispanics/Latinos (27 to 33 percent). For Asian American respondents, the share that reported owning only retirement accounts rose from 27 percent to 29 percent across the six-year period. For white respondents, it increased from 29 percent to 34 percent. Increases in retirement account ownership were greatest for white and Hispanic/Latino respondents; the proportion of white and Hispanic/Latino who owned a retirement account increased by 17 and 22 percent, respectively.

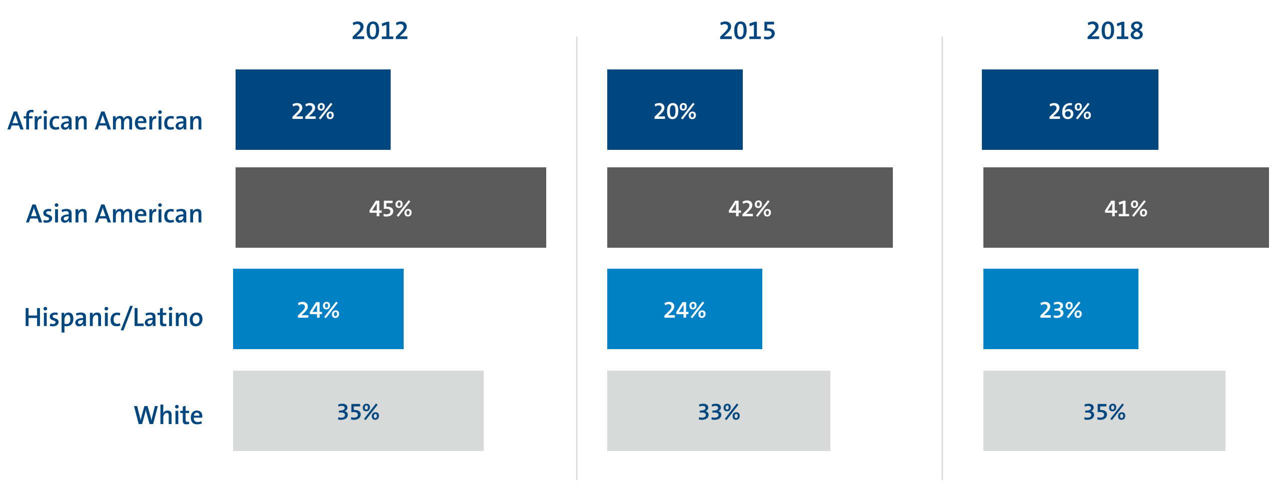
Figure 3. Proportion of Respondents Owning Only Retirement Account(s), By Race and Ethnicity



Households Owning Taxable Investment Accounts

Among African American respondents, 22 percent reported having a taxable investment account in 2012 (Figure 4). The number rose to 26 percent in 2018. Of all Hispanic/Latino respondents, 24 percent reported having a taxable investment account in 2012. The proportion remained steady through the years, falling only slightly to 23 percent in 2018. Thirty-five percent of white respondents reported having a taxable investment account in 2012. The number was relatively stable, falling to 33 percent in 2015 and rising back to 35 percent in 2018. Asian American adults had the highest proportion of taxable investment account owners. Forty-five percent of Asian Americans reported owning a taxable investment account in 2012. While this number fell to 41 percent by 2018, this proportion was substantially higher than that of other races and ethnicities examined.

Figure 4. Proportion of Respondents Owning Taxable Investment Account(s), by Race and Ethnicity



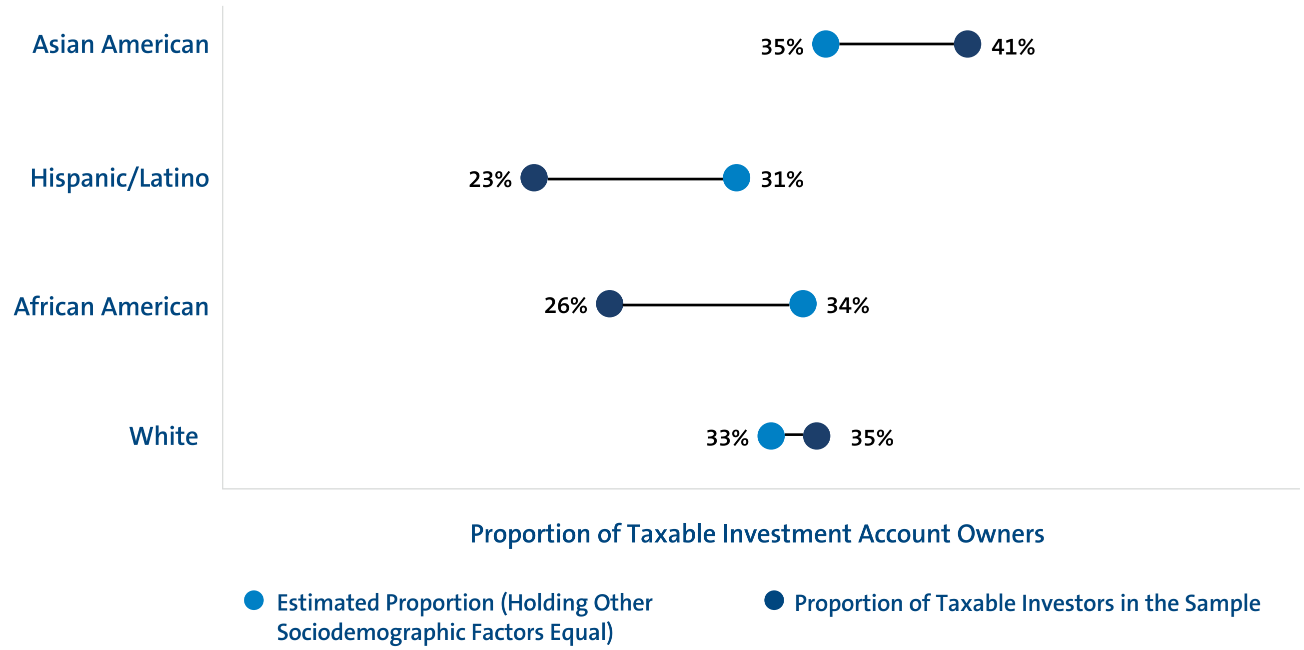
A Closer Look at Taxable Investment Account Holders: Is the Race/Ethnicity Gap Closing?

The racial/ethnic composition of investing households indicates sizeable gaps between some communities of color and white respondents throughout the six-year period studied. Focusing on those with taxable investment accounts, African American and Hispanic/Latino adults are underrepresented relative to white respondents, although for African American respondents, the gap seems to be closing.

Still, understanding the role that race and ethnicity play in the likelihood of owning a taxable investment requires consideration of other key factors. Many people of color face obstacles that can hinder their capacity to invest. For example, income, wealth and educational disparities, stemming largely from structural racism, create barriers unique to this population. By taking into account sociodemographic differences beyond race and ethnicity, we can better understand the unique role of race and ethnicity. We controlled for a series of sociodemographic factors, including age, income, educational level, employment status, marital status, the presence of dependents, as well as financial correlates of taxable account ownership, including emergency savings, home ownership status, financial knowledge and risk tolerance. Upon doing so, we found that gaps between white and non-white respondents' likelihood of owning a taxable investment accounts closed significantly.[4]

Figure 5 shows the proportion of taxable investment account owners across different races and ethnicities when other sociodemographic factors are and are not controlled for.

Figure 5. Observed and Estimated Proportion of 2018 Taxable Investment Account Owners



Results shown using **dark blue dots** reflect the observed proportion of white, African American, Hispanic/Latino and Asian American respondents in our sample who owned a taxable investment account in 2018. Large discrepancies were observed between white and non-white adults in 2018. Thirty-five percent of white respondents owned taxable investments, whereas this figure dropped to 26 percent for African Americans and 23 percent for Hispanics/Latinos. Forty-one percent of Asian Americans owned taxable investment accounts.

Results shown using **light blue dots** reflect what the estimated proportion of white, African American, Hispanic/Latino and Asian American respondents owning a taxable investment in 2018 would have been if other key sociodemographic factors were controlled for. These findings hold all other sociodemographic factors constant to examine the unique role of race and ethnicity. That is, they allow us to compare respondents of differing racial/ethnic background who are otherwise demographically identical, in terms of their gender, age, income level, employment status, education level, marital status, number of dependents, risk tolerance, home ownership status, availability of emergency savings and financial knowledge. In doing so, we can isolate and more accurately assess the unique association that exists between race/ethnicity and taxable investment account ownership. After accounting for important demographic factors, we estimate that, in 2018, 33 percent of white adults would have owned a taxable investment account. Similarly, we estimate 34 percent of African Americans and 31 percent of Hispanics/Latinos would have owned a taxable investment in 2018, whereas the proportion of Asian Americans owning a taxable investment account would have dropped to 35 percent. As observed by the light blue dots, after controlling for demographic factors other than race/ethnicity, the likelihood of owning a taxable investment is quite similar across the different groups examined.

Together, the findings indicate that many racial and ethnic differences may be driven largely by sociodemographic factors that impede people of color from owning taxable investments. Once these factors were controlled for, the impact of race and ethnicity was minimal. However, it is important to emphasize that while this analysis statistically controls for key demographic variables, thereby creating a “level playing field” for individuals of different races and ethnicities, the reality is that many people of color face hurdles and barriers that many white persons do not. Therefore, these results are hypothetical in nature. Overall, few changes were observed across the six-year period in the likelihood of owning taxable investment account. However, among African Americans there was a clear upwards trend; the likelihood of owning a taxable investment account increased over the six-year period examined even when other demographics were accounted for.

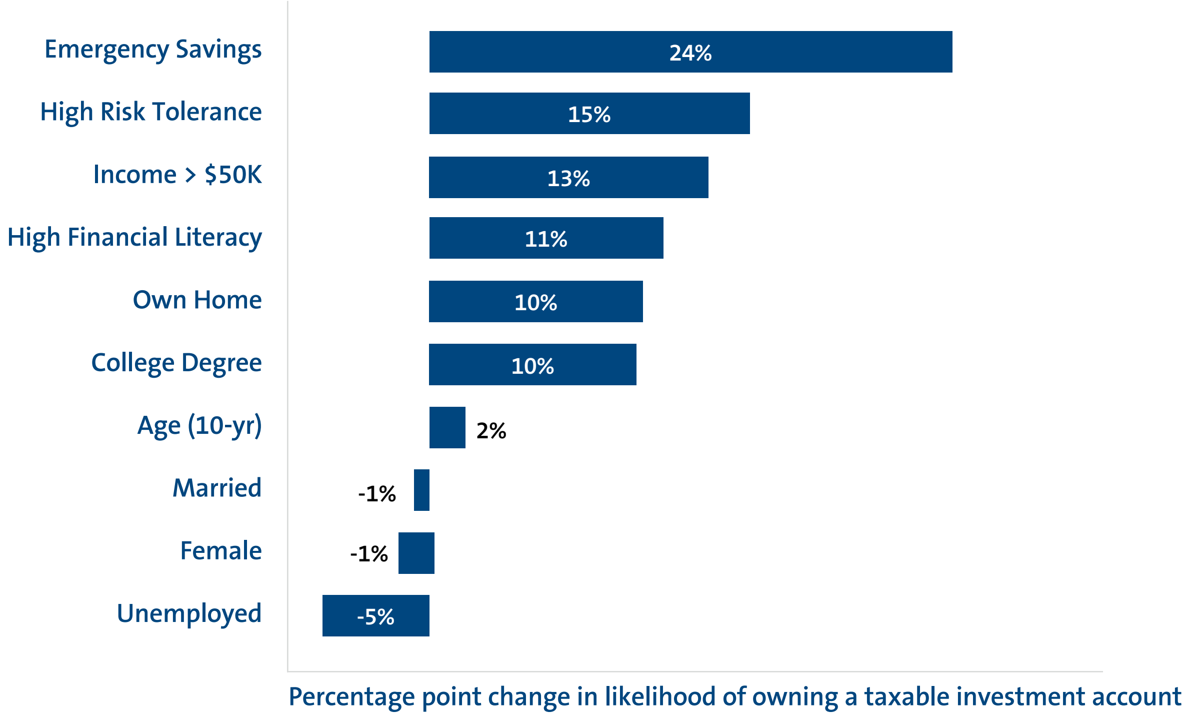
Other Factors Linked to Taxable Investment Account Ownership

In various instances, factors beyond race and ethnicity are much more highly related to taxable investment account ownership. Education level, income, age, marital status and employment status were each tied to the likelihood of owning a taxable investment account. After controlling for the sociodemographic variables noted above, those who had obtained at least a college degree were 10 percentage points more likely to have a taxable investment account than those who had not, while households with annual incomes surpassing $50,000 were 13 percentage points more likely to own a taxable account than those earning lower wages. Unemployed respondents were 5 percentage points less likely to own a taxable account. Age had a subtle, but noteworthy effect; the likelihood of having a taxable investment account increased by 2 percentage points with each 10-year increase in age (Figure 6).

Emergency savings, home ownership, financial risk tolerance and literacy were also tied to taxable investment account ownership. Respondents who had set aside rainy day funds were 24 percentage points more likely to own a taxable investment account than those who had not. Similarly, adults who owned their home were 10 percentage points more likely to have a taxable investment account than those who did not. Respondents willing to take high financial risks were 15 percentage points more likely compared to those who were unwilling to do so, while those with high financial literacy were 11 percentage points more likely than those with lower levels of literacy. It is important to note these findings rely on non-longitudinal data. That is, because we did not examine how the same respondents changed over time, we cannot conclude that these financial factors led to a higher likelihood of taxable investment account ownership or occured as the result of having a taxable investment account.

Finally, we found a very small gender effect. For women, the likelihood of owning a taxable investment account was 1 percentage point lower than that of men. However, the effect of gender differed markedly by race and ethnicity. The next section examines how the intersection of race/ethnicity and gender played a role in the likelihood of owning a taxable investment account.

Figure 6. Factors Related to Taxable Investment Account Ownership[8]

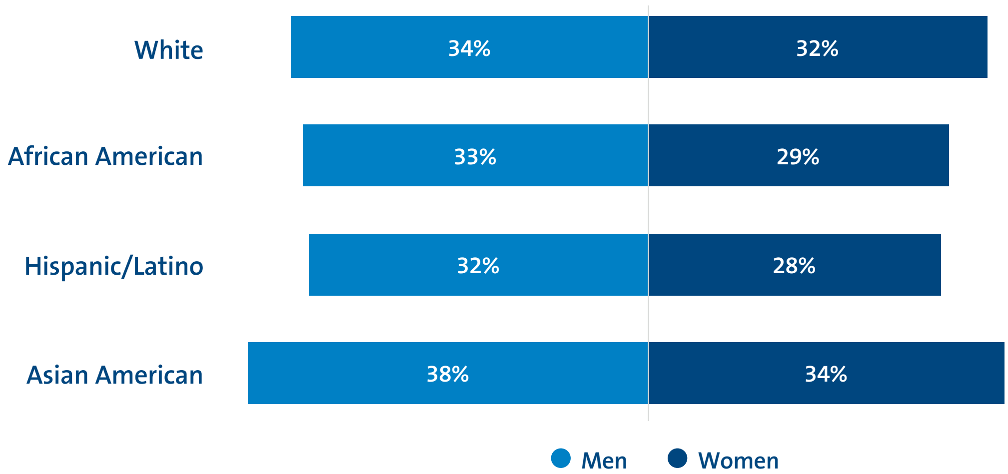


Note: While bars represent true values, numerical labels have been rounded.

The Intersection of Race/Ethnicity and Gender

Racial and ethnic gaps in the taxable investing world are insidious and even more pronounced when the intersection of race/ethnicity and gender is considered. Even after controlling for important sociodemographic factors, the likelihood of owning a taxable investment account is much lower for women of color than men of color (*see* Figure 7). From 2012 to 2018, we estimate the proportion of white men (34 percent) and white women (32 percent) owning a taxable investment account would have been somewhat similar, once other sociodemographic factors were accounted for. However, 33 percent of African American men would have owned a taxable investment account compared to only 29 percent of African American women; 32 percent of Hispanic/Latino men and 28 percent of Hispanic/Latina women, and 38 percent of Asian American men compared to 34 percent of Asian American women. That is, even after controlling for other sociodemographic factors relative to their male counterparts, African American women and Hispanic/Latina women were about 14 percent less likely to own a taxable investment account and Asian American women 12 percent less likely. When compared to white men, African American women were 15 percent less likely to own a taxable investment account and Hispanic/Latina women were 18 percent less likely.[5] These gaps may signal barriers for market participation that extend beyond those studied here. Among others, limited resources, a lack of accessibility to market processes, products and knowledge, as well as a diminished sense of identity as an investor threaten non-white women's ability to own a taxable investment account.[6]

Figure 7. Estimated Likelihood of Owning a Taxable Investment Account by Gender and Race/Ethnicity, Controlling for Other Sociodemographic Factors: An Average From 2012-2018.



Conclusion

We examined three segments of households, each comprising roughly a third of the population: households with taxable investment accounts; households whose only financial investments are in retirement accounts; and households without any investment accounts. Over the course of six years, from 2012 to 2018, the composition of these household segments remained relatively consistent. However, over time, some changes were observed. In particular, the proportion of households reporting that they did not have any investment accounts fell from 39 to 35 percent across the six-year period.

There was a large disparity between the investment account ownership of some communities of color and that of white adults. African Americans and Hispanic/Latino respondents were underrepresented among households with a taxable investment account and overrepresented among households without any type of investment account. Among African American and Hispanic/Latino respondents, nearly half reported not having a taxable investment account, while only about a quarter reported having taxable investment accounts. However, the proportion of African Americans owning taxable investment accounts increased from 22 to 26 percent from 2012 to 2018—a small but encouraging increase, particularly in the face of adversity encountered by this population segment. A study by the Federal Reserve Bank of St. Louis found a narrowing gap between African American and white families from 2016 to 2019 for overall wealth, as well. However, those findings also suggest a narrowing gap for Hispanic/Latino families relative to white Americans, a result that we did not observe in our analyses of investment account ownership.[7] Our study also found that the proportion of Asian American investors owning a taxable investment was much higher than that of any other race/ethnicity. Over two-fifths reported owning a taxable investment account, well higher than the proportion reported by white respondents.

One of our study's more revealing findings was the critical role of sociodemographic factors, beyond race and ethnicity, in the likelihood of owning a taxable investment account. Once other factors are accounted for, gaps between the different races and ethnicities closed dramatically. The estimated proportion of adults owning a taxable investment account for African American adults (34 percent) became virtually identical to that of white Americans (33 percent). Hispanic/Latino adults lagged only slightly (31 percent). For Asian Americans, controlling for these factors lowered the proportion of taxable investment owners to 35 percent, only slightly higher than other studied populations, suggesting that sociodemographic factors play an important role for this population, as well. Our findings suggest that understanding and addressing the challenges that people of color face are imperative to closing race and ethnic gaps in investing.

Among people of color, gender plays an important role in the likelihood of owning a taxable investment account. Even after controlling for other factors, African American and Hispanic/Latina women were each 14 percent less likely to own a taxable investment account than their male counterparts. Asian American women were 12 percent less likely than their male counterparts to own a taxable investment account.

The findings confirm and extend our understanding of racial and ethnic investing disparities among American families. Comparatively fewer African American and Hispanic/Latino respondents reported owning taxable investment accounts and a sizeable portion did not hold any investment accounts. Our research suggests that these differences may be partly driven by factors that disproportionally affect people of color, including income and education disparities, low levels of financial knowledge and low risk tolerance. Once these factors are taken into consideration, divides between white investors and those of color narrow significantly. These results also highlight a need to consider the joint roles that gender, and race/ethnicity play in the propensity to invest through taxable accounts. Women of color, particularly African American and Hispanic/Latina women, are least likely to own taxable investments.

Understanding and addressing the challenges people of color, and women of color, in particular, face can provide valuable information for initiatives seeking to promote diversity, equity and inclusion in the financial market. Of course, while our findings are informative, the results are not exhaustive. Closer examination of other population segments (including Native Americans and those who identify with multiple race/ethnicities) is required for a more comprehensive understanding of the demographics of retail investors in the United States. Further, a closer examination of the unique patterns among Asian American respondents is needed to better understand the factors that affect this population.

Notes

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About the Data

This brief uses data from three waves (2012, 2015, 2018) of the State-by-State National Financial Capability Study, each funded and led by the FINRA Investor Education Foundation and conducted by ARC. The sample included a total of 80,164 adults ages 18 and over. Of this total, 27,091 participated in the 2018 NFCS survey, 27,564 in the 2015 survey and 25,509 in the 2012 survey. Respondents were recruited via non-probability quota sampling using established online panels consisting of millions of individuals who have been recruited to join and who are offered incentives in exchange for participating in online surveys. These panels use industry-standard techniques to verify the identities of respondents and ensure that demographic characteristics provided are accurate and current. All NFCS surveys were self-administered by respondents on a website. Fielding was conducted from June 2018 to October 2018 for the 2018 NFCS survey, from June 2015 to October 2015 for the 2015 NFCS survey, and from July 2012 to October 2012 for the 2012 NFCS survey. National figures are weighted to be representative of the national population in terms of age, gender, ethnicity, education and Census Division (weights are based on data from the American Community Survey). The data used for this brief as well as detailed methodological information, including the questionnaires, can be found at USFinancialCapability.org.

Footnotes

1. Taxable investments include investments in stocks, bonds, mutual funds or other securities outside of retirement accounts (*see* question B14 on the FINRA Investor Education Foundation's 2018 National Financial Capability Survey).
2. *See* Pew Research Center Sept. 2020 report, "Few in U.S. owned stocks outside of 401(k)s in 2019, fewer said market had a big impact on their view of economy."
3. Some of the statistics pertaining to Asian American respondents are based on small sample sizes (Asian Americans comprised under 3 percent of sample) and should be interpreted with caution.
4. Linear Probability Models (LPM) were used to estimate regressions.
5. To calculate relative percentages, we used the following formula: Relative Percentage = (male value – female value)/male value.
6. Commonwealth & Aspen Institute (2021). *A Framework for Inclusive Investing: Driving Stock Market Participation to Close the Wealth Gap for Women of Color*.
7. Kent, A.H., & Rickets, L.R. (2020, December 2). Has Wealth Inequality in America Changed over Time? Here Are Key Statistics. Federal Reserve Bank of St. Louis.
8. Regression analyses also controlled for the presence of dependents. However, because having a dependent did not significantly contribute to the likelihood of owning a taxable investment in the full regression model, we omitted it from Figure 6. All other factors emerged as statistically significant at conventional levels ($\alpha = .05$)

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ABSTRACT

Black Entrepreneurs, Job Creation, and Financial Constraints*

Black-owned businesses tend to operate with less finance and employ fewer workers than those owned by Whites. Motivated by a simple conceptual framework, we document these facts and show they are causally connected using large firm-level surveys linked to universal employer data from the Census Bureau. We find that the racial financing gap is most pronounced at start-up and tends to narrow with firm age. At any age, Black-owned firms are less likely to receive bank loans, more likely to refrain from applying because they expect denial, and more likely to report that lack of finance reduces their profitability. Yet the observable characteristics of Black entrepreneurs are similar in most respects to Whites, and in some ways - higher education, growth-oriented motivations, and involvement in the business - would seem to imply higher, not lower, demand for finance. Concerning employment, we find that Black-owned firms have on average about 12 percent fewer employees than those owned by Whites, but the difference drops when controlling for firm age and other characteristics. However, when the analysis holds financial variables constant, the results imply that equally well-financed Black-owned firms would be larger than White-owned by about seven percent. Exploiting the credit supply shock of changing assignment to Community Reinvestment Act treatment through a Regression Discontinuity Design in a firm-level panel regression framework, we find that expanded credit access raises employment 5-7 percentage points more at Black-owned businesses than White-owned firms in treated neighborhoods.

JEL Classification: J15, G20, H81

Keywords: business ownership, racial inequality, firm employment, Community Reinvestment Act

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1 Introduction

Financial constraints are frequently portrayed as an important factor in the persistence of racial inequality. Greater liquidity problems may not only lower current consumption, but also reduce investments, mobility, and wealth accumulation, in a self-reinforcing cycle. Recent data from the Federal Reserve's Survey of Consumer Finances show an enormous racial wealth gap, with Black families having both median and mean wealth less than 15 percent of that of Whites. This relationship appears largely unchanged since at least the 1960s.[1]

One important type of financial constraint is that faced by entrepreneurs trying to grow a business. Because Black owners tend to have fewer resources, both personally and through family and friends, they are more dependent on outside funding. An upward-sloping supply curve for external finance implies they face worse financing terms, such that otherwise profitable projects are less likely to be undertaken. Discrimination and greater information asymmetries, associated for instance with a different racial make-up of lenders versus entrepreneurs, may further exacerbate the disparity in the availability and terms of outside finance. If Black owners are less able to finance expansion, even given the same investment opportunities, then their firms will tend to be smaller at all firm ages. To the extent that hiring is segregated, in the sense that Black entrepreneurs are more likely than Whites to hire Black employees, the consequence of tougher financial constraints is lower demand for Black labor and fewer jobs in Black communities.[2]

Motivated by these considerations, this paper analyzes differences in financial constraints and firm employment by race of the owner. We focus on Black-White differentials and start with a conceptual framework that clarifies how differences in personal wealth, information asymmetries, and discrimination can lead to inequality in access to finance and in firm growth. The framework also shows how a policy that expands capital supply may disproportionately aid Black entrepreneurs.

Our empirical analysis begins by documenting basic facts about the amounts and sources of finance and the characteristics of business owners. For this purpose, we draw upon microdata from the 2014 Annual Survey of Entrepreneurs (ASE), a random sample of all U.S. employer-firms with information on 288,000 owners of 184,000 firms (in our regression sample). The data contain a rich set of financial measures, including the reported amounts and

[1] Bhutta et al. (2020) contains the 2019 data, while earlier studies of racial wealth differences include Terrell (1971) and Blau and Graham (1990).

[2] Bates (1988) and Carrington and Troske (1998) document the clustering of Black employees at Black-owned firms. Stoll, Raphael and Holzer (2004) and Giuliano, Levine and Leonard (2009) document the correlation of race between hiring agents/managers and employees, so that the probability of a Black being hired is greater when the decision-maker is also Black.

sources of finance at start-up and in a recent year and the subjective evaluations of business owners on their constraints. We describe the racial gaps in these measures, and in a style similar to previous research, we examine how these gaps change when we control for firm and owner characteristics. The ASE includes information not only on firm age and industry, but also unusually detailed characteristics of owners: demographics, education, previous entrepreneurial experience, entrepreneurial motivations, and the owners' choices about the firm and their roles in it. Estimating with alternative sets of controls allows an assessment of robustness of the racial gap in financial access, taking into account possible correlates of the demand for finance.

Next, we link the ASE to universal data on U.S. employers from the Longitudinal Business Database (LBD) to measure the number of employees. We investigate how the estimated racial gap in employment for Black versus White owners changes with alternative sets of controls, including owner age, education, and motivations, and firm age and industry. Particularly relevant for this paper are specifications including controls reflecting financial access. These estimates permit a first assessment of the degree to which financial constraints affect the relative employment of firms owned by Blacks.

Yet even with the extensive sets of control variables, there remains the possibility that unobservables, including characteristics and opportunities of entrepreneurs, could bias the estimated racial gap in firm-level employment as well as the influence of financial variables. For example, unmeasured differences in demand for finance resulting from different levels of ambition or aspiration for the business might in principle account for some of the racial gap. To address this identification problem, we examine a policy experiment that shifts the supply of credit, estimating the differences by owner race in the causal effect on employment of the Community Reinvestment Act (CRA).

The CRA incentivizes banks to provide credit and other financial services in lower income neighborhoods. Although much of the motivation for the policy stemmed from the history of "redlining" neighborhoods, the policy does not explicitly target race. But our conceptual framework explains how racial differences in financial constraints may produce different impacts of a credit supply shift. Our identification strategy relies on the CRA design, which is implemented at the Census tract level based on a threshold for median family income (MFI) relative to a reference area, generally that for the Standard Metropolitan Statistical Area (MSA). The MFI calculation changed substantially in 2012, enabling us to apply methods based on regression discontinuity and difference-in-differences with firm fixed-effects. Changes in CRA treatment assignment also resulted from changes in tract boundaries, in reference area incomes, and in tract-level MFI. The last of these may reflect relative decline of the neighborhood, so that the estimated average treatment effect may be downward-biased, providing a lower bound on the true effect. In this case, our estimates of the Black-White difference can be interpreted as a triple-difference estimator, in which White-owned businesses are controls for Black-owned firms in tracts becoming treated. For estimation, we construct a new firm-level panel database for the 2003-2015 period. In order to identify the characteristics of owners, we pool data from three Surveys of Business Owners (2002, 2007, and 2012) and two ASEs (2014 and 2015). Linking to CRA data provides a treatment indicator and distance from the threshold for each tract-year, and linking with the LBD provides 8,220,000 firm-year observations on employment in 952,000 firms.

Summarizing our findings briefly, although Black-owned businesses tend to start up with less finance, we find smaller differences from White-owned businesses once they are going concerns. But the sources are different in that Black-owned firms are less likely to receive bank loans either at start-up or later in their life cycle. Black business owners are much more likely to refrain from applying for loans because they expect to be denied and to report that lack of financial access reduces their profitability.

The financing gap is not explained by observable characteristics associated with demand. We find that Black owners are generally similar to their White counterparts and are actually somewhat more likely to report strong entrepreneurial motivations along a variety of dimensions, to aspire for their firms to grow, and to hold advanced degrees, characteristics likely to be associated with higher demand for capital.

Nevertheless, Black-owned businesses tend to have lower employment than White-owned, on average. The difference disappears once firm age is controlled for, as firms owned by Blacks tend to be younger. While the size difference remains negligible with a wealth of other controls, including other demographics, human capital, and entrepreneurial motivation, it shifts when financial variables are included: the results imply that with the same financial access Black-owned businesses would be on average about 7 percent larger than those owned by Whites. Finally, we find that Black-owned businesses in neighborhoods becoming treated by the CRA increase employment about 5-7 percentage points more than White-owned businesses in the same areas.

This research relates to several distinct bodies of research. Within the broad literature on racial inequality, earnings and income differences have received the most attention (e.g., Bayer and Charles (2018*a*), Chetty et al. (2020), and Derenoncourt and Montialoux (2021)). More directly relevant to our focus on business owners are studies of firm-level data that document lower levels of finance in Black-owned businesses. Bates (1997) uses the 1992 Characteristics of Business Owners (CBO) survey and reports lower capitalization and loan receipts among Black-owned relative to White-owned start-ups. Fairlie, Robb and Robinson (2020) use the Kauffman Firm Survey (KFS) to study the evolution of amounts and sources of finance in a cohort of start-ups entering in 2007. Robb and Fairlie (2007) link a large racial wealth gap to lower start-up rates, smaller size, and higher failure probabilities among Black-owned than White-owned businesses. Fairlie and Robb (2007) examine work experience in a family business and having family members in self-employment. In a paper that overlaps with part of ours, Robb (2018) reports publicly available tabulations of responses to finance questions by race from the 2014 ASE, finding that Black-owned businesses use less start-up capital, are more likely to not apply for a loan because they don't think the lender would approve it, and more frequently report that lack of access to capital negatively affect their profitability.[3] We build on this work in several ways: using the extensive owner characteristics in the confidential ASE data to build up a detailed portrait of Black entrepreneurs and their motivations, relating firm finance and growth through regression analysis using the detailed controls, and estimating the impact of the CRA as an exogenous credit supply shift.

A closely related literature examines racial disparities in denials of loan applications. Many of these focus on personal loans (mortgages) rather than business lending.[4] Cavalluzzo and Cavalluzzo (1998), Blanchflower, Levine and Zimmerman (2003), Blanchard, Zhao and Yinger (2008), and Fairlie, Robb and Robinson (2020) study lending to small businesses. Except for Fairlie, Robb and Robinson (2020), these papers rely upon various waves of Survey of Small Business Finances (SSBF), which has detailed measures of financial characteristics of the sampled businesses. This is particularly true in the 1998 data analyzed by Blanchflower, Levine and Zimmerman (2003) and Blanchard, Zhao and Yinger (2008), containing credit scores, owner wealth, and other proxies for ability to repay and to offer collateral. The 2014 ASE, which we use in part of our analysis, is somewhat weaker in such measures, but it is relatively strong in measuring the amounts and sources of finance, both at start-up and in the year 2014. It also contains much more detail on owner characteristics, including previous business ownership, motivations for ownership, and the roles the owner plays in the firm, including hours of work. These variables reflect on the orientation and degree of ambition of the business, and thus on its demand for capital. The sample sizes in the ASE are two orders of magnitude greater than in the SSBFs and KFS, each of which have just a few thousand observations.[5] Our method in the part of the paper that examines racial gaps

[3]These papers all use data from firm surveys. Another related set of papers uses individual data to study differences in self-employment by race, e.g., Fairlie and Meyer (1996), Fairlie (1999), Hout and Rosen (2000), and Fairlie and Meyer (2000).

[4]Munnell et al. (1996), Ladd (1998), and Casey, Glasberg and Beeman (2011) study racial discrimination in mortgage lending.

[5]The regression samples for loan denial equations using the SSBF are even smaller, containing about 2000 firms in 1993 and 1000 in 1998, as reported in Blanchflower, Levine and Zimmerman (2003, p. 935), for example.

in the measures of financial access is similar to the loan denial research and to research on racial (and gender) gaps in wages.[6]

Distinct from this research on discrimination in loan denials is our estimation of the impact of differential financial constraints on the employment of Black-owned versus White-owned businesses. Although the studies described above have documented lower average levels of finance and smaller average sizes of Black-owned firms, they do not link these two facts directly, through an explicit statistical analysis, as is our purpose in this paper.[7] Our efforts to do so are related to an extensive body of theoretical and empirical research on the relationship of finance and growth (e.g., Levine, 2005; Clementi and Hopenhayn, 2006). As emphasized in the review by Beck (2009), a standard identification problem involves the direction of causality between growth and finance. Despite a long list of empirical studies, the degree to which financial development promotes economic growth at the macro level remains controversial. Most studies use aggregate country-level data (e.g., King and Levine, 1993; Demetriades and Hussein, 1996). Jayaratne and Strahan (1996) use state-level panel data to relate per capita income growth to bank branching deregulation. Pagano and Pica (2012) use international industry-level data on financial development and employment growth. Micro-data would seem more appropriate, but even in this case financial constraints are very difficult to measure (Hubbard, 1998; Farre-Mensa and Ljungqvist, 2016).

Some recent studies have advanced this literature by employing firm-level data and studying particular programs. Banerjee and Duflo (2014) use changes in firm size eligibility for directed credit in India to identify the effects on firm growth. Two papers, Lelarge, Sraer and Thesmar (2010) and Bach (2014), study a French loan guarantee program. Brown and Earle (2017) also study financial access through a government program, SBA loans, using an identification strategy based on geographic variation in the branches of banks supplying most SBA loans. Krishnan, Nandy and Puri (2015) and Bai, Carvalho and Phillips (2018) both exploit state-level banking deregulation in combination with manufacturing firm data to estimate, respectively, effects on productivity and effects on employment growth and reallocation, with consequences for aggregate productivity. None of this recent work on finance-labor links considers differential effects by race or how policies to expand financial access in low-income areas may reduce inequality.

[6]See, for instance, Card and Lemieux (1994), Neal and Johnson (1996), Heckman, Lyons and Todd (2000), Western and Pettit (2005), and Bayer and Charles (2018*b*).

[7]The closest is an analysis by Fairlie and Robb (2007) of the log of sales using 1992 CBO data, finding that the coefficient on Black owner changes from -0.4636 to -0.3215 when dummies for the amount of start-up capital are added to the equation. Using a start-up cohort from the 2007 SBO, Brown et al. (2019) report that the probability of a Black-owned firm being in the top 5 percent of the employment size distribution is about 50 percent less than the cohort average, but this declines to about 20 percent after 7 years, and it becomes positive when demographic and finance controls are added.

Finally, this paper relates to previous research on the CRA. Most research on the CRA has focused on mortgage loans (Bhutta, 2011; Lee and Bostic, 2020). A few studies also estimate the CRA impact on the amount of small business lending (Ding, Lee and Bostic, 2020; Bostic and Lee, 2017; Chakraborty et al., 2020). Bates and Robb (2015) aim to examine racial differences in the CRA lending effect using the the rich information but small sample in the Kauffman Firm Survey, although they do not measure CRA treatment and instead focus on minority zip codes. Immergluck (2002) examines rates of loan receipt for firms in predominantly Black areas, again with controls for firm size, credit scores, and other factors. But these studies do not measure CRA treatment at the tract level, and they do not examine firm-level employment outcomes. No previous study estimates the impact of tract-level CRA treatment on firm-level differences in employment by race of the owner.[8]

The paper is organized as follows. We first present a conceptual framework that motivates our estimation of financial constraints, firm employment size, and the effects of the CRA for Black-owned relative to White-owned firms. The next section then describes our data sources and construction, and the one following explains our econometric methods, including the identification strategy for estimating the causal effects of financial access through the CRA. Results are provided in several subsections. The first provides descriptive statistics on racial differences in owner and business characteristics, while the second describes the amounts and sources of finance at start-up and in 2014, as well as some subjective measures of financial constraints. The next subsection concerns firm employment differences by race of the owner and the role of finance and other variables in accounting for the racial gaps. The last subsection contains our estimates of the CRA effect on firm-level employment by owner race. The final section of the paper provides a brief conclusion.

2 Conceptual Framework

Our approach to estimating financial constraints relies on standard theories of financial market imperfections augmented by considerations of racial differences and discrimination. The key racial differences lie in the assets an entrepreneur can bring into a business as internal capital, the "wedge" in raising external capital given informational problems that may lead to moral hazard and/or adverse selection, and discrimination by external suppliers

[8]Ours is not the first study of the CRA to exploit the income threshold, using RD to estimate the impact across tracts (Avery, Calem and Canner, 2003; Bhutta, 2011; Avery and Brevoort, 2015; Bostic and Lee, 2017; Lee and Bostic, 2020), and some have used difference-in-differences based on changes in CRA eligibility resulting from MSA boundary changes (Ding and Nakamura, 2021; Ringo, 2017; Ding, Lee and Bostic, 2020), although none of these use firm-level data or examine racial inequality. Our identification of the CRA effect exploits a much large number of changes associated with the redefinition of CRA eligibility nationwide, as described further below.

of finance, whether based on personal prejudice or statistical discrimination.

Building on Hubbard (1998) and the broader literature on financial factors in investment, we consider a simple model of the demand for and supply of capital, K, in terms of costs and returns, r. Demand, $D = D(r)$, reflects the return on investment, and we assume for the purposes of exposition that the demand function does not vary by race. In practice, demand for capital may vary with the entrepreneur's human capital, motivations, and choices about the business. As we will show, the racial differences in these factors tend to favor Black over White entrepreneurs, as the former are more likely to have graduate education, to express strong motivations for entrepreneurship and aspirations for their firm to grow, and to choose active roles and long work hours in the business. We will control for these factors and others in some empirical specifications. But of course we cannot control for unobservable factors that may underlie demand, which is the essence of the identification problem, as we discuss further below.

The key differences by race instead appear in the capital supply function. Following Hubbard (1998), we distinguish internal and external sources of finance. As shown in Figure 1, the supply functions for both Blacks, S_b, and Whites, S_w, are initially horizontal, up to the amount of the entrepreneurs' personal assets, A_b and A_w, respectively, at a level equal to the opportunity cost to an entrepreneur of investing in the business, r_0. If desired $K > A$, then the business owner must seek external finance, $X = K - A$, which is more expensive than r_0 because of agency costs arising from imperfect information. The result is a "wedge" between the costs of internal and external finance. The supply curve after A is upward sloping because of increasing costs associated with higher levels of finance, and increasing information asymmetries between a business and ever more informationally distant financial sources. The wedge in general leads to sub-optimal levels of investment and capital stock relative to the first best K^*.

Racial differences exist, first, because of differences in assets. On average, $A_w \gg A_b$ ($A_w/A_b \simeq 7$, according to Bhutta et al. (2020), as noted above). This by itself implies that Black entrepreneurs face worse financial terms as they are more likely to need external finance, and they are likely to be higher on the rising X part of the K supply function, for a given total K. In addition, information asymmetries, and therefore agency costs, may be higher for Black than White entrepreneurs, for instance if lenders tend to be White and there is some degree of residential segregation by race.[9] In this case, the slope of the K supply function is steeper for Blacks than Whites. Finally, if Blacks face discrimination from lenders, the K supply function slope becomes still greater for Blacks, compared to

[9] Bates (1973) finds that the discriminant analysis used by banks to evaluate credit-worthiness does not effectively predict default for Black business borrowers.

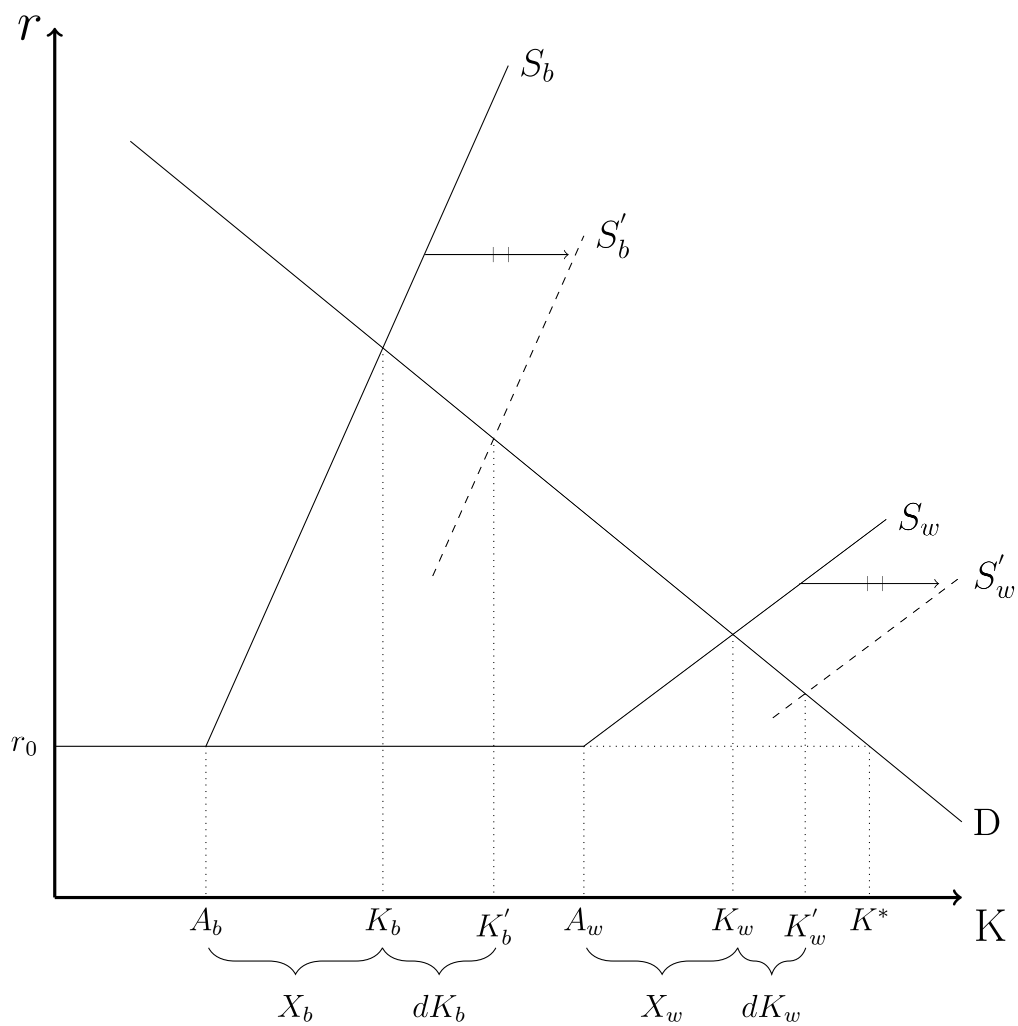

Figure 1: Financial Constraints of Black- and White-Owned Businesses

Whites.

Each of these factors implies that Black entrepreneurs will operate farther up on the upward-sloping portion of the K supply curve than do Whites. Blacks will use less K, so that $K_b < K_w$. Holding everything else equal, Blacks will operate with a smaller firm size, even with the same K demand. However, because their personal assets are lower, they may actually use more external finance than Whites, $X_b > X_w$, even though external finance is more expensive for them, $r_b > r_w$, in equilibrium. Thus, observed differences in access to outside funding, for instance through bank loans, may not capture the differences in financial constraints.

This framework is therefore useful in conceptualizing the difference in the toughness of financial constraints faced by Black relative to White entrepreneurs. Testing the model is difficult because of possible unobservables in capital demand. If we could pin down the capital demand function, then any differences in total capital usage could be attributed to differences in supply, but we otherwise face a fundamental identification problem. Our approach to this problem, besides controlling for a rich set of owner and firm characteristics, is to exploit the shift in capital supply resulting from the CRA. The CRA incentivizes banks to lend in particular "eligible" neighborhoods (census tracts) through regular reporting and periodic examination by the banking supervisory agencies. Banks are evaluated based on the number and volume of their small loans and small business loans, as well as their provision of other kinds of financial services, in these neighborhoods.

In terms of our model, the CRA shifts the supply curves out, as shown in Figure 1 for S_b shifting to S_b' and S_w shifting the same amount to S_w'. We assume the shift is equal for Blacks and Whites, because the CRA gives credit for lending in the eligible tracts regardless of the race of the borrower.[10] For a given outward shift, the increase in K is greater, the higher the slope of the S curve. Since Blacks in this analysis are located on the steeper portion of the S curve, the expansion of S will raise their K and firm size more.

Demonstrating this intuition more formally, suppose that capital demand is linear in r and common across races, given by

$$D = D(r) \tag{1}$$

and suppose that capital supply by race is given by

$$S_i = S_i(r, C) \tag{2}$$

where r is the rate of return on K and C is an indicator for CRA treatment for a race i, which is either White (w) or Black (b). As shown in Figure 1, supply curves differ by position and slope such that not only is $r_b > r_w$ (so that $K_b < K_w$) but also the S_b curve is steeper. This implies that $\partial S_b/\partial r < \partial S_w/\partial r$. In equilibrium, $D = S_i$ for both Whites and Blacks. Total differentiation of the equilibrium condition yields

$$(\partial D/\partial r)dr = (\partial S_i/\partial r)dr + (\partial S_i/\partial C)dC \tag{3}$$

which can be rearranged as follows:

$$dr/dC = (\partial S_i/\partial C)/(\partial D/\partial r - \partial S_i/\partial r). \tag{4}$$

[10] Although the CRA was motivated by racial discrimination, the policy gives equal incentives for loans across races. According to Baradaran (2017), "the CRA's justification was to remedy a history of discriminatory redlining, and its mission was to require mainstream banks to lend a fair proportion of their loans to the ghetto. Although redlining had been based on explicit racial discrimination, the CRA had to be designed to be color-blind" (p. 232).

In Equation 4, $(\partial S_i/\partial C) > 0$, $(\partial D/\partial r) < 0$, and $(\partial S_i/\partial r) > 0$. Therefore, $dr/dC < 0$. Note this implies $dK/dC = (\partial D/\partial r)(dr/dC) > 0$, as the equilibrium moves along the demand curve (D). As $\partial S_i/\partial r$ decreases, $|dr/dC|$ increases, implying greater responsiveness of r to C.

We have argued that lower wealth, higher information costs, and discrimination lead to racial differences in supply such that the rising portion of S_b is at a lower K than S_w and $\partial S_b/\partial r < \partial S_w/\partial r$. This latter relationship implies that $dr_b/dC < dr_w/dC$, so that r falls more for Blacks than Whites. It follows that $dK_b/dC > dK_w/dC$: CRA treatment increases capital and firm size for Black entrepreneurs more than for Whites.

Our estimates of racial differences in firm size and in the CRA effect use the number of employees both because it is the best available proxy for firm size, as discussed in the next section, and because it reflects job creation for Black workers, given racial segregation in hiring (Bates, 1988; Carrington and Troske, 1998). To the extent that labor is an (imperfect) substitute for capital, the estimated impact of the CRA will reflect factor substitution, as well as a scale effect. If, however, Black- and White-owned firms operate with the same production functions or at least similar elasticities of substitution between capital and labor, then the relationship will be the same for both, and differenced away in our empirical specification. In estimating the CRA effect, the assumption is still weaker: by constraining the sample to firms with unchanging ownership and controlling for firm fixed effects, the assumption is that CRA treatment does not change the elasticity of capital-labor substitution in Black-owned firms in a way which is systematically different compared to any change which might occur in White-owned firms.

Final points relevant to the simple model relate to demand. First, we assume that investment opportunities are unaffected by the CRA, because census tracts are very small, likely much smaller than the product markets of most firms. Moreover, CRA eligibility is a patchwork, and the roughly 30 percent of tracts that are eligible have ineligible neighbors adjacent and nearby. Finally, if there is a demand shift, then our estimation with triple differences still identifies the differential effect of the supply shift on Blacks if the demand shift is similar for the two races.

A second aspect of capital demand is the assumption that the demand curve is the same across racial groups. The assumption of a common linear demand curve is sufficient (together with the assumption of steeper supply of external finance for Black compared to White-owned firms) to generate a larger CRA effect for Black entrepreneurs, but it is not necessary. In the nonlinear case, such that $\partial D_i/\partial r$ differs for Black and White-owned firms, a sufficient condition for Black-owned firms to grow more with CRA treatment is $(\partial D_b/\partial r)/(\partial S_b/\partial r) < (\partial D_w/\partial r)/(\partial S_w/\partial r)$, implying that the relative steepness of the Black supply curve is greater than the relative steepness of the Black demand curve. We have argued for a relatively steep Black supply function on the basis of informational asymmetries and discrimination, but we have no a priori reason to believe that the slope of the capital demand function would differ by race.

Of course, entrepreneurs may vary in their desired investment depending on such characteristics as their human capital and motivations for business ownership. We show empirically that the observable patterns are similar for Black and White entrepreneurs and if anything consistent with a higher, not lower, level of demand for capital by Blacks. In examining the relationship between reported use of finance and firm employment, we control for such variables.[11] When we estimate the CRA effect, we control for demand differences across firms with unchanging owners using firm fixed effects. Assuming any racial differences in demand do not change coincidentally with the CRA change, the fixed effects control for them, and we are able to identify the impact of the shift in supply.

3 Data

We link multiple large firm-level databases to assess whether financial constraints vary by race and whether they account for differences in firm employment. First, we study the 2014 ASE from the U.S. Census Bureau. The ASE contains rich information on characteristics of business and their owners, and it provides unusually detailed finance variables. We link the ASE to the LBD, an annual, longitudinally linked database covering all U.S. firms and establishments with payroll employment in the non-farm sector. This linkage allows us to follow firms over time and study employment differences between Black- and White-owned firms. In order to examine the impact of the CRA on firms by owner race, we further link these data to the Survey of Business Owners (SBO), the antecedent of the ASE, in 2002, 2007, and 2012, and to the 2015 ASE. Lastly, we link to Federal Financial Institutions Examination Council (FFIEC) CRA compliance data, which provide information on median family income (MFI) and CRA tract eligibility. The following section describes each of these sources in turn.

The ASE surveys non-farm businesses with at least one paid employee and receipts of $1,000 or more. Using the Census Bureau Business Register (BR) as the sampling frame, the ASE sample is stratified by the 50 most populous Metropolitan Statistical Areas (MSAs), state, the firm's number of years in business, and the sampling frame based on the probability

[11]There may be unobservables as well. One could be consumer discrimination as in Borjas and Bronars (1989). Also, Bone, Christensen and Williams (2014) argue that "systemic restricted choice" affects decision-making of Blacks in seeking outside finance.

of ownership by minorities or women. The sample is randomly selected within strata, except for large companies that are selected with certainty. The initial 2014 ASE sample included about 290,000 employer firms, and the response rate was 74 percent. We restrict the sample to firms with an individual owner having at least 10 percent of the business. The sample is also slightly reduced by missing values. Our final sample for analysis contains 288,000 owners of 184,000 firms.

The ASE provides detailed characteristics of up to four owners with the largest shares in the firm, from which we build owner-level ASE data. Much of our analysis uses the firm-owner as the observational unit, to facilitate controlling for a long list of owner characteristics. However, so that the data are representative of all employer-firms, we construct a composite weight for each owner by multiplying the firm-level sampling weight by the owner's share. Therefore, each owner is represented in proportion to their ownership share in the firm. This procedure clearly makes no difference for single-owner firms, but it takes into account firms with multiple owners and varying characteristics.[12]

We use the detailed information in the ASE to compare finance in Black- and White-owned firms while controlling for a large set of possibly confounding factors that may affect the gaps: human capital, other demographic characteristics, motivations for ownership, choice of industry, and other owner choices about the firm. We define Blacks as non-Hispanic individuals who select a race of Black/African American, including those who select multiple races (i.e., including Black and other races), irrespective of their birthplace. We focus on comparisons of Blacks with non-Hispanic Whites as the reference group. Other race and ethnicity categories include Hispanic, Asian, and other race. Demographic characteristics include gender, age, and immigrant (defined as not born a U.S. citizen). Age is expressed as six categorical variables for less than 25, 25-34, 35-44, 45-54, 55-64, and 65 or over. In cases of multiple owners, the data also include the relationships among business owners, including whether ownership is by a married couple, non-couple family, or multi-generational. We construct dummy variables for diversity in terms of gender (distinguishing within-family from unrelated gender diversity), race and ethnicity, and immigrant status within the owner team. Human capital variables include educational attainment, prior business ownership, and veteran status. Educational attainment is defined as the highest degree prior to owning the business (less than high school graduate, high school graduate, vocational/some college/associate degree, Bachelor's degree, and graduate degree). Prior business experience and veteran status are dummy variables.

Especially useful for this study, the ASE contains unusually rich measures of finance,

[12]The owner-level ASE has been used in previous research. See Brown et al. (2019) and Brown et al. (2020) for the details of the owner-level data and weight construction.

both at startup and for the year 2014. The amount of startup capital is a variable with ten categories ranging from less than $5,000 to $3 million or more, as well as "none needed" and "don't know." We include all of these variables as controls (in specifications including "finance controls"), but to simplify when we use the startup capital amount as a dependent variable, we construct a dummy variable for greater than $100,000. Sources of startup capital are provided as indicators for each of the following: personal savings, home equity loan, credit cards, bank loan, government loan, family loan, venture capital (VC), and grants.

Pertaining to 2014 (the survey reference year), we create two dummy variables for outside funding: a positive amount up to $100,000 and an amount exceeding $100,000 that year. The ASE also has detailed questions related to new funding relationships with banks, credit unions, other financial institutions, angel investors, VC, other investor businesses, and grants. Along with these, the ASE indicates whether they received the total amount of the requested funding or not from each of those sources. We use this information to create indicators for whether they received the total amount requested for each type of new relationship. The final two finance variables are more subjective. The ASE allows us to identify "discouraged borrowers," an indicator for owners who chose not to apply for a loan in 2014 despite needing additional funding, because they expected not to be approved by a lender. Lastly, we create a dummy variable which indicates whether access to financial capital is reported to negatively affect the profitability of the business.

In order to describe the racial differences in funding patterns, we provide summary statistics for all these variables for Black and White owners separately. Robb (2018) presents similar means by race based on publicly available tabulations of the 2014 ASE, but we go further, using the confidential firm-level data to examine the racial difference controlling for other owner and firm characteristics. However, when we examine the degree to which financial access may affect the racial difference in firm employment size, we restrict the set of finance-related variables included as covariates to those that seem most likely to reflect constraints: dummy variables for bank and VC startup capital sources, a new funding relationship with banks, angel investors, VC, and other investor businesses in addition to ten categories on the startup capital amount and 2014 funding amount.

Differences in the amount, sources, and attempts to obtain finance may result from differences in demand for capital, as discussed in the Conceptual Framework section above. While demand is not directly observable, it may be related to a number of owner characteristics, including demographics, and it may also be related to motivations for owning the business. In general, nonpecuniary motivations for lifestyle reasons, such as work/family balance, would seem to imply less ambition to grow the business, and thus lower demand for capital. On motivations, the ASE asks the importance for owning the business of nine different motivations, with the options of “very important,” “somewhat important,” or “not important.” For each motivation, we construct two dummy variables representing very important and somewhat important. The motivations are as follows: 1) “Best avenue for my ideas/goods/services” (Ideas); 2) “Opportunity for greater income/wanted to build wealth” (Income); 3) “Couldn't find a job/unable to find employment” (No Job); 4) “Wanted to be my own boss” (Own Boss); 5) “Working for someone else didn't appeal to me” (Work for Self); 6) “Always wanted to start my own business” (Always Wanted); 7) “An entrepreneurial friend or family member was a role model” (Role Model); 8) “Flexible hours” (Flexible Hours); 9) “Balance work and family” (Balance Family). These questions allow us to address the possibility that Blacks and Whites may differ on average in their motivations for business ownership, which could affect both the demand for finance and firm employment size.

The ASE also includes variables representing owner choices about the business. Like motivations, we include these in some specifications because they could reflect owner preferences about the business that might matter for finance and employment. Job function is a set of dummy variables for the owner's role(s) in the business including manager, good/service provider, financial controller, and none of these roles. Primary income is a dummy variable indicating whether this business is the owner's primary income source. Hours worked is a categorical variable for ranges of average weekly hours the owner spends managing or working in the business. Home-based is a dummy variable indicating whether the business operates primarily from home.

We link the ASE to the LBD, which consists of all firms and establishments with payroll employment in the U.S. non-farm business sector. The main LBD variables used in the 2014 ASE analysis are number of employees and firm age, as of 2014. The number of employees is a common measure of firm size, primarily for reasons of availability and reliability, in research on finance and growth. But we are especially interested in employment because it reflects opportunities for workers and thus wider potential impacts of capital constraints than those affecting only business owners. In order to estimate the impact of the CRA, we use the panel LBD from 2003 to 2015, because our identification strategy in this part of the paper relies on changes over time; other firm characteristics (including age) are absorbed by firm fixed effects in this longitudinal analysis.

To measure owner race over this longer period for a large sample, we use not only the 2014 ASE but also the Survey of Business Owners (SBO) for 2002, 2007, and 2012, and the 2015 ASE. The SBO is similar to the ASE in providing detailed owner characteristics, of which race is most important for present purposes. Each of these sources is a sample survey, so the data are not complete or sufficiently well-developed to examine changing characteristics over time. We assume that the characteristics are fixed, and, except for the race interaction with CRA treatment, they drop out of the estimating equation with firm fixed effects, as we explain below. We exclude firms appearing in more than one of these surveys that report inconsistent characteristics, because we cannot distinguish ownership change from measurement error.

Because the characteristics are thus excluded in the CRA analysis (again, except for the race-CRA interaction), we use a firm-level race variable in this part of the paper. We define a firm as Black-owned if any of its owners are non-Hispanic and report Black race. To estimate the CRA impact, we link the LBD, SBOs, and ASEs to annual tract-level information from the Federal Financial Institutions Examination Council (FFIEC) for 2003-2015. The important variable in these data is the tract's median family income (MFI) ratio, its MFI relative to the reference area (the MSA or Metropolitan Division of the tract, or the state for non-MSA tracts). If a tract's MFI ratio is less than 80 percent, the tract is designated as Low-Moderate Income (LMI). LMI tracts are "eligible" for the CRA, which means that loans to individuals and small businesses in the tract count towards a positive CRA rating in the bank examination periodically carried out by regulators.[13] We use the distance of the MFI ratio to the 80 percent threshold in the Regression Discontinuity Design (RDD), explained below.

CRA eligibility is time-varying at the tract level because of the periodic recomputation of the MFI ratio, which may change either because the tract MFI or reference area MFI changes. During the 2003-2015 period, the major recomputation of MFI was based on the 2006-2010 American Community Survey and applied beginning in 2012. CRA eligibility is time-varying at the firm-level not only because of MFI changes, but also because of changes in tract boundaries, which makes it possible that a firm in a fixed location may move from CRA ineligibility to eligibility. The major change in tract boundaries during the 2003-2015 period also took place in 2012, based on the 2010 Census. A second change came from redrawing some MSA boundaries in 2014. Our methods, described in the next section, exploit these sources of variation as well as the eligibility threshold in a panel framework with firm fixed-effects and RDD combined.[14]

[13]Because of some ambiguity as to which establishment of a multi-unit firm benefits from the loan, we exclude multi-units from the CRA analysis. And because only loans to small businesses are eligible, we exclude firms that always have revenue over $500,000 throughout 2003-15.

[14]The tract code for each establishment comes from the Business Register. It varies over time as tract boundaries are redefined. Studies of CRA effects at the tract level face the problem that these changes make it difficult to follow tracts over time. Our use of firm-level data solves this problem as we follow firms even when tract boundaries change.

4 Methods

We start by describing the differences in firm financing and owner characteristics by race. Of course, both the levels and sources of finance are jointly determined by the supply and demand for finance. Without more data it is impossible to distinguish a situation in which, for example, Black owners face worse credit supply conditions from one where Blacks prefer to operate with less outside finance than do Whites. Put differently, it is possible that unmeasured factors correlated with race are driving the observed differences in levels and sources of finance.

We address this identification problem in several ways. First, we estimate the racial gaps in financial measures controlling for firm and owner characteristics. To take one example, firm age is generally positively correlated with financial access. If Blacks tend to own younger firms, then this factor alone might account for a gap in finance. Additional factors that are potentially relevant include other owner demographic characteristics (age and gender), human capital (education, veteran experience, previous business ownership), motivations for ownership, and owner choices about running the business, including the industry in which to operate.

In an approach similar to that in research on wage gaps, we first estimate the raw gap in measured access and then examine how the gap changes when we include alternative sets of covariates. The most general specification of the regression for racial gaps in access to finance is the following:

$$F_{ij} = \alpha + \beta B_{ij} + \sum_{k} \delta^k G_{ij}^k + \boldsymbol{Z_j \theta} + \boldsymbol{X_{ij} \gamma} + M_{ij} + S_j + O_{ij} + \epsilon_{ij} \tag{5}$$

where F_{ij} represents the various financial measures for owner i at firm j, B_{ij} is an indicator for a Black owner, and G_{ij}^k is a dummy variable for a race/ethnicity group k (i.e., Hispanic, non-Hispanic Asian, and other minorities, so that non-Hispanic White is the reference group). Because businesses in our sample are at different stages of the life cycle and their ownership teams vary in size, we control for a set of categories of firm age (0-2, 3-5, 6-10, 11-15, and more than 15 years since entry, defined in the LBD as the first year in which employees are hired by any of the firm's current establishments) and the number of owners (1, 2-4, 5 or more, and "don't know"), represented by Z_j. Other controls for a vector of owner characteristics, X_{ij}, include demographic variables (owner age, gender, immigrant, and ownership team diversity) and proxies for human capital (educational attainment categories, prior business experience, and veteran status). M_{ij} is a set of motivation variables about the reasons for owning a businesses, as described in the data section. S_j is the set of 4-digit NAICS industry dummies.

Finally, O_{ij} is the set of choice variables (owner's role in business, average hours per week worked in business, primary source of income from business, and home-based business).

The dependent variables are financial measures available from the 2014 ASE: an indicator for start-up capital amount greater than \$100,000, start-up capital sources (e.g., personal savings and other assets, home equity loans, personal or business credit cards, bank loan, government loan, family loan, VC, and grants), any outside and investor funding in 2014, outside and investor funding in 2014 greater than \$100,000, and source of funding received in 2014 (bank, angel investor or VC, other investor businesses, and grants). Two other dependent variables are relevant for difficulty in obtaining additional finance in 2014: not applying because they expected to be turned down, and profitability negatively affected by lack of finance. These questions are necessarily subjective and qualitative, but they may provide evidence on different supply conditions faced by Blacks compared to Whites.

The coefficient on the Black owner indicator (β) captures the gap between Black and White owners. To understand how much of the Black-White gap in access to finance is explained by owner- and firm-level characteristics, we start with simple regressions of the finance measures on only race/ethnicity. We successively add sets of control variables, including firm age and number of owners, demographic characteristics, and human capital variables. Arguably, such characteristics are pre-determined with respect to access to finance. In other specifications, we also add controls for motivations, choice of industry, and other choices (owner roles, hours worked, primary source of income, and home-based). While some of these variables may be jointly determined with use of capital, examining alternative specifications including them sheds light on the degree to which racial gaps in financial access remain even after such variables are controlled. Any remaining racial gaps may be interpreted as tougher financial constraints faced by Black entrepreneurs. But they could also reflect some other type of unobserved heterogeneity, for instance some common factor affecting the financial measures.

Next, we study gaps by owner race in the number of employees at the firm level. Again, we consider alternative specifications of a regression with different control variables. The important difference here is that we add a set of financial variables, as our main purpose is to assess the extent to which firm employment differences may be explained by differences in finance. The most general specification is the following equation:

$$E_{ij} = \alpha + \beta B_{ij} + \sum_{k} \delta^k G_{ij}^k + \boldsymbol{Z_j \theta} + \boldsymbol{X_{ij} \gamma} + M_{ij} + K_j + S_j + O_{ij} + \epsilon_{ij} \tag{6}$$

where E_{ij} is the log of the number of paid employees. K_j is the set of detailed categories of finance variables as described in the data section (amounts of start-up finance, amount of outside finance received in 2014, indicators for sources of startup capital, and indicators for new funding relationship sources). The rest of the terms in the equation, M_{ij}, S_j, and O_{ij}, are the same as in Equation 5.

The final way in which we address the identification problem in estimating racial differences in firm employment and finance uses the CRA as a policy experiment affecting credit supply. We estimate the causal effect of the CRA on Black-owned businesses using the geographic and time variation in the CRA tract-level treatment. We exploit the regulatory discontinuity created by the tract-level MFI threshold, which provides treatment and control groups that are very similar, except for CRA eligibility, among those close to the threshold, in an RDD. We further exploit changes over time in the CRA treatment, resulting from changes in the recomputation of the MFI ratio or by changing tract boundaries.

For simplicity, we focus here on tracts that were ineligible before 2012 (going back to 2003), and examine the impact of becoming eligible from 2012-2015. Because firm-level fixed effects address time-invariant owner characteristics, we also focus on firm-level variation. Firms are linked longitudinally, permitting us to estimate the following equation with firm-level fixed effects:

$$E_{jct} = \alpha + \beta_0 D_{ct} + \beta_1 D_{ct} * B_{jct} + f(MFI_{ct}, D_{ct}) + \rho_j + T_t + \epsilon_{jct} \tag{7}$$

where E_{jct} is employment for firm j in census tract c at time t, and D_{ct} is an indicator for whether the designated tract is CRA-eligible or not in time t. B_{jct} indicates whether the firm has a Black owner or not. The Black owner dummy is not included separately in the regression, because it is collinear with the firm fixed effects. $D_{ct} * B_{jct}$, our main variable of interest, is an interaction between CRA treatment and Black ownership, and β_1 is the associated coefficient representing the difference in the CRA effect relative to firms with White ownership. MFI_c is the relative MFI ratio, the running variable in the RDD set-up, and $f(MFI_{ct}, D_{ct})$ is a polynomial function of the running variable allowed to vary with treatment; we consider linear and quadratic forms with different bandwidths. ρ_j are firm fixed effects, and T_t are year fixed effects. This equation provides a credible estimate of the causal effect of improved access to finance under the CRA for Black-owned relative to White-owned firms (β_1). As discussed in the Conceptual Framework section, the coefficient on the CRA main effect, β_0, may be downward biased to the extent that CRA treatment is associated with a declining tract economy. In this case, β_1 can be interpreted as a triple-difference estimator. But CRA treatment may also result from changes in other parts of the tract's reference area for the relative MFI calculation or from changes in tract boundaries that move firms between tracts with no changes in MFI. To the extent that these latter sources of variation dominate, the sum of β_0 and β_1 can be interpreted as the total effect of increased financial access for Black entrepreneurs under the CRA.

To assess robustness and following conventional RDD methods, we not only examine the full sample of firms in tracts that were ineligible prior to 2012, but we also estimate on two constrained bandwidths: firms in tracts with an MFI ratio up to 20 percentage points above the threshold (i.e, MFI ratio from 80 to 100), and firms in tracts with an MFI ratio up to 5 percentage points above the threshold (i.e., MFI ratio from 80 to 85), in both cases measured prior to the change in 2012.

5 Results

5.1 Characteristics of Black-Owned Businesses

Tabulations of the characteristics of Black owners of employer-businesses in the 2014 ASE provide a detailed portrait of these entrepreneurs and their businesses. Table 1 contains basic statistics on demographic variables. Starting with race/ethnicity, the data indicate that non-Hispanic Blacks own only 1.72 percent of employer firms in the U.S., while non-Hispanic Whites own 84 percent, non-Hispanic Asians 9 percent, and Hispanics 5 percent. The share of women among Black owners is much higher than for Whites (38 versus 27 percent). Black owners tend to be younger than Whites: 26 percent of Blacks are less than 45, compared with 20 percent for Whites, while 32 percent of Blacks and 52 percent of Whites are aged 55 or older. Black owners are more likely to be immigrants: 20 percent versus 7 for Whites.[15].

Turning to ownership structure, Table 2 provides information on the size and composition of ownership teams. The data contain two ways of measuring the number of owners: a direct question on the total number of owners, and the number of owners for whom detailed information is provided. The two variables yield consistent, but not identical results, both showing that Black owners are more likely to be the sole owner than Whites: for each variable, the difference in sole ownership is more than 10 percentage points. Conversely, Blacks are much less likely to be members of multi-owner teams: for teams of 2-4 owners, the percentage for Blacks is 29 percent, versus 38 percent for Whites, and Whites are nearly twice as likely to own firms with more than 4 owners. Among the sole owners, Blacks are much more likely to be female (27 percent of Blacks, compared with 14 percent of Whites). The table also shows four different types of diversity, the most common being within-family

[15]These characteristics are similar to those of self-employed Blacks and Whites in household surveys, as shown in Lee et al. (Forthcoming)

Table 1: Summary Statistics: Owner Race/Ethnicity, Gender, Owner Age, Immigrant

	(1) All	(2) Black	(3) White
Owner Race/Ethnicity			
Non-Hispanic Black	0.017	1.000	0.000
Non-Hispanic White	0.835	0.000	1.000
Non-Hispanic Asian	0.088	0.000	0.000
Non-Hispanic other race	0.008	0.000	0.000
Hispanic	0.052	0.000	0.000
Gender			
Female	0.280	0.379	0.269
Male	0.720	0.621	0.731
Owner Age (years)			
35	0.053	0.053	0.049
35 - 44	0.166	0.209	0.150
45 - 54	0.290	0.319	0.282
55 - 64	0.310	0.271	0.323
64	0.181	0.149	0.196
Immigrant			
Immigrant	0.155	0.201	0.066
Non-immigrant	0.845	0.799	0.934

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms. All variables are dummy variables for the particular category; therefore, the numbers represent the proportion of the sample in the category. Owners are weighted by their ownership share in the firm and by the ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-001).

gender diversity (15 percent of Black owners and 22 percent of Whites). Blacks are much more likely to participate on teams that are racially or ethnically diverse, which to some extent follows mechanically for minority groups, and they are slightly more likely to be on a multi-owner team with unrelated members of the opposite sex or with both immigrant and non-immigrant owners. Table 2 also shows differences in firm age: Black-owned businesses tend to be much younger than White-owned: 22 percent for Blacks versus 13 percent for Whites are recent start-ups less than three years old, and 42 versus 26 percent are less than six years old, while only 34 percent versus 53 percent are more than 10 years old. Firm age is highly correlated with firm growth and behavior, so it should be taken into account when making comparisons across businesses.

Table 2: Summary Statistics: Ownership Structure and Firm Age

	(1) All	(2) Black	(3) White
Number of Owners Per Firm			
Single owner	0.585	0.685	0.581
2 - 4 owners	0.378	0.292	0.381
>4 owners	0.033	0.019	0.034
Don't know	0.005	0.005	0.004
Sole Owner			
Female	0.148	0.269	0.138
Male	0.458	0.445	0.463
Diversity			
Race/ethnicity	0.031	0.086	0.018
Family gender	0.213	0.154	0.215
Unrelated gender	0.039	0.043	0.037
Immigrant	0.034	0.039	0.026
Firm Age (years)			
0 - 2	0.142	0.224	0.129
3 - 5	0.146	0.199	0.134
6 - 10	0.214	0.240	0.207
11 - 15	0.471	0.318	0.500
>15	0.027	0.019	0.030

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms. All variables are dummy variables for the particular category; therefore, the numbers represent the proportion of the sample in the category. Number of Owners is measured from an explicit question ("In 2014, how many people owned this business?"), while owner characteristics are measured for each of the largest owners separately; thus, their totals differ slightly. Owners are weighted by their ownership share in the firm and by the ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-001).

Human capital differences between Black and White employer-owners in the ASE sample are shown in Table 3. Black owners are much more likely to have advanced degrees: 34 percent of Blacks versus 23 percent of Whites. On the other hand, Whites are more likely to have prior business experience: 32 percent for Whites versus 27 percent for Blacks. Blacks are somewhat more likely to be veterans of the armed forces: 13 versus 11 percent for Whites.

Table 4 shows racial differences in the motivations for business ownership. The numbers refer to the proportion of the sample responding that the given reason was "very important" (rather than "not important" or "somewhat important"). Blacks are substantially more

Table 3: Summary Statistics: Human Capital Characteristics of Owners

	(1) All	(2) Black	(3) White
Education			
Less than high school	0.033	0.027	0.025
High school	0.186	0.132	0.188
Some college	0.264	0.264	0.272
Undergraduate	0.277	0.239	0.283
Graduate	0.239	0.339	0.233
Prior business experience	0.322	0.273	0.322
Veteran	0.100	0.126	0.111

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms. All variables are dummy variables for the particular category; therefore, the numbers represent the proportion of the sample in the category. Owners are weighted by their ownership share in the firm and by the ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-001).

Table 4: Summary Statistics: Motivation and Aspiration for Business Ownership

	(1) All	(2) Black	(3) White
Motivations			
Wanted to be Own Boss	0.566	0.609	0.568
Flexible Hours	0.438	0.527	0.430
Balance Work and Family	0.476	0.555	0.466
Opportunity for Greater Income	0.542	0.626	0.536
Best Avenue for Ideas/Goods/Service	0.499	0.578	0.494
Unable to Find Job	0.067	0.091	0.059
Unappealing to Work for Someone Else	0.274	0.277	0.275
Always Wanted to Start Business	0.414	0.580	0.394
Entrepreneurial Role Model	0.240	0.279	0.234
Aspirations to Grow Business	0.636	0.756	0.637

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms. The motivations variables are dummy variables for the owner reporting the particular motivation as a "very important" reason for owning the business (rather than "not important" or "somewhat important"). Aspirations to grow is a dummy if the owners would like the firm to have larger sales or profits in five years (rather than smaller or the same). Owners are weighted by their ownership share in the firm and by the ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-001).

likely than Whites to cite both pecuniary and non-pecuniary motivations for business ownership, especially for "wanted flexible hours," "balance work and family," and "opportunity for greater income." For each of these, the rate at which Blacks cite them as "very important" is about 10 percentage points higher than for Whites. Blacks are also more likely to cite the creative motivation "best avenue for ideas" by a similar margin. Concerning the measure of "necessity entrepreneurship" ("unable to find employment"), the rate is higher for Blacks, but low for both groups, at nine and six percent, respectively. The largest difference is for the motivation "always wanted to start a business," cited by 58 percent of Blacks and 39 percent of Whites. There is a relatively small difference in having an "entrepreneurial role model," but again Blacks are more likely to cite this motivation than Whites: 28 versus 23 percent, respectively. Finally, Table 4 also contains information on business aspirations based on the ASE question "Where would the owner(s) like this business to be in five years?" Responses include larger, smaller, or about the same "in terms of sales or profits," and the table shows the proportion responding "larger." Black owners are more likely to aspire for a larger firm: 76 percent versus 64 percent for White owners. Below, we show that these racial differences in motivations for business ownership remain even after controlling for other demographic and human capital characteristics. In sum, these measures of motivations and aspirations provide no support for any notion that Black owners might be culturally conditioned towards less ambitious goals for their businesses.

Table 5 shows the industry composition of businesses owned by Blacks and Whites. Black ownership is relatively much higher than Whites in health care, with 27 percent of Black owners versus 10 percent of Whites. White ownership is more common in construction, manufacturing, and wholesale and retail trade. Other industries are more similar in their racial proportions or are small for both: Black entrepreneurs are twice as likely to be in the education sector, for example, but the figures for the two race groups are just two and one percent.

In addition to industry, business owners choose other aspects of the business and their involvement, which may influence outcomes. Table 6 shows ASE data on these choices. Black owners tend to work longer hours in their businesses than do White owners: 29 percent of Blacks work more than 60 hours, compared to 20 percent of Whites. Other differences are slight. Blacks are more likely to work as managers (83 versus 80 percent for Whites) and as producers (67 versus 63 percent), but they are less likely to exercise financial control (71 versus 74 percent). Blacks and Whites report similarly on whether the business is their primary source of income (71 and 73 percent) and on whether the business is home-based (25 percent for both).

Table 5: Summary Statistics: Industry

	(1) All	(2) Black	(3) White
Primary sector	0.010	0.004	0.011
Construction	0.125	0.071	0.137
Manufacturing	0.047	0.013	0.051
Wholesale trade	0.055	0.019	0.055
Retail trade	0.115	0.059	0.111
Transportation	0.029	0.050	0.029
Information	0.012	0.013	0.013
Finance	0.045	0.051	0.048
Real estate	0.049	0.030	0.052
Professional and management	0.163	0.171	0.168
Administrative and support	0.061	0.088	0.063
Education	0.011	0.021	0.010
Health	0.112	0.275	0.102
Art and entertainment	0.017	0.017	0.018
Accommodation and food	0.078	0.048	0.062
Other services	0.067	0.067	0.064
Missing sector	0.005	0.003	0.006

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms. The "Primary sector" includes NAICS sector 11, 21 and 22: Agriculture, Forestry, Fishing and Hunting, Mining, and Utilities. Manufacturing comprises NAICS 31-33. Retail trade comprises NAICS 44-45. Transportation comprises NAICS 48-49. Professional and management comprises NAICS 54-55. Owners are weighted by their ownership share in the firm and by the ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-001).

5.2 Racial Gap in Financial Access

Racial differences in financial access, as measured in the ASE, are shown in Table 7. Finance is measured as of start-up and in the reference year of 2014. For the amount of start-up capital, a higher share of White-owned businesses have greater than $100,000 compared with Black-owned: 18 versus 14 percent. Concerning sources of start-up capital, Blacks are more likely to use personal assets and credit cards, but less likely to receive a bank loan, at 15 versus 19 percent. The fraction receiving venture capital is about 1 out of 200 firms, with a slightly higher rate for Blacks compared to Whites. Most of the variables for 2014 finance focus on outside investment. While Black owners are slightly more likely to have positive amounts of outside finance, at 37 versus 36 percent, they are slightly less likely to receive new outside finance greater than $100,000, at 11 versus 12 percent. Blacks are again less likely to receive new bank loans (8 versus 10 percent), and too few receive other forms to

Table 6: Summary Statistics: Owner Choices

	All	Black	White
Owner Role in Business			
Manager	0.798	0.825	0.799
Producer	0.624	0.671	0.633
Financial control	0.729	0.710	0.748
None listed	0.063	0.049	0.062
Average Hours Per Week Owner Works in Business			
None	0.057	0.040	0.058
<20	0.135	0.115	0.137
20 - 39	0.148	0.144	0.149
40	0.152	0.133	0.146
41 - 59	0.302	0.278	0.309
>59	0.206	0.290	0.202
Business is primary source of income	0.728	0.709	0.726
Home-based	0.238	0.252	0.250

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms. All variables are dummy variables for the particular financial measure, as explained in the text. Owners are weighted by their ownership share in the firm and by the ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-001).

merit comparison; for instance, angels and venture capital investments were received in 2014 by only about one in 400 firms, again slightly more by Black than White owners.

The table shows two variables measuring financial constraints from the owner's viewpoint. The first asks if the reason why the firm needed finance but did not apply was "expected lender would not approve": 15 percent of Blacks say yes to this, compared with only 4 percent of Whites. The second question asks whether lack of access to capital negatively affected their profits: 27 percent of Black owners and 10 percent of White owners respond affirmatively. Thus, the data show some evidence, varying depending on the specific measure employed, of a Black disadvantage in finance, but the differences are often small. It will be important to evaluate the racial differences when other factors, including firm age and owner demographics and human capital are controlled.

Differences in the financial measures by race may reflect other characteristics of owners and their opportunities. Hence, our next step is to estimate finance regressions where race is the main variable of interest, while controlling for such characteristics. Some covariates are potentially endogenous, jointly determined with business ownership, success, and demand for finance. Our approach is to gradually add sets of variables and examine how the estimated

Table 7: Summary Statistics: Finance

	All	Black	White
Start-up Capital >$100k	0.191	0.144	0.184
Start-up Capital Source			
Personal savings and other assets	0.691	0.745	0.678
Home equity loans	0.075	0.079	0.073
Personal/business credit cards	0.127	0.199	0.122
Bank loan	0.184	0.154	0.190
Government loan	0.023	0.035	0.023
Family loan	0.052	0.033	0.052
Venture capital	0.005	0.006	0.005
Grants	0.002	0.006	0.002
Outside and Investor Funding in 2014			
>$0	0.353	0.373	0.356
>$100k	0.120	0.106	0.121
Funding received in 2014, by source:			
Bank	0.096	0.079	0.099
Angel investor/ VC	0.003	0.003	0.002
Other investor business	0.003	0.003	0.002
Grants	0.002	0.004	0.002
Financial Constraints			
Didn't apply; expected lender would not approve	0.046	0.149	0.043
Lack of capital reduces profits	0.107	0.273	0.096

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms. All variables are dummy variables for the particular financial measure, as explained in the text. Owners are weighted by their ownership share in the firm and by the ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-001 and CBDRB-FY20-CES009-002).

racial gap in finance changes.

Table 8 and Table 9 contain the results for these regressions for the same finance variables shown in Table 7. The first column shows the raw differences between Black and White owners, while the others add successive sets of control variables. Starting with amounts of finance, the gap of 4 percentage points in the probability of having more than $100,000 at start-up is remarkably robust across all specifications. Comparing to the overall mean of 19 percent (from Table 7), this implies that Black entrepreneurs are more than 20 percent less likely to obtain such large levels of finance when starting up. The estimated gap in the

Table 8: Regression-Adjusted Racial Gaps in Startup Finance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Startup Capital	-0.040	-0.036	-0.039	-0.040	-0.043	-0.042	-0.046
Greater than 100k	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Source:							
Personal Savings	0.066	0.053	0.046	0.047	0.042	0.045	0.046
or Other Assets	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Home Equity	0.007	0.008	0.007	0.008	0.007	0.005	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Credit Cards	0.077	0.065	0.062	0.062	0.059	0.057	0.055
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Banks	-0.036	0.021	-0.012	-0.016	-0.019	-0.023	-0.025
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Government Loan	0.012	0.013	0.013	0.012	0.011	0.010	0.010
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Family Loans	-0.019	-0.018	-0.017	-0.017	-0.016	-0.016	-0.016
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Venture Capital	0.001	0.001	0.001	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Grants	0.004	0.004	0.004	0.004	0.004	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Race/Ethnic Groups	✓	✓	✓	✓	✓	✓	✓
Age & N of Owners		✓	✓	✓	✓	✓	✓
Demographics			✓	✓	✓	✓	✓
Human Capital				✓	✓	✓	✓
Motivations					✓	✓	✓
4-digit Industry						✓	✓
Other Choices							✓
Observations	288,000	288,000	288,000	288,000	288,000	288,000	288,000

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms. Each cell in the table contains an estimate of the African-American owner coefficient (and associated standard error), with the dependent variable indicated in bold and the specification controlling for the various sets of regressors listed in the bottom panel of the table. The dependent variables are explained in the text, with summary statistics provided in Table 7. Owners are weighted by their ownership share in the firm and by ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. Robust standard errors are in parentheses. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-002).

probability of having more than \$100,000 in outside finance during 2014 is a negative 1.6 percentage points, about 13 percent of the overall mean, but the gap essentially disappears once controls for firm age and number of owners are added, and is negligible across the remaining specifications. The probability of any outside finance that year is actually higher for Blacks than Whites, and it increases to greater than 3 percentage points with some sets of controls. While this gap in favor of Black owners is always statistically significant, it is less than 10 percent of the overall mean of this variable (35 percent, in Table 7).

Table 9: Regression-Adjusted Racial Gaps in 2014 Finance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2014 Outside Funding	-0.016	-0.003	-0.002	0.001	-0.003	0.001	-0.001
Greater than 100k	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2014 Outside Funding	0.017	0.027	0.032	0.035	0.028	0.036	0.031
Greater than Zero	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Source:							
New Funding	-0.020	-0.018	-0.013	-0.012	-0.015	-0.015	-0.016
from Banks	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
New Funding	0.000	0.000	-0.001	-0.001	-0.001	0.000	0.000
from Angel Investors/VC	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
New Funding	0.001	0.000	0.000	0.000	0.000	0.000	0.000
from Other Business	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
New Funding	0.002	0.002	0.002	0.002	0.002	0.002	0.002
from Grants	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Financial Constraints:							
Avoid Additional Funding	0.106	0.102	0.100	0.101	0.099	0.100	0.097
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Access to Finance Negatively	0.176	0.168	0.164	0.167	0.162	0.165	0.160
Impacts Profitability	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Race/Ethnic Groups	✓	✓	✓	✓	✓	✓	✓
Age & N of Owners		✓	✓	✓	✓	✓	✓
Demographics			✓	✓	✓	✓	✓
Human Capital				✓	✓	✓	✓
Motivations					✓	✓	✓
4-digit Industry						✓	✓
Other Choices							✓
Observations	288,000	288,000	288,000	288,000	288,000	288,000	288,000

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms. Each cell in the table contains an estimate of the African-American owner coefficient (and associated standard error), with the dependent variable indicated in bold and the specification controlling for the various sets of regressors listed in the bottom panel of the table. The dependent variables are explained in the text, with summary statistics provided in Table 7. Owners are weighted by their ownership share in the firm and by ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. Robust standard errors are in parentheses. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-002).

Concerning sources of funding at start-up, the higher probability for Blacks to use personal resources is robust and only slightly attenuated when other covariates are added. The lower probability of starting up with a bank loan is moderately attenuated, but remains statistically significant even with all controls included. The probability of a new funding relationship with a bank remains significantly lower for Black than for White owners, with some slight attenuation that varies across sets of covariates. Compared with a mean of 9.6 percent, these results imply a disadvantage for Blacks of about 15-20 percent.

The final two dependent variables in Table 9 pertain to difficulties in raising finance in 2014. The estimated racial gaps are hardly affected by the addition of any of the sets of control variables.[16] The results imply that avoiding finance applications because of an expectation the lender would refuse is 10 percentage points higher for Blacks than for Whites, again implying Blacks are three times more likely to be in this category. And they imply that Blacks are 16-17 percentage points (nearly three times) more likely than Whites, even when all the controls are added to the equation, to say that their profitability is negatively affected by difficulties with access to finance.

To summarize briefly, these results provide strong support that Black owners are more likely to perceive financial access as a problem. The analysis of actual outcomes shows smaller differences than do the perceptions, but other factors on the demand and supply side may also help explain outcomes. The two types of outcomes for which there is a clear Black disadvantage are in the amount of finance at start-up and in obtaining bank loans both at start-up and in 2014.[17] These results are robust to including many control variables intended to account for differences in demand for capital.

5.3 Black Ownership and Firm Employment

Summary statistics for the number of employees are displayed in Table 10. Black-owned firms have 9.1 employees on average compared with 10.8 among White-owned ones, a difference of 19 percent when using the Black average as the base.

Table 10: Summary Statistics: Firm Performance

	(1) All	(2) Black	(3) White
Employment in 2014	10.32	9.056	10.77

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 184,000 employer-firms. The sample is weighted by the ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector.The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-001).

Table 11 contains regression estimates with log employment in 2014 as the dependent

[16]This is similar to the result in Fairlie, Robb and Robinson (2020) that the Black-White gap for not applying for a loan due to fear of denial is little affected by controls.

[17]Robb and Robinson (2014) emphasize the importance of bank loans for entrants and young firms in the Kauffman Firm Survey.

variable. In Specification (1), with no controls, employment in 2014 is about 12 percent lower on average in Black-owned firms. But Specification (2) shows that this mean difference is associated with younger firm age and a smaller number of owners among firms with Black owners, patterns observed in Table 2. Once these two factors are added as controls, Black-owned firms are on average three percent larger than White-owned, although the estimate is not statistically significant at conventional levels. The coefficient is fairly similar with controls for demographics, and it rises slightly with human capital, probably because of Blacks' lower rate of prior business experience. It falls about 0.025 with controls for motivations, consistent with Blacks having a somewhat stronger growth orientation relative to Whites. But it jumps to 0.073 when the financial variables are added in Specification (6). This result suggests that worse access to finance lowers employment at Black-owned businesses; once this is taken into account, their employment is on average seven percentage points larger than that of White-owned businesses.

Table 11: Regression Results: Employment in 2014 on Black

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	-0.122 (0.021)	0.031 (0.021)	0.032 (0.021)	0.044 (0.021)	0.020 (0.021)	0.073 (0.020)	-0.028 (0.019)	-0.044 (0.018)
Race/Ethnic Groups	✓	✓	✓	✓	✓	✓	✓	✓
Age & N of Owners		✓	✓	✓	✓	✓	✓	✓
Demographics			✓	✓	✓	✓	✓	✓
Human Capital				✓	✓	✓	✓	✓
Motivations					✓	✓	✓	✓
Finance						✓	✓	✓
4-digit Industry							✓	✓
Other Choices								✓
Observations	288,000	288,000	288,000	288,000	288,000	288,000	288,000	288,000

Note: Data are from the 2014 Annual Survey of Entrepreneurs (ASE). N = 288,000 individual owners of 184,000 employer-firms in the ASE. Each cell in the table refers to an estimate of the African-American coefficient (and associated standard error) for an equation in the text, with the dependent variable indicated in bold and the specification controlling for the various sets of regressors listed in the bottom panel of the table. The dependent variables are explained in the text, with summary statistics provided in Table 1d. Owners are weighted by their ownership share in the firm and by ASE weights, so the sample is representative of all employer-firms in the U.S. non-farm private sector. Robust standard errors are in parentheses. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY20-CES009-002).

When 4-digit industry controls are added, the coefficient declines and becomes negative, but small and insignificant, as shown in Specification (7). This suggests that Black owners tend to choose industries where firms have more employees on average. Finally, the coefficient becomes somewhat more negative and significant at the five percent level when owners' choices are included as regressors in Specification (8). This result provides further support for the interpretation that Black owners have more growth-oriented involvement in their businesses. Similarly to motivations, when this factor is held constant, their firms are smaller on average.

The employment regression results suggest that Black-owned firms have several characteristics associated with being larger, including presence in industries with larger average firm size, and higher owner education, growth-oriented motivations, and involvement in the firm. These factors are outweighed, however, by being younger and having fewer owners and less financing, which are associated with smaller size.[18] Black-owned firms would be larger than those owned by Whites if they had the same access to finance.

5.4 Impact of the Community Reinvestment Act

The estimation results so far are consistent with an interpretation that Black entrepreneurs face tougher financial constraints that impede their ability to grow. The data we study provide detailed information on access to finance at the firm level, and the comprehensive information on firm age and industry and on owner characteristics, motivations, and choices also allows an assessment of the extent to which racial gaps may be "explained" by these correlated observables. But the results could also be explained by unobservables affecting firm employment size and use of finance. For instance, some entrepreneurs may have lower goals for the growth of their firms and consequently lower demand for finance. The rich set of measures on motivations and aspirations in the ASE provide no evidence that Blacks have lower goals, but the observable measures may not fully account for unobserved demand for finance. Our final step in this paper is therefore to estimate the impact of varying credit conditions resulting from CRA changes.

Summary statistics for the principal variables are shown in Table 12. The full sample covers 8,220,000 firm-years with 952,000 firms, all of which are in ineligible (untreated) tracts during 2003-2011. Of these, 69,000 are switchers, firms located in CRA tracts starting in 2012. In terms of firm-years, 3.0 percent of all, and 4.7 percent of Black-owned firm-years are in 2012 or later in CRA tracts. Within the full sample, Black-owned firms tend to be in tracts with lower MFI ratios, but employment is similar when comparing all firms to those owned by Blacks. With a 20 percent bandwidth (MFI ratio from 80 to 100 percent before 2012), the total sample shrinks to 2,591,000 firm-years, 297,000 firms, and 50,000 firms switching into CRA-eligible tracts in 2012. With a 5 percent bandwidth (MFI ratio from 80 to 85 percent), the sample falls to 591,000 firm-years, 68,000 firms, and 19,500 switchers. The sample does

[18]Note that firm age and the number of owners have implications for financing. Younger firms tend to have more difficulty attracting external financing. More owners create the potential for more self-financing, as well as additional collateral and networks to attract external financing.

Table 12: Summary Statistics: CRA Analysis

Sample Used	(1) Full Sample	(2)	(3) 20% Bandwidth	(4)	(5) 5% Bandwidth	(6)
Means	All	Black Owner	All	Black Owner	All	Black Owner
CRA	0.03	0.05	0.07	0.10	0.12	0.14
Tract/MSA Income Ratio	126.10	121.80	93.88	92.08	86.44	84.98
Tract/MSA Income Ratio*CRA	1.98	3.03	4.77	6.38	7.95	9.10
Employment	11.84	11.64	12.69	12.21	12.88	10.44
Employment (standard deviation)	40.84	41.54	40.26	47.64	37.78	27.30
N of Firm-year Obs.	8,220,000	149,000	2,591,000	53,000	591,000	14,000
N of Firm Obs.	952,000	19,000	297,000	6,800	68,000	1,700
N of Switching Firms	69,000	2,000	50,000	1,500	19,500	500

Note: Data are from the 2003-2015 Longitudinal Business Database (LBD) linked to 2002, 2007, and 2012 Survey of Business Owners (SBO) and 2014 and 2015 Annual Survey of Entrepreneurs (ASE). The results presented in this table are approved for dissemination by the DRB (CBDRB-FY2020-CES005-034).

not fall as rapidly as the bandwidth, because it is thicker close to the threshold. The number of switchers falls even less, because the probability of switching is higher for firms in tracts with MFI ratios close to the threshold. As a result, the sample still provides a good basis for estimation, although it should be noted that the number of Black-owned firms that switch is substantially lower: 2000, 1500, and 500 in the three samples. Thus, there may be a tradeoff between a smaller bandwidth, which provides more convincing interpretation of an "as if random" allocation of the firms across CRA eligibility, and the precision of the estimates. For this reason we report regression results for all three samples.

These regression results are presented in Table 13. For each of the three samples described above, three specifications are shown: one omits the MFI ratio, the second includes it, and the third allows the coefficient on it to change with CRA status. The MFI and interaction variables have small coefficients and they make little difference for the results of interest. Results are also similar if the running variable MFI ratio enters the equation in quadratic form.

The main CRA effect in the full sample (β_0 in the equation above) is estimated to be positive and statistically significant, but small at 0.4 percent. It is negative and small in all the other specifications and samples. The variable of interest is the CRA interaction with Black owner, and the estimated coefficients are remarkably similar across samples and specifications. The implied effect on employment is 5 to 7 percent, with the larger estimates for the smallest sample based on the 5 percent bandwidth. Although the standard errors are

Table 13: RD-DD Regression Results: Racial Gap in the Impact of the CRA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CRA	0.0040	-0.0033	-0.0138	-0.0132	-0.0151	-0.0264	-0.0176	-0.0216	-0.0273
	(0.0020)	(0.0021)	(0.0026)	(0.0025)	(0.0027)	(0.0033)	(0.0045)	(0.0051)	(0.0059)
CRA*Black	0.0633	0.0633	0.0628	0.0539	0.0538	0.0528	0.0677	0.0676	0.0674
	(0.0129)	(0.0129)	(0.0129)	(0.0145)	(0.0145)	(0.0145)	(0.0219)	(0.0219)	(0.0219)
MFI		-0.0002	-0.0002		-0.0001	0.0000		-0.0001	-0.0001
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0001)	(0.0001)
CRA*MFI			-0.0008			-0.0011			-0.0006
			(0.0001)			(0.0002)			(0.0003)

Note: RD-DD stands for Regression Discontinuity-Difference-in-Differences. Data are from the 2003-2015 Longitudinal Business Database (LBD) linked to 2002, 2007, and 2012 Survey of Business Owners (SBO) and 2014 and 2015 Annual Survey of Entrepreneurs (ASE). Observations = 8,220,000 for the full sample, 2,591,000 for the 20 percent bandwidth sample, and 591,000 for the 5 percent bandwidth sample. All regressions include firm and year fixed effects. Firm-level clustered standard errors are reported in parentheses. The results presented in this table are approved for dissemination by the DRB (CBDRB-FY2020-CES005-034).

larger with a smaller bandwidth, all the estimates are highly significant.

These coefficients are β_1 in the equation above, representing the difference in the CRA effect on firms with Black owners relative to those with White owners. To obtain the estimated effect on Black owners, it is necessary to sum β_0 and β_1. Because β_0 is estimated to be negative,[19] this total effect is smaller than β_1, but because β_0 is estimated to be small in magnitude relative to β_1, the sum is still positive and different from zero at any conventional level of statistical significance. Depending on the sample and specification, the estimated total impact on Black-owned firms ranges from 3 to 6 percent. An alternative interpretation is that the main effect also captures a downward bias associated with the dip in measured MFI. In this case, β_1 is a triple-difference estimator, and the range of the estimated impact is 5 to 7 percent.

In either case, the magnitudes are not large, but it should be borne in mind that the estimates here are only "intent-to-treat." We do not observe whether any particular firm receives a loan, or a larger loan, as a result of the CRA. But CRA tracts are about 30 percent of all tracts in the US, and thus our estimates could imply a 1.5-2.5 percent increase in employment in Black-owned businesses nationwide. This additional job creation would be substantial for the predominantly Black neighborhoods where most Black-owned businesses are located. Also relevant is that the costs of the CRA essentially involve extra time spent by bank examiners who are focused on issues of financial stability. As a caveat, however,

[19]The non-positive CRA benefit for White-owned firms is consistent with the Bates and Robb (2016) finding that White-owned businesses' credit access is not sensitive to whether they are located in minority or majority-White neighborhoods.

the estimates here do not account for possible displacement effects, whereby banks might transfer lending activity from non-CRA to CRA tracts, resulting in no net gain. This possibility would have implications for a welfare evaluation of the CRA, but it does not in any way undermine the conclusion that increased access to finance benefits Black-owned firms.

These results provide evidence not only concerning a particular policy, the CRA, but also on the general issue of financial constraints. A plausible interpretation of the results is that Black entrepreneurs typically face greater constraints in the form of a supply curve steeper and to the left of the one faced by their White counterparts. The CRA relaxes those constraints, and Blacks benefit more because their constraints were greater. A possible alternative explanation is that Black owners have some unobserved skills that permits them to take better advantage of relaxed financial constraints. But it is unclear what those skills might be. While logically possible, this interpretation seems implausible. Coupled with the evidence on the financial disadvantages of blacks at start-up and in receiving formal loans from banks, the results here imply that financial access is indeed a major obstacle for Black-owned businesses.

6 Conclusion

In this paper, we have presented several perspectives and types of evidence on the question whether the growth and job creation of firms owned by Black entrepreneurs is impeded by tougher financial constraints that those faced by Whites. Our conceptual framework showed the role of wealth disparities in raising the relative cost of funds for Blacks, a difference likely to be exacerbated by greater informational asymmetries and racial discrimination. The model shows that the latter factors under some conditions additionally imply that an expansion in financial access, for instance through a policy like the CRA, could stimulate greater growth at Black-owned than at White-owned businesses.

While the simple model assumes the demand for capital is the same across races, our analysis of characteristics of owners of employer-businesses in the ASE reveals that Black owners have several observable characteristics - younger age group, higher levels of education, greater motivations for entrepreneurship, higher aspirations to grow, more recent start-up, and choice of industry - that are associated with higher demand for capital, on average compared to Whites. Not all these differences are large, and there may be components of demand we do not observe, but the observable patterns of these variables are wholly inconsistent with the notion that Black-owned firms have lower demand for capital.

The first type of evidence consists of measures of the firm's sources and amounts of finance at start-up and in 2014, plus some subjective questions on financial constraints. We find that Black-owned firms generally operate with less finance, especially at start-up and from outside sources, particularly bank credit. These results are statistically and quantitatively important, and they are robust to inclusion of several sets of controls, including other demographic characteristics and entrepreneurial motivations and choices that could proxy for demand for finance. In its approach, this analysis complements previous research, and it is similar in style to studies of wage gaps by race or gender.

The other two types of evidence focus on how financial constraints affect firm employment size. In the first of these, we show that Black-owned employer-firms have about 12 percent fewer employees compared with White-owned firms. But once we control for firm age and number of owners, this difference becomes essentially zero, and it jumps to a positive, statistically significant 7 percent when we control for the financial measures. This result implies that with the same financial access, Black-owned firms would actually be significantly larger than White-owned. This result is also consistent with the qualitative pattern in the data that Black owners tend to cite every type of entrepreneurial motivation and to be more likely to have growth aspirations relative to White owners, on average.

In the final empirical analysis, we estimate the impact of an intervention to expand financial access - the CRA - on the relative employment of Black-owned versus White-owned firms. The results from estimating causal effects using regression discontinuity and difference-in-differences methods imply that the increased financial access benefits employment in Black-owned firms about 5-7 percentage points more than in White-owned. Taken together, these results consistently support the hypothesis that Black entrepreneurs face tougher financial constraints that reduce their firms' employment growth.

Available data are not sufficient to disentangle the relative importance of discrimination of various types, information problems, and pre-existing wealth differences in these results. But they do suggest that policies designed to expand financial access, such as the CRA, can contribute to alleviating the disparity. To the extent that Black-owned firms draw their employees disproportionately from the Black population, reducing their financial constraints has the potential to contribute more broadly to diminishing racial inequality.

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Decomposition of Racial/Ethnic Differences in the Alternative Financial Services Market Participation

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Decomposition of Racial/Ethnic Differences in the Alternative Financial Services Market Participation

Abstract

This study examined racial/ethnic differences in AFS markete participation and attributable factors to explain the racial/ethnic gps in AFS usage. Using the 2018 NFCS dataset, this study analyzed four major types of AFS use such as title loans, payday loans, pawnshops, and RTO stores proxied for AFS market participation. The logistic regression results indicated significant racial/ethnic gaps in the use of AFS: Blacks were more likely to use title loan, payday loans, pawnshops, and RTO than were whites. Hispanics and Asian/others were less likely to use title loans, but Hispanics were more likely to use payday loans compared to whites. Further, objective financial literacy was negatively related while subjective financial literacy was positively associated with the likelihood of AFS use across four different types consistently. Results from the decomposition analyses showed that both objective and subjective financial literacy are contributing factors to explain the racial/ethnic gaps in AFS use, but patterns are different across three pair-wise comparisons. Among various sociodemographic factors, transitory income shock, age, risk tolerance, and having a dependent child were identified as strong and common factors attributable to the racial/ethnic gaps compared to White. Results of this study provide important insights into the racial/ ethnic differences in AFS market participation that have implications for consumer policymakers, educators and researchers.

***Keywords*:** Race; ethnicity; alternative financial services; financial literacy; decomposition

***JEL Classification*:** D12; J15; G5; G53

Introduction

The Alternative financial services are a growing business. By 2020, that number grew to thirty-six billion dollars (research and market ,2020). Opponents of alternative financial services characterize use of AFS as economically irrational borrowing (Galperin and Weaver, 2014) and argue AFS offer predatory loans disproportionately targeted at communities where few other credit options exist with costs not reasonably justified by borrower creditworthiness (Tippett, 2011). Empirical evidences (e.g. Hunt, 2003) of racialized targeting in “marketing, structuring, and placing predatory loans disproportionately” to racial and ethnic minorities communities exist. On the other hand, others see AFS as a rational response to credit constraints stemming from poverty (Galperin and Weaver, 2014). Also, alternative financial services providers argue that they offer a legitimate option to those who may be risky borrowers with low creditworthiness and few borrowing alternatives, many describe alternative financial services as exploitive due to their exorbitant high fees and interest rates, as well as lack of verification of borrowers’ ability to repay (Tippett, 2011).

Alternative financial services is a term often used to describe the array of financial services offered by providers that operate outside of federally insured banks and thrifts (Bradley et al., 2019). AFS providers includes checkcashing outlets, money transmitters, car title lenders, payday loan stores, pawnshops, and rent-to-own stores (Bradley et al., 2019). They server those who are financially fragile or do not prefer to use traditional financial services companies. Over the past two decades, the alternative financial services sector has seen tremendous growth. The report from Research and markets (2020) examined the AFS sector - a $36 billion business comprised of fragmented and loosely regulated (Research and markets, 2020). The data on the volume of AFS transactions, however, are incomplete because there is the lack of a clear definition of AFS and because this sector is highly fractured among many different providers that are often small or privately held. (Bradley et al., 2019) and and loosely regulated (ResearchAndMarkets, 2020).

The growth of the AFS industry generally can be explained in four ways. First, the Depository Institutions Deregulation and Monetary Control Act of 1980 eliminated usury limits for most loans made by banks(Edmiston, 2011). AFS sector such as payday lenders have partnered with banks to take advantage of looser usury laws. Other lenders or types of loans are subject to their own specific laws (Edmiston, 2011). This Act set the stage for the AFS sector (Bostic and Lee, 2009). The bank deregulation and the incorporation of the banking industry caused many low and middle class households not to have access to banks, and the AFS sector moved to fill the gap (Stoez 2014). Second, much of the AFS sector is less regulated or unregulated at the federal level catering to lower income individuals (Fowler, Cover, & Kleit, 2014), although recently the Consumer Financial Protection Bureau (CFPB) exercise the authority provided by Congress to address these harms, including through vigorous market monitoring, supervision, enforcement, and, if appropriate, rulemaking (Uejio, 2021). The relative lack of federal regulation over much of the AFS sector has drived growth in the AFS

Third, after the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 was enacted, states began to distribute public assistance benefits, such as food stamps and cash payments, and unemployment benefits electronically onto electronic benefits transfer (EBT) cards (Barr et al., 2011). Beneficiaries of federal and state public benefits are more recently being dispensed the option to have their benefits issued delivered through the EBT cards. The federal government also uses the EBT card to deliver payments to unbanked Social Security beneficiaries (Barr et al., 2011). In addition, the Earned Income Tax Credit (EITC) recipients tend to have no a savings or checking account or many of them tend to be under-banked relying on high cost financial services from alternative financial service providers (Caskey, 2001). Fourth, recently getting payday loans via the internet has markedly increased. This makes it even easier for some payday lending operations to use deceptive and illegal practices to take advantage of financially strapped Consumers consumers (Government of the District of Columbia Department of Insurancem securities, and banking , 2019).

Several empirical studies on AFS have focused on the socio-demographic and economic characteristics of individuals those who used AFS, providing a picture of the most vulnerable groups. The lower-income households, less-educated households, the youngest and oldest households, racial/ethnic minorities households, and working-age disabled households were less likely to use most mainstream credit products (*Berkeley Economic Review* , 2019). AFS institutions tend to offer exorbitant h high-interest small loans intended to carry subprime and unbanked borrowers through temporary cash shortages. The high fees and interest rates, sometimes exceeding 400 percent, mean that using AFS can in turn exacerbate financial difficulties by trapping people in cycles of debt (Standaert and Davis, 2017). AFS use may be associated with financial distress *(Braga and McKernan, 2021)*. Even poor financial decisions are proxied as the use of AFS(Nitani, Riding, and Orser, 2020). Due to ther drawbacks,   it is important to question why people are avoiding banks in favor of riskier alternatives. The AFS user group is increasingly a focus of policy and program effors among those interested in poverty alleviation to encourage and faciliate access to *the* formal financial system.

Previous studies on AFS use have not mainly focused on racial/ethnic disparities in its usage. Some studies (e.g., Kim, Lee & Lee, 2019) found significant racial/ethnic gaps in AFS use, but factors attributable to the gaps and the existence of potential unexplained gap have been understudied. Thus, this study investigated racial/ethnic disparities in the Alternative Financial Services Usage and its contributing factors where such gap stems focusing on the role of financial literacy. Using a decomposition analysis (Fairlie 2005), we addressed identified the relative contribution of various factors attributable to the racial/ethnic gaps. Among various household characteristics, we focused on the role of financial literacy measured in two forms: objective and subjective literacy to explain the racial/ethnic disparities.

Literature Review

Racial/ethnic differences in alternative financial services usage

Access to credit var across sociodemographic populations, which would tell group differences in creditworthiness. The difference is theoretically derived from the nature of creditworthiness and the lenders' assessment of the default risk of their borrowers. If they think that an applicant barely qualified for the set level of creditworthiness, they would charge higher interest rates and lend smaller amounts of credit (Lyons, 2001). In this sense, population characteristics are supposed to strictly be formed based on the creditworthiness. However, empirical studies (e.g., Hayashi, 1985; Jappelli, 1990; Cox & Jappelli, 1993; Shinkel, 1979) indicated that credit constraints, such as a disparity between credit applied and actual credit granted, are associated with consumer demographic characteristics, such as race and ethnicity, after controlling for creditworthiness of consumers (Carr & Megbolugbe, 1993).

While racial/ethnic minorities, immigrant communities, and low-income groups encounter greater constraints of access to credit (Garcia, 2010; Pauwels, 2012), AFS has aggressively expanded its market to unbanked or underbanked consumers, representing these communities (Bradley et al., 2009; Burkey & Simkins, 2004). AFS is geographically concentrated in racial/ethnic minority neighborhoods, such as large African American, Latino, or Native American communities whose per capita availability to payday lenders is three to eight times higher than White neighborhoods (Pauwels, 2012). Although not much is empirically tested about the racial/ethnic disparity in AFS use, Kim et al. (2019) indicated racial and ethnic differences in the use of AFS. In their study, racial and ethnic minority groups were more likely to use AFS. For example, blacks were more likely to use payday loans, pawnshops, and rent-to-own stores while Hispanics were more likely to use payday loans and pawnshops than whites. Asians/others were more likely to use payday loans than whites.

Financial literacy and alternative financial services usage

The association between financial knowledge and AFS use has been documented in previous studies (Birkenmaier & Fu, 2016; Lusardi &Tufano, 2015; Robb et al., 2015; Stearns et al. 2006). Lusardi and Tufano (2015) found the association between financial literacy (e.g., debt literacy), financial experiences including the use of AFS, and debt loads. After controlling for demographic characteristics, individuals with low levels of debt literacy were likely to use AFS, incurring higher fees and finance charges. Birkenmaier and Fu (2016) the association between financial knowledge, unbanked status, other sociodemographic characteristics, and AFS use using the 2012 NFCS; Respondents with no financial education experience, lower levels of financial knowledge, lower income, lower education, lower financial education and knowledge, and those who are male, younger, racial minorities, living with a partner, and renters were more likely to use AFS. The unbanked status which relates to the AFS use can be also associated with lower financial knowledge (Federal Deposit Insurance Corporation, 2012). The unbanked see banks hostile environments, ill-adapted to their needs and untrustworthy, and simply believed that they did not need or deserve a bank account. Over 60% of unbanked households visit a payday outlet, check-cashing store, pawnshop, and other AFS regularly when they need to borrow small amounts of money and obtain cash quickly (Burkey and Simkins, 2004).

Robb et al. (2015) examined financial knowledge's effect on the use of AFS by focusing on the difference between objective and subjective knowledge using the 2009 and 2012 NFCS. They found that increased objective financial knowledge decreased the likelihood of AFS use (e.g., pawnshops and tax refund anticipation), while increased subjective knowledge increased the probability of AFS use (e.g., payday, auto-title, and tax refund anticipation loans, or RTO). When the effect of the interaction between objective and subjective knowledge on AFS use was considered, households with low objective and high subjective knowledge were more likely to use AFS, while those with both high objective and subjective knowledge and those with high objective and low subjective knowledge were less likely to do so. These results suggest that a significant portion of AFS users may select these products without performing appropriate searches.

Empirical framework and proposed research hypotheses

Based on previous empirical studies on AFS usage discussed above, we have constructed the following research hypotheses. To test these hypotheses, we conducted several logistic regressions on each type of AFS usage.

H_1: Whites were less likely to use alternative financial services than minority groups.

H_{1-1}: Whites were less likely to use alternative financial services than Blacks.

H_{1-2}: Whites were less likely to use alternative financial services than Hispanics.

H_{1-3}: Whites were less likely to use alternative financial services than Asian/others.

In addition, given the main focus of this study exploring the role of financial literacy to explain the racial/ethnic gap in AFS usage, we have constructed the following research hypotheses. To test these hypotheses, we conducted an appropriate decomposition technique following the approach of Fairlie (2005)'s designed for nonlinear model. We will discuss details of empirical model in method section.

H_2: Financial literacy factors contribute more than other socio-demographic factors to explain the racial/ethnic gap in afs usage.

H_{2-1}: Financial literacy factors contribute more than other socio-demographic factors to explain the Black–White gap in afs usage.

H_{2-2}: Financial literacy factors contribute more than other socio-demographic factors to explain the Hispanic–White gap in afs usage.

H_{2-3}: Financial literacy factors contribute more than other socio-demographic factors to explain the Asian/others–White gap in afs usage.

Methods

Dataset and sample selection

This study used the 2018 National Financial Capability Study (NFCS) dataset sponsored and released by the FINRA Investor Education Foundation. The NFCS dataset has been collected cross-sectioinally and released every three years since 2009. The NFCS is drawn from established online panels with non-probability sampling and included approximately 500 respondents per state with oversamples of 1,250 respondents from the state of Oregon and Washington. The total sample size of the 2018 NFCS is 27,091 and our analytic sample included 22,968 respondents, excluding missing variables of selected variables.

Dependent variables: Alternative financial services usage

The NFCS collects the number of times respondents have used among five different types of AFS such as auto title, payday loans, refund anticipation check, pawnshops, and RTO stores. Among five available sources of AFS, refund anticipation check is less riskier with lower interest than other AFS options. Thus, follwing the previous studies on AFS, we focused on four types of AFS except for the refund anticipation check. For empirical analyses, each type of AFS usage was defined as a binary indicator whether or note respondents had used the option in the past 5 years.

Focal independent variables

Race/ethnicity

The public version of 2018 NFCS dataset provides a binary category of race/ethnicity; white and non-white. However, the restricted dataset allows researchers to use seven categories of race/ethnicity by the following question, “Which of the following best describes your race or ethnicity?” and includes (a) White/Caucasian, (b) Black/African American, (c) Hispanic/Latino, (d) Asian, (e) Native Hawaiian or other Pacific Islander, (f) American Indian or Alaska Native and (g) others. Given the small sample size of some minority groups of (d) to (g), we created the composite variable of Asians/others. For convenience, we refer to four racial/ethnic groups as whites, blacks, Hispanics, and Asians/others, respectively.

Financial literacy

In this study, financial literacy was measured in two aspects, i.e., objective and subjective literacy. The NFCS provides a series of six questions incorporating the topics of interest rate, inflation, bond price, mortgage, compound interest in mortgage and risk. The objective financial literacy variable was measured by each respondent's number of correct answers to the six financial literacy questions (ranged 0-6). The subjective financial literacy was measured and ranged from 1 to 7 by the following question, "On a scale from 1 (very low) to 7 (very high), how would you assess your overall financial knowledge?"

Other independent variables

In this study, we also included a set of independent variables as follows; age; gender (male, female); marital status (married, single, separated/divorced/widowed); presence of a dependent child (yes/no); employment status (selfemployed, salaried worker, part-time worker, homemaker, student, disabled, unemployed, retired); education (high school diploma or lower, some college, associate degree, bachelor's degree, post-bachelor's degree); household income; homeownership (yes/no); health insurance ownership (yes/no); transitory negative income shock (yes/no); risk tolerance (ranged from 0 to 10); have an emergency fund (yes/no); bank account ownership (yes/no); and current credit record (very good, good, about average, bad, very bad). Lastly, we controlled for the state of residence to consider variations in AFS use due to the unobserved restional factors as well as state-level policies and regulations.

Empirical specification

Logistic Regression Model

Following the approach by Shin and Hanna (2015), we used logistic regression models with a pooled sample and subsample of racial/ethnic groups as follows.

$$Pr_i(AFS_j) = \alpha R_k + \beta X_i + \varepsilon_i$$

Where R_k denotes racial/ethnic group that the ith respondent is reported, and X_i represents a vector of household i's characteristics.

$$Pr_{ij}(AFS_j) = \beta X_{ik} + \varepsilon_{ik}$$

Where X_{ik} represents a vector of household i's characteristics in racial/ethnic group k. A further decomposition method is applied based on the coefficients estimated from logistic regressions. As Hanna, Kim and Lindamood (2018) suggested, we used the repeated imputation inference (RII) method for logistic regression models to obtain more accurately estimated variances.

Decomposition analysis: Fairlie decomposition technique

We investigate the racial/ethnic differences in using an each type of AFS options following the approach of Fairlie (2005) designed for nonlinear model. In particular, the decomposition model for the difference between whites and blacks can be specified as follows.

$$\overline{AFS_J}^W - \overline{\overline{AFS_J}}^B = \left[\sum_{i=1}^{N^W} \frac{F(X_i^W \hat{\beta}^W)}{N^w} - \sum_{i=1}^{N^B} \frac{F(X_i^B \hat{\beta}^W)}{N^B}\right] + \left[\sum_{i=1}^{N^B} \frac{F(X_i^B \hat{\beta}^W)}{N^B} - \sum_{i=1}^{N^B} \frac{F(X_i^B \hat{\beta}^B)}{N^B}\right]$$

where $\overline{AFS_J}$ denotes the average of predicted probabilities of using j^{th} type of AFS option for racial/ethnic group *k*. N^W and N^B denotes the sample size of White and Black respondents and F(.) indicates the cumulative distribution function from the logistic regression. In addition, X_i^W and X_i^B are the vectors of average values for household characteristics and $\hat{\beta}^W$ and $\hat{\beta}^B$ are the vectors of coefficient estimates for each racial/ethnic group. The first term indicates the racial/ethnic gap caused by group differences in the distribution of X, and the second term represents a racial/ethnic gap resulting from differences in the coefficients determining levels of each type of AFS usage, and differences in unmeasurable or unobserved endowments. As discussed in Shin and Hanna (2015), we conducted further steps of calculation to estimate contributions of various factors to the racial/ethnic differences. In this study, we conducted the 100 times of sampling process and obtained the calculated mean values of estimates.

Results

Descriptive results

Table 1 presents the descriptive results of AFS use and level of fnancial literacy by diferent races/ethnicities. Chi-squared tests were conducted to examine the AFS use of difererentracial/ ethnic groups across the four types of AFS services. Compared with the rate of whites, other racial/ethnic groups had higher rates of AFS use across the four types. Also, t-tests results showed that white group had the higher levels of objective fnancial literacy (3.24) than did blacks (2.48),and Hispanics (2.85). Similarly, whites had higher levels of subjective fnancial literacy (5.18) than blacks (5.20), Hispanics (4.98) and Asians/others (5.08). Other household characteristics are presented in Appendix.

[Insert Table 1]

Logistic regression analyses

Logistic regressions on four different types of AFS are presented in Table 2 and the magnitude of the results was reported by odds ratio. Blacks were more likely to use title loan, payday loans, pawnshops, and RTO than were whites. Hispanics and Asian/others were less likely to use title loans, but Hispanics were more likely to use payday loans compared to whites. Objective financial literacy was negatively related while subjective financial literacy was positively associated with the likelihood of AFS use across four different types consistently. In particular, the odds of using title loans, payday loans, pawnshops, and RTO decreased by 18.5%, 16.9%, 15.4%, and 21.0%, respectively, with a one unit increase in objective literacy. As a one unit increase in subjective literacy, the odds of using title loans, payday loans, pawnshops, and RTO increased by 17.6%, 12.5%, 11.7%, and 19.9%, respectively.

With respect to control variables, age was negatively associated with the likelihood of using AFS products. Males were more likely to use AFS products than females. Married couple had higher odds of using title loans and RTO than singles, but they were less likely to use payday loans, pawnshop and RTO than those separated, divorced, or widowed. The presence of a dependent child was positively related to the likelihood of AFS use. Salaried workers were more likely to use AFS products than some types of employment status (part-time worker, homemaker, student, and unemployed), but disabled households were more likely to use pawnshop and RTO than salaried workers. Respondents attanining a bachorlor's degree were less likely to use all of four AFS products and those with associate degree and post-bachelor's degree were less likely to use pawnshop and RTO. Respondents with household income ($15,000-34,999) had higher likelihood of using title loans, payday loans and pawnshop than those with lowest income category. Health insurance ownership and banking ownership were negatively while substantial income drop and risk tolerance were positively associated with the likelihood of AFS use. Lastly, respondents who reported "very good" or "good" were less likely to use AFS, while those who reported "bad" were more likely to use AFS compared to households who reported about a "very bad" credit record,

[Insert Table 2]

Decomposition analyses

Decomposition analyses: Blacks vs. Whites

Results from the decomposition analyses for the Black-White differences across utilization of four AFS products were presented in Table 3. The estimated total difference in the use of AFS products was ranged from 0.1438 to 0.2148 and the explained difference between Black and White respondents was ranged from 46.2% to 66.1%. Transitory income shock and age were two most important factors accounted for 26.7%-46.8%, 16.1% to 23.9% and respectively. In addition, objective financial literacy, risk tolerance and having a dependent child were important contributing factors with high percentages of explained differences to estimate the Black-White difference in AFS use. Most contributing factors had positive values of percentages explained, which indicated that the characteristics contributed to widen the Black-White differences in AFS use.

[Insert Table 3]

Decomposition analyses: Hispanics vs. Whites

Results from the decomposition analyses for the Hispanic-White differences across utilization of four AFS products were presented in Table 4. The estimated total difference in the use of AFS products was ranged from 0.0342 to 0.0867 and the explained difference between Hispanic and White respondents was ranged from 69.4% to 108.3%. Similar to the results in Table 3, age, transitory income shock, having a dependent child and risk tolerance were important factors to explain differences in each AFS use between Hispanic and White respondents. All contribution factors were contributed to widen the Hispanic-White differences in AFS use.

[Insert Table 4]

Decomposition analyses: Asian/others vs. Whites

Results from the decomposition analyses for the Asian/others-White differences across utilization of four AFS products were presented in Table 5. The difference of title loans and RTO usage were not found to be significant, so the rates of explained difference were not discussed. The estimated total difference in the use of payday loans and pawnshop were 0.0238 and 0.0338, respectively and the explained difference between Asian/others and White respondents were 66.4% (payday loan) and 59.6% (pawnshop). Similar to previous results in Table 3 and 4, transitory income shock, age, having a dependent child and risk tolerance were important factors to explain differences in AFS use between Asian/others and White respondent and these factors were used to widen the Asian/others-White differences in AFS use. Notably, objective financial literacy and education had high percentages of explained differences to estimate the Asian/others-White difference in AFS use with negative values, which indicated that characteristics contributed to narrow the ethnic/racial gap in payday loan and pawnshop usage.

[Insert Table 5]

Discussion and Implications

This study examined racial/ethnic gaps in AFS use by accounting for the gaps, attributable factors, and the existence of potential unexplained gap. Using the 2018 NFCS dataset, this study used four types of AFS use such as title loans, payday loans, pawnshops, and RTO stores, and estimated logistic regression coefficients before the Fairlie decomposition was conducted. The logistic regression results showed racial/ethnic gaps in the use of AFS, which support Hypotheses 1s partially. In particular, Blacks were more likely to use title loan, payday loans, pawnshops, and RTO than were whites. Hispanics and Asian/others were less likely to use title loans, but Hispanics were more likely to use payday loans compared to whites. Objective financial literacy was negatively related while subjective financial literacy was positively associated with the likelihood of AFS use across four different types consistently.

This study also found the relative contribution of each factors to the racial/ethnic gaps through the decomposition analysis although the difference of title loans and RTO usage were not significant between Asian/others and White. For example, transitory income shock, age, risk tolerance, and having a dependent child were identified as strong, common factors attributable to the racial/ethnic gaps compared to White, which were all positive and widened the gaps despite the relative difference in the importance of the variables. When it comes to the two types of financial literacy, subjective literacy only explained the gap between Blacks and Whites in the use of RTO while objective financial literacy expaliend the gap between Blacks and Whites and Asian/others and Whites. Specifically, both objective and subjective financial literacy increased the gap between Blacks and Whites while objective financial literacy decreased the gap between Asian/others and Whites.

Other factors were either depentdent variable specific or racial/ethnic group specific. For example, household income negatively contributed to the difference between Blacks and Whites in the use of title loan while it positively contributed to the difference between Hispanics and Whites in the use of RTO. Education and household income were a positive contributing factor of pawnshop and RTO use of the difference between Hispanics and Whites, respectively. In the difference between Asian/others and Whites, education was only significant in the use of pawnshop and household income was not significant. Current credit score and education were identified as a positive contributing factor of most AFS uses in all racial/ethnic groups.

The findings show racial/ethnic differences in the use of AFS and different contributing factors accorss the types of AFS use as well as racial/ethnic groups. The findings of this study have implications for educators. Educators should note differences in the use of AFS among racial/ethnic groups and relatating factors when desining and implementing education programs. In particular, results indicating contributing factors for the gap between Whites and racial/ethnic minority groups highlight what factors should be considered when they provide education programs to targeted communities with large minority populations. Further, results from this study have policy implications. Even though there have been high rate of formal financial market participation, e.g., banking system, AFS market fills a supplementary niche in the consumer financial marketplace, especically for minority groups. Policymakers and formal financial institutions need to monitor the use of AFS and develop policy to help financially vulernable groups. Given the significant role of financial literacy to explain the racial/ethnic gaps in AFS use, fostering collaborative efforts between social service organizations and financial educators could assist minority groups to improve their level of financial literacy, leading to discouraging AFS market participation in the future.

There are limitations to note in this study. First, this study used the 2018 NFCS, a cross-sectional dataset. Thus, a potential endogeneity issue in identifying a causal relationship was not fully addresssed despite the decomposition methodologies which can be used with estimation methods that are robust regarding endogeneity issues (Barrado et al., 2021; Morduch & Sicular, 2002). The issue is left for future studies using different methogologies such as data and analysis techniques. Second, this study identified the racial/ethnic differences in the use of AFS with various contributing factors. However, unexplained gaps from unobservable characteristics still are considered attributable to the gaps which could be examined by future research. In spite of these limitations, this study provides an open avenue to examine the issue of AFS market participation across different racial/ethnic groups. Future researchers should revisit and analyze the AFS use in the aftermath of COVID-19 once dataset is available.

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Table 1. Racial/ethnic disparities in AFS use, 2018 NFCS

	(1) Title loan		(2) Payday loan		(3) Pawnshop		(4) Rent-to-own	
Overall rate	10.62%		13.12%		17.39%		11.12%	
Race/ethnicity	Percentage	Difference	Percentage	Difference	Percentage	Difference	Percentage	Difference
Black	22.41	+14.38***	30.32	+21.31***	34.64	+21.48***	24.91	+16.97***
Hispanic	11.45	+3.42***	16.99	+7.98***	21.83	+8.67***	12.67	+4.73***
Asian/others	8.85	+0.82	11.39	+2.38**	16.55	+3.39***	8.97	+1.03
White	8.03	Reference	9.01	Reference	13.16	Reference	7.94	Reference

	Objective financial literacy (0-6)		Subjective financial literacy (1-7)	
Mean (S.D.)	3.2368 (1.5967)		5.1782 (1.3136)	
Race/ethnicity	Mean	Difference	Mean	Difference
Black	2.4836	-0.9872***	5.2000	-0.0138***
Hispanic	2.8493	-0.6215***	4.9830	-0.2308**
Asian/others	3.4358	+0.0350	5.0812	-0.1326*
White	3.4708	reference	5.2138	reference

Unweighted results. Chi-square and t-tests were conducted for pair-wise comparisons in AFS use and financial literacy variables. Significance level: $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 2. Logistic regression: Racial/ethnic difference in AFS utilization, 2018 NFCS

	(1) Title loan		(2) Payday loan		(3) Pawnshop		(4) Rent-to-own	
Variables	Odds ratio	Chi-square	Odds ratio	Chi-square	Odds ratio	Chi-square	Odds ratio	Chi-square
Racial/ethnic status (ref.: Whites)								
Blacks	1.5752***	45.0902	2.2576***	174.5822	1.6240***	70.3205	1.7104***	65.6780
Hispanics	0.8450*	6.0724	1.2435***	12.7968	1.0113	0.0410	0.8768	3.7929
Asians/others	0.8157*	4.2397	0.9943	0.0039	0.9475	0.4417	0.8623	2.1913
Objective financial literacy	0.8147***	135.9941	0.8312***	127.1053	0.8463***	130.6996	0.7896***	179.4957
Subjective financial literacy	1.1763***	63.9422	1.1248***	41.6350	1.1166***	45.6768	1.1994***	85.0220
Age	0.9615***	245.5215	0.9738***	133.7666	0.9646***	309.6007	0.9679***	172.3232
Gender (ref.: female)	1.5182***	57.0858	1.5798***	78.9876	1.5340***	86.5047	1.5061***	54.6684
Marital status (ref.: married)								
single	0.8330**	7.9151	0.9392	1.0744	0.9275	1.8825	0.7406***	21.2464
separated/divorced/widowed	0.9153	1.0467	1.3227***	14.6294	1.3147***	17.1207	1.2573**	8.3115
Presence of a dependent child (ref.: No)	1.7531***	99.1838	1.8218***	132.8274	1.6553***	114.1601	1.9923***	151.9315
Employment status (ref.: salaried worker)								
self-employed	0.8556	2.9574	0.8057*	6.3707	1.2767**	10.4490	0.9364	0.5322
part-time worker	0.6514***	20.5101	0.6728***	21.6838	0.8585*	4.1702	0.8311*	4.3066
homemaker	0.7000***	11.9052	0.6934***	14.5911	0.9035	1.4497	0.7243**	10.2064
student	0.8713	1.3072	0.6879**	10.0152	0.7538**	7.4721	0.9314	0.3436
disabled	1.0649	0.2432	1.1700	2.2536	1.6187***	27.8994	1.5442***	15.7510
unemployed	0.4534***	34.7468	0.4672***	43.6317	0.8777	1.9562	0.4599***	37.7620
retired	1.1537	1.6756	0.8885	1.2853	0.9528	0.2665	0.7905*	3.9081
Education (ref.: high school diploma or lower)								
some college	0.9266	1.4508	1.0399	0.4518	0.9589	0.6668	0.8992	2.9774
associate degree	0.9192	0.9780	0.9480	0.4462	0.7711***	12.9074	0.7376***	12.0861
bachelor's degree	0.7029***	18.9342	0.8312*	5.9472	0.6822***	31.7774	0.6933***	20.0470
post-bachelor's degree	0.8935	1.2989	0.9264	0.6071	0.6369***	23.9909	0.8070*	4.1690

	(1) Title loan		(2) Payday loan		(3) Pawnshop		(4) Rent-to-own	
Variables	Odds ratio	Chi-square	Odds ratio	Chi-square	Odds ratio	Chi-square	Odds ratio	Chi-square
Household income (ref.: less than $15,000)								
$15,000-$24,999	1.3698**	8.9544	1.5226***	20.7045	1.3019***	11.4183	1.1764	2.9097
$25,000-$34,999	1.6611***	23.2509	1.8938***	46.0753	1.2692**	8.5663	1.2074	3.6412
$35,000-$49,999	1.1194	1.1160	1.6308***	27.2623	1.1034	1.4921	0.9975	0.0006
$50,000-$74,999	1.2710	5.1345	1.3655**	10.2855	0.9344	0.6617	0.9272	0.5610
$75,000-$99,999	1.6998***	22.3495	2.0320***	46.2202	1.1410	2.0507	1.2629*	4.6197
$100,000-$149,999	1.4396**	8.9897	1.2898*	4.6772	0.7826*	5.5304	0.8991	0.7603
$150,000 or more	0.8236	1.3886	0.7903	1.8864	0.5943***	12.7886	0.4495***	18.8042
Homeownership (ref.: No)	1.2477***	14.2720	0.8909*	4.6485	0.9001*	4.7832	0.9792	0.1312
Health insurance ownership (ref.: No)	0.7792***	12.1976	0.9068	2.1839	0.8315**	9.8473	0.8304**	7.1402
Transitory income shock (ref.: No)	2.9752***	437.1444	2.9203***	498.7506	2.4385***	411.6403	3.1022***	494.0509
Risk tolerance	1.1325***	146.9721	1.1685***	268.1111	1.1311***	208.9537	1.1658***	227.5578
Have an emergency fund (ref.: No)	1.1047	2.9580	0.9331	1.5617	1.1010	3.7614	1.1236*	3.9168
Bank account ownership (ref.: No)	0.6664***	22.0343	0.8296*	5.6412	0.4633***	127.4930	0.5565***	54.1028
Current credit record (ref.: Very bad)								
very good	0.6792***	14.8546	0.2736***	193.4506	0.3916***	129.8074	0.4871***	53.5165
good	0.8870	1.4634	0.4716***	71.2151	0.5822***	46.6157	0.6880***	15.2383
average	1.0313	0.1029	0.7638**	10.5322	0.9108	1.5593	0.8710	2.2986
bad	1.2363*	4.6093	1.4530***	20.7733	1.5700***	36.3113	1.4819***	19.0426
Regional fixed effect (State of residence)	yes		Yes		yes		yes	
Mean concordance rate	78.9%		84.9%		84.2%		84.8%	
Pseudo R^2								

Unweighted results. Significance level: $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 3. Fairlie Decomposition Analysis, Black vs. White, 2018 NFCS

	(1) Title loan		(2) Payday loan		(3) Pawnshop		(4) Rent-to-own	
Component	Contribution to difference	% of explained difference	Contribution to difference	% of explained difference	Contribution to difference	% of explained difference	Contribution to difference	% of explained difference
Objective financial literacy	0.0109*	11.52%	0.0142*	14.37%	0.0154*	11.47%	0.0153**	13.89%
Subjective financial literacy	0.0014	1.49%	0.0009	0.88%	0.0007	0.54%	0.0021*	1.95%
Age	0.0219***	23.03%	0.0159**	16.11%	0.0320***	23.87%	0.0198***	18.01%
Gender	0.0023**	2.44%	0.0010	1.03%	0.0025***	1.87%	0.0022**	1.96%
Marital status	-0.0016	-1.68%	0.0011	1.09%	0.0021	1.60%	0.0006	0.54%
Education	0.0023*	2.40%	0.0028*	2.87%	0.0043**	3.24%	0.0018	1.61%
Having a dependent child	0.0055**	5.81%	0.0080**	8.08%	0.0106***	7.89%	0.0087***	7.86%
Employment status	0.0005	0.49%	0.0039**	3.99%	0.0011	0.85%	0.0013	1.21%
Household income	-0.0073*	-7.67%	-0.0058	-5.84%	0.0050	3.72%	-0.0023	-2.12%
Homeownership	-0.0061**	-6.39%	0.0010	1.01%	-0.0009	-0.69%	0.0000	0.02%
Health insurance ownership	0.0003	0.32%	-0.0012	-1.25%	0.0005	0.39%	-0.0003	-0.26%
Transitory income shock	0.0445***	46.79%	0.0448***	45.51%	0.0357***	26.69%	0.0388***	35.26%
Risk tolerance	0.0158***	16.58%	0.0130***	13.19%	0.0114***	8.54%	0.0189***	17.18%
Have an emergency fund	0.0006	0.62%	0.0006	0.61%	-0.0001	-0.08%	0.0009	0.85%
Bank account ownership	0.0023	2.43%	0.0015	1.50%	0.0084***	6.24%	0.0024	2.18%
Current credit record	0.0022***	2.32%	0.0028***	2.85%	0.0037***	2.76%	0.0009	0.79%
State of residence	-0.0004	-0.47%	-0.0053*	-5.41%	0.0009	0.67%	-0.0012	-1.07%
Total difference	0.1438***		0.2130***		0.2148***		0.1697***	
Explained difference	0.0950		0.0985		0.1339		0.1100	
Unexplained difference	0.0487		0.1146		0.0809		0.0597	
% of explained difference to total difference		66.1%		46.2%		62.3%		64.8%

Note: Coefficients from a pooled model of Black and White race/ethnicity groups are used for analysis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Fairlie Decomposition Analysis, Hispanic vs. White, 2018 NFCS

	(1) Title loan		(2) Payday loan		(3) Pawnshop		(4) Rent-to-own	
Component	Contribution to difference	% of explained difference	Contribution to difference	% of explained difference	Contribution to difference	% of explained difference	Contribution to difference	% of explained difference
Objective financial literacy	0.0014	3.85%	0.0007	1.18%	0.0020	2.74%	0.0008	1.91%
Subjective financial literacy	-0.0005	-1.48%	0.0012	2.25%	-0.0004	-0.56%	-0.0029	-6.76%
Age	0.0155***	41.86%	0.0094*	17.00%	0.0262***	35.55%	0.0064	14.76%
Gender	-0.0009	-2.36%	-0.0040*	-7.30%	-0.0028*	-3.82%	-0.0016	-3.74%
Marital status	-0.0005	-1.43%	0.0004	0.68%	0.0008	1.08%	-0.0006	-1.29%
Education	0.0008	2.13%	0.0007	1.19%	0.0031**	4.19%	0.0008	1.90%
Having a dependent child	0.0077***	20.94%	0.0105***	18.94%	0.0085***	11.52%	0.0053**	12.23%
Employment status	0.0005	1.26%	0.0011	2.00%	0.0003	0.47%	-0.0004	-0.82%
Household income	-0.0004	-1.21%	0.0029	5.32%	0.0042	5.74%	0.0139**	32.04%
Homeownership	0.0004	1.02%	0.0082**	14.83%	0.0076*	10.32%	0.0071*	16.36%
Health insurance ownership	0.0017	4.60%	0.0004	0.72%	0.0007	0.94%	0.0002	0.43%
Transitory income shock	0.0061**	16.61%	0.0111***	20.07%	0.0079***	10.66%	0.0080***	18.47%
Risk tolerance	0.0028*	7.52%	0.0040**	7.29%	0.0047**	6.42%	0.0038*	8.70%
Have an emergency fund	0.0007	1.99%	0.0068***	12.28%	0.0029	3.91%	0.0001	0.35%
Bank account ownership	0.0005	1.36%	0.0003	0.57%	0.0072***	9.79%	0.0024	5.48%
Current credit record	0.0017***	4.64%	0.0030***	5.35%	0.0017*	2.36%	0.0010	2.27%
State of residence	-0.0005	-1.30%	-0.0009	-1.64%	-0.0008	-1.13%	-0.0008	-1.85%
Total difference	0.0342***		0.0797***		0.0867***		0.0473***	
Explained difference	0.0370		0.0553		0.0737		0.0433	
Unexplained difference	-0.0028		0.0244		0.0130		0.0040	
% of explained difference to total difference		108.3%		69.4%		85.0%		91.5%

Note: Coefficients from a pooled model of Hispanic and White race/ethnicity groups are used for analysis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Fairlie Decomposition Analysis, Asian/others vs. White, 2018 NFCS

	(1) Title loan		(2) Payday loan		(3) Pawnshop		(4) Rent-to-own	
Component	Contribution to difference	% of explained difference	Contribution to difference	% of explained difference	Contribution to difference	% of explained difference	Contribution to difference	% of explained difference
Objective financial literacy	-0.0061***	-27.28%	-0.0057***	-36.11%	-0.0049***	-24.34%	-0.0058***	-40.53%
Subjective financial literacy	-0.0001	-0.28%	0.0001	0.55%	-0.0003	-1.38%	-0.0001	-0.91%
Age	0.0081***	36.16%	0.0029	18.10%	0.0122***	60.61%	0.0050***	35.27%
Gender	-0.0002	-0.95%	-0.0007	-4.66%	-0.0009	-4.29%	-0.0001	-0.92%
Marital status	-0.0002	-0.75%	-0.0004	-2.77%	0.0004	1.96%	-0.0007	-4.64%
Education	0.0025	11.01%	-0.0037	-23.67%	-0.0081**	-40.40%	-0.0047	-32.97%
Having a dependent child	0.0032*	14.41%	0.0030*	19.08%	0.0041**	20.37%	0.0037*	26.19%
Employment status	-0.0003	-1.16%	0.0012	7.70%	-0.0005	-2.24%	-0.0004	-3.02%
Household income	0.0000	-0.01%	0.0000	-0.19%	0.0000	-0.10%	0.0002	1.16%
Homeownership	-0.0001	-0.46%	0.0028	17.74%	0.0025	12.57%	-0.0001	-0.95%
Health insurance ownership	-0.0001	-0.65%	-0.0008	-5.28%	0.0007	3.23%	-0.0002	-1.72%
Transitory income shock	0.0061***	27.05%	0.0087***	55.34%	0.0097***	48.05%	0.0073***	50.82%
Risk tolerance	0.0065**	29.19%	0.0045*	28.69%	0.0015	7.54%	0.0056**	39.30%
Have an emergency fund	0.0001	0.53%	0.0019*	11.71%	0.0015*	7.42%	0.0019	12.96%
Bank account ownership	0.0003	1.17%	0.0014*	9.04%	0.0025***	12.56%	0.0011	7.63%
Current credit record	0.0018***	7.86%	0.0020***	12.53%	0.0009*	4.67%	0.0025***	17.37%
State of residence	0.0008	3.56%	-0.0013	-8.33%	-0.0016	-7.89%	-0.0008	-5.91%
Total difference	0.0082		0.0238**		0.0338***		0.0103	
Explained difference	0.0224		0.0158		0.0202		0.0143	
Unexplained difference	-0.0142		0.0080		0.0137		-0.0040	
% of explained difference to total difference		274.0%		66.4%		59.6%		139.0%

Note: Coefficients from a pooled model of Asian/others and White race/ethnicity groups are used for analysis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 1. Descriptive statistics of Appendix. Descriptive statistics of analytic sample, 2018 NFCS

Variables	Percentage
Racial/ethnic status	
Whites	66.9
Blacks	11.3
Hispanics	14.6
Asians/others	7.2
Mean (median) age	46.9 (48.0)
Gender	
Male	49.0
Female	51.0
Marital status	
Married	53.7
Single	29.9
Separated/divorced/widowed	16.5
Presence of a dependent child	36.4
Employment status	
Salaried worker	39.5
Self-employed	7.1
Part-time worker	9.5
Homemaker	8.4
Student	4.8
Disabled	4.4
Unemployed	5.7
Retired	20.7
Education	
Less than high school	2.3
High school diploma	25.1
Some college	31.4
Associate degree	12.2
Bachelor’s degree	17.9
Post-bachelor’s degree	11.2
Household income	
Less than $15,000	11.3
$15,000-$24,999	11.2
$25,000-$34,999	10.8
$35,000-$49,999	15.2
$50,000-$74,999	20.5
$75,000-$99,999	13.1
$100,000-$149,999	12.2
$150,000 or more	5.7
Homeownership	62.4
Health insurance ownership	89.4

Transitory income shock	22.7
Mean (Median) risk tolerance	5.2 (5.0)
Having an emergency fund	49.6
Bank account ownership	93.6
Current credit record	
Very good	43.4
Good	19.1
About average	17.5
Bad	11.6
Very bad	8.4

Unweighted results.

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ORIGINAL PAPER

How Financial Socialization Messages Relate to Financial Management, Optimism and Stress: Variations by Race

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Abstract

This study explored how explicit family financial socialization as reflected in three types of parental financial messages (messaging about saving, banking, and investing) relate to three financial outcomes (financial management, financial stress, and financial optimism) and how these relationships varied by race. We used cross-sectional data from 14,662 respondents from the 2014 National Student Financial Wellness Survey (NSFWS), a nationally representative dataset inclusive of students from 52 colleges and universities across the United States. Results from this study offer an understanding of how specific financial messages regarding saving, banking, and investing shape college students' financial management behaviors and attitudes and how race/ethnicity is associated with the specific types of messaging in one's family of origin. Specifically, results demonstrated that African American students received significantly fewer saving and banking messages and Hispanic students received fewer investing messages compared to other racial/ethnic groups. Across all racial categories, those who received the investing message reported better financial management, higher financial optimism, and experienced less financial stress.

Financial socialization has been defined as "the process of acquiring and developing values, attitudes, standards, norms, knowledge, and behaviors that contribute to financial viability and individual well-being" (Danes 1994 p. 128). Both intentional and unintentional education by parents have a lifelong influence on their children's financial attitudes (Gudmunson and Danes 2011), and financial management (Hudson et al. 2017). In addition, Danes and colleagues (2008) wrote that race/ethnicity has created cultural differences that influence the practices of financial socialization. Despite the importance of exploring the impact of culture on financial socialization, Gudmunson and Danes (2011) reported that only 13% of the literature on financial socialization linked financial socialization to any demographic characteristics. Even fewer studies have explored the specific differences around these processes due to race or ethnicity. Gudmunson and Danes (2011) stated that the field of financial socialization "can be advanced by turning greater attention towards understanding why these variables predict financial outcomes" (p. 648). Recent studies in personal finance literature define financial well-being as more complex than simply knowing how to manage one's money (Brüggen et al. 2017; CFPB 2015; CFSI 2015; Netemeyer et al. 2018). Financial well-being encompasses both objective financial knowledge and subjective well-being measures, such as an individual's optimism about their financial

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future. For example, Gielan (2019) found that financial optimists were more likely to experience better financial health and engage in more positive financial behaviors than pessimists. Financial optimism may have help individuals stay motivated in the face of financial downturns and instill a belief that, with proper management, they can overcome financial stressors (Prawitz et al. 2013). Researchers have also found that cultural experiences shape financial management, optimism, and beliefs (Chang et al. 2001; Gielan 2019; Grable and Joo 2006; Hughes et al. 2014). However, the specific financial socialization messages received and their influence on financial outcomes remain unexamined.

The current study contributes to the financial socialization literature by exploring how explicit family financial socialization is reflected in three types of parental financial messages (saving, banking, and investing) related to three financial outcomes (financial management, financial stress, and financial optimism) and how these relationships varied by race. Fulk and White (2018) found that financial socialization in the form of discussions about money prior to college was positively related to financial outcomes, but that the strength of the relationship varied by race. Recent evidence has suggested that race also contributed to the intensity of financial stress experienced and shaped financial optimism (Puri and Robinson 2005; White 2020). Although the financial socialization literature has shown that financial discussions between parent and child may be beneficial, to the authors' knowledge, the influence that specific messages exert on financial outcomes remains overlooked. This study aimed to fill this gap by examining the following two research questions (RQ):

RQ1: How do the types of financial socialization messages given by parents to their children vary by race?

RQ2: How do the relationships between particular financial socialization messages and financial outcomes vary by race?

Family Financial Socialization Theory

The Family Financial Socialization Theory systematized the family's financial socialization process to evaluate the nuances potentially correlated with healthier financial behaviors and well-being (Gudmunson and Danes 2011). This theory purports that, although financial socialization is life-long, the family serves as the primary socializing agent for most individuals (Bakir et al. 2006; Gudmunson and Danes 2011; Mandrik et al. 2005). According to Gudmunson and Danes (2011), it is not only important to understand how demographic differences impact financial outcomes, but also consider the indirect effects that family socialization processes have on financial outcomes.

This paper specifically focused on the pathways between family characteristics that led to explicit financial socialization within the context of the Family Financial Socialization Theory. Please note that Gudmunson and Danes (2011) have used the term purposive socialization to express intentional socialization, however, it is often difficult to ascertain the intentions of parents. Thus, the term explicit financial socialization is used in lieu of purposive in this paper. Explicit financial socialization is defined as intentional financial socialization through overt communication and practices (Clarke et al. 2005). Explicit financial socialization messages are often looked at as binary; individuals either report that their parents talked about money or not. To the authors' knowledge, few studies have parsed out what kinds of explicit financial socialization provided the catalyst to healthier financial behaviors and financial well-being. For example, does explicit financial socialization around saving impact financial behaviors or financial well-being differently than explicit financial socialization around investing?

Additionally, the association between race and financial socialization messaging has gone unstudied. Based on the Family Financial Socialization Theory, Gudmunson and Danes' (2011) model links sociodemographic characteristics, such as race, with explicit financial socialization which has been associated with an individual's financial capabilities, financial behaviors, and financial well-being. Gudmunson and Danes (2011) wrote that financial socialization efforts vary by race and reflect differences in how family members engage in explicit financial practices used to influence each other. This means that race plays a role in the types of financial conversations and attitudes (such as optimism) individuals are exposed to. For example, Porto (2016) wrote that Latino households have consistently been found to be a less financially capable group. Latino households have fewer experiential learning opportunities with traditional financial institutions, which could be a potential factor for their lower levels of financial well-being (Porto, 2016). Additionally, African Americans consistently demonstrate lower levels of financial literacy and well-being than other races (Yakoboski et al. 2019). Sherraden (2013) found that parents who possessed lower levels of financial literacy lacked the proper information and skills to model positive financial behaviors to their children. Thus, it is possible that Latino and African American's lower levels of financial literacy and wellness can adversely impact how financial socialization is transferred in these households.

Literature Review

Using the Family Financial Socialization Theory, this paper explored the aforementioned research questions by evaluating how different forms of explicit financial socialization (e.g., type of financial messaging received by parents) interact with young adults' racial and ethnic identities to lay the foundation for their financial management (which includes confidence) and financial well-being outcomes (stress and optimism) (Gudmunson and Danes 2011). This literature review explored what is known about explicit financial socialization and how this construct was related to financial management, financial stress, and financial optimism for college students.

Financial Well-being

How researchers have defined and measured financial well-being has varied greatly in the personal finance literature (Brüggen et al. 2017). Brüggen et al. (2017) wrote "financial well-being is the perception of being able to sustain current and anticipated desired living standards and financial freedom" (p. 229). According to the Family Financial Socialization Theory, financial well-being is defined as inclusive of objective measures of financial health (debt level, income, etc.) and subjective indicators of financial wellness (perceptions of financial health) (Gudmunson and Danes 2011). Objective measures of financial behaviors are easier to quantify, but subjective indicators require a more nuanced examination of perceptions of one's financial health. This study focused primarily on the subjective perceptions of financial well-being as research has found that people vary in how they view their financial situation even when their objective financial numbers are all the same (Garman et al. 2004).

Financial stress is a commonly used marker of financial well-being. Unfortunately, some racial groups experience financial stress at disproportionately higher levels than other groups. White and Heckman (2016) found an income and wealth gap between different racial groups with African American households having lower income, lower net worth, and fewer financial assets compared to White and Asian households. Financial stress has been found to be related to many adverse outcomes such as poor health (Choi 2009), adverse financial practices (Lim et al. 2014), academic problems (Montalto et al. 2019; Robb 2017), and relational conflict (e.g., Dew et al. 2012; Kiernan and Mensah 2009). Additionally, financial stress within the family can cross over onto the children in these homes (Hubler et al. 2016). According to Luhr (2018), adolescents from working-class homes often saw only "fragmented glimpses" of their parent's financial situation and were less likely to discuss financial matters in the home. This led to these individuals feeling more uncertain and apprehensive about their financial future in adulthood. However, parental financial socialization could be one solution to reduce financial stress by promoting financial optimism, or in other words, a sense that they have a greater ability to make the right financial decisions to improve their financial well-being (Jorgensen et al. 2017). In fact, Luhr (2018) found that explicit financial socialization can aid adolescents in being relatively optimistic about their futures. Given that financial optimism has been conversely linked to financial stress (Heckman et al. 2014), it is a valuable variable to explore.

Explicit Financial Socialization Messaging

Explicit financial socialization messages are related to the overt ways parents educate their children about money (Grinstein-Weiss et al. 2012; Gudmunson and Danes 2011; Jorgensen and Savla 2010; Serido et al. 2010). According to LeBaron et al. (2018), "open communication about the family's finances was also strongly desired by participants as a way for parents to teach children finances more effectively. Open communication provides a way for children to learn both good and bad examples of how to use money in a safe environment from parents they trust" (p. 230). Communication often falters when parents feel unequipped and unable to enter into conversations about financial management. Taboos about money conversations within the parent–child relationship foster this sense of inadequacy (Trachtman, 1999; Romo 2011; Jorgensen et al. 2019). Parents reported wanting to protect their children from financial issues, thus avoiding these types of conversations entirely (Romo 2011; Jorgensen et al. 2019; Luhr 2018).

Jorgensen and Savla (2010) found that parents were perceived to have a greater influence on participants' financial well-being when financial socialization occurred explicitly rather than implicitly. In fact, Kim and Torquati (2019) stated that explicit financial socialization may compensate for the effects of negative implicit socialization. Studies have found that explicit financial socialization is related to increased financial responsibility (Kim and Torquati 2019), increased financial confidence (Jorgensen and Savla 2010; Shim et al. 2015), increased financial literacy and knowledge (Clarke et al. 2005), increased savings (Bucciol and Veronesi 2014; Webley and Nyhus 2013), and increased asset ownership (Kim and Chatterjee 2013). Conversely, explicit financial socialization was also negatively associated with student loan stress (Fan and Chatterjee 2019), materialism (Flouri 2004), and negative financial behaviors in adulthood (Cho et al. 2012; Hibbert et al. 2004; Pinto et al. 2005). In a sample of African American participants, parents were found to be the most influential financial socialization agents in the lives of their children (Hudson et al. 2017). Yet, only a few studies have examined the impact of racial and ethnic differences in explicit financial socialization (Fulk and White 2018; Danes et al. 2008; Danes and Yang 2014).

Financial Management

Financial management is an important factor when examining financial well-being (Gudmunson and Danes 2011). Gutter et al. (2014) explained, "race and ethnicity is representative for the shared history and socialization of a group and thus should impact financial preferences" (p. 778). The authors posit that factors such as discrimination, wealth disparity, labor force instability, and a history of less exposure to financial markets and financial information may impact financial socialization practices. For example, Gutter et al. (2014) found that there was a similar lack of opportunity for diverse financial topics in African American families. They reported that participants who were White were more likely to have interactions around saving and investing with their parents than African American participants.

Financial management skills and literacy are essential components of financial well-being but are far from the only contributing factors. Beyond financial ability, Henager and Cude (2016) highlighted the importance of confidence in one's financial ability. In a follow-up study, Henager and Cude (2019) found that one's confidence around their financial ability had a stronger association with financial behaviors than either financial literacy or ability alone. A recent study by White et al. (2019), suggested that financial confidence may interact with financial knowledge and financial management differently for African Americans when compared to White respondents. However, little is known about financial confidence across racial/ethnic groups as prior research has primarily focused on differences in gender and socioeconomic status (Gudmunson and Danes 2011). Thus, we aim to test how the types of financial socialization messages given by parents to their children vary by race and how the relationships between particular financial socialization messages and financial outcomes vary by race.

Methods

Data

This study used data from the 2014 National Student Financial Wellness Survey (NSFWS), collected at The Ohio State University (Study on Collegiate Financial Wellness 2014). The NSFWS was designed to capture the financial wellness of undergraduate students across the United States (US) by examining their financial attitudes, financial behaviors, and financial capability. Online surveys were sent to a random sample of 163,714 undergraduate students at 52 participating two-year public (n = 8), four-year public (n = 32), and four-year private (n = 12) colleges and universities across the US. The survey had a response rate of 11.5% (N = 18,795).

There were 14,662 students that recorded a status for race/ethnicity. A total of 10,544 (71.9%) students reported being White, 727 (5.0%) African American, 826 (5.6%) Hispanic or Latino, 815 (5.6%) Asian or Asian American, 1143 (7.8%) Multiracial (More than one race/ethnicity selected), and 607 (4.1%) Other (Hawaiian or Pacific Islander, Native American or American Indian or Alaskan Native, Middle Eastern or Arab American, Other, and Prefer not to say). The students ranged in age from 18 to 60 years or older, with 72% of students being traditional undergraduate age (18–23 years old) and an additional 13% being 24–29 years old.

Table 1 Factor loadings of key scales

	Financial management	Financial stress	Financial optimism
Weekly or monthly budget that I follow	0.71		
Track my spending	0.83		
Track transactions/checks	0.65		
Confident manage my finances	0.52		
Manage money well	0.59		
Stressed about finances in general		0.79	
Worry about current monthly expenses		0.83	
Worry about pay for school		0.63	
Enough money for same activities as peers		− 0.87	
Enough money for activities I enjoy		− 0.86	
Optimistic about future			0.69
Support myself financially			0.75
Cost of college/university a good investment			0.55
Reliability (α)	0.74	0.86	0.67

Source: Study on Collegiate Financial Wellness: Factor Analysis of Key Scales Research Brief

Dependent Variables

The three dependent variables were selected to represent factors related to the financial well-being of college students. Each dependent variable was a scale created using exploratory factor analysis (EFA) of items from the 2014 NSFWS. The three scales were financial management, financial stress, and financial optimism (Study on Collegiate Financial Wellness 2014). The internal consistency reliability of each scale was measured using Cronbach's alpha. Please see Table 1 for factor loading of measures.

The team of researchers at The Ohio State University who collected and developed the data included 33 items in the initial EFA based on their expertise in research on the financial wellness of college students along with three other criteria: (1) whether they believed the items to be representative of psychological subconstructs of financial wellness, (2) whether the items were distributed to the entire sample, and (3) whether the items were ordered binary, ordinal, or continuous in scale (Study on Collegiate Financial Wellness 2014). The Keiser–Meyer–Olkin measure of sampling adequacy (0.82) and Bartlett's test of sphericity ($p < 0.0001$) were used to indicate whether the data was appropriate for the EFA. Principal axis factoring and a promax (oblique) rotation were used to conduct the EFA (Study on Collegiate Financial Wellness 2014).

An iterative process of data analysis was used in the EFA. Items were removed if (1) they failed to load significantly on at least one factor due to communalities below 0.30, or (2) they loaded on more than one factor, except in the case of theoretical alignment. The EFA followed standards established by Fabrigar et al. (1999) for interpretability and stability. All factors met the standard suggesting they can be interpreted in the context of existing theory and research, and they contain at least three item loadings of at least 0.50 (Study on Collegiate Financial Wellness 2014).

Financial Management

Financial management was a scale created from five survey items. Three of the items measured financial behaviors such as budgeting, tracking spending, and balancing accounts. Responses ranged from 1 (Never) to 4 (Always). The other two items measured respondents' confidence in managing their money (Montalto et al. 2019). Responses ranged from 1 (Strongly Disagree) to 4 (Strongly Agree). The reliability of this scale was $\alpha = 0.74$. The Pearson correlations of the five items ranged from 0.206 to 0.616 ('have a budget' and 'track spending' had the strongest correlation), and each correlation was significant at the 0.01 level in a 2-tailed test (see Table 2).

Financial Stress

The financial stress scale measured respondents' perceptions of their current financial situation. The scale was created from five items pertaining to generalized stress about money, worry about paying expenses, and having money to participate in activities (Lim et al. 2014). Responses ranged from 1 (Strongly Disagree) to 4 (Strongly Agree). The two items about having enough money to participate in activities, had negative loadings to represent the presence of financial stress (Study on Collegiate Financial Wellness 2014). The reliability of the scale was $\alpha = 0.86$. The Pearson correlations of the five items ranged from $-$ 0.520 to 0.783 ('have money to participate in same activities as peers' and 'have money to participate in activities I enjoy' had the strongest correlation), and each correlation was significant at the 0.01 level in a 2-tailed test (see Table 2).

Financial Optimism

Financial optimism was a scale meant to measure respondents' views of their financial future. The scale was created using 3 items (Heckman et al. 2014; Regan and McDaniel 2019). Responses ranged from 1 (Strongly Disagree) to 4 (Strongly Agree). The reliability of this scale was $\alpha = 0.67$. The lower reliability could be due to having only three items and a weaker variable loading of one of the items (Study on Collegiate Financial Wellness 2014). Removing the lowest loading item, 'college is a good investment', increased Cronbach's α to 0.69, which is still in the "questionable" range (0.60–0.69) but reduced the stability by lowering the factor to two items (Kline 2000 p. 13). Therefore, all three items were retained in the factor since each of the three items were above the loading threshold of 0.50. The Pearson correlations of the three items ranged from 0.342 to 0.526 ('optimism about the future' and 'supporting myself financially' had the strongest correlation) and each correlation was significant at the 0.01 level in a 2-tailed test (see Table 2).

Independent Variables

There were three key variables of interest in this study. Each variable represented a different financial socialization message respondents explicitly received prior to college from their parents (Montalto et al. 2019). Students were asked to answer "yes" or "no" to questions used to identify messages received related to saving, banking, and investing (Jorgensen et al. 2019; Luhr 2018).

The model also included demographic covariates selected because they influence financial socialization and financial wellness. The covariates were the gender of respondent (Fan and Chatterjee 2019), education of respondent's mother,

Table 2 Pearson Correlation Coefficients

	Budget	Track spending	Track checks	Confident finances	Manage money well	Optimistic future	Support self	College good investment	Stress general	Stress monthly expenses	Stress pay school	Money peers	Money self
Budget	1												
Track spending	.616**	1											
Track checks	.383**	.546**	1										
Confident finances	.210**	.242**	.206**	1									
Manage money well	.237**	.301**	.237**	.635**	1								
Optimistic future	.028**	.022**	.034**	.284**	.227**	1							
Support self	.069**	.059**	.051**	.309**	.231**	.526**	1						
College good investment	0.005	0.008	.024**	.129**	.096**	.342**	.358**	1					
Stress general	.090**	.075**	.036**	− .251**	− .254**	− .358**	− .263**	− .171**	1				
Stress monthly expenses	.121**	.080**	.032**	− .236**	− .251**	− .302**	− .222**	− .146**	.723**	1			
Stress pay school	.106**	.108**	.060**	− .165**	− .132**	− .313**	− .237**	− .168**	.624**	.595**	1		
Money peers	− .123**	− .077**	− .027**	.267**	.273**	.315**	.224**	.146**	− .470**	− .520**	− .403**	1	
Money self	− .113**	− .069**	− .018*	.268**	.268**	.313**	.225**	.155**	− .462**	− .512**	− .388**	.783**	1

**Correlation is significant at the 0.01 level (2-tailed)

*Correlation is significant at the 0.05 level (2-tailed) education of respondent's father, annual income of respondent's parents, employment status of respondent (Shim et al. 2010), GPA of respondent (Heckman et al. 2014), and age of respondent (Henager and Cude 2016; Jorgensen et al. 2019). We include parent's education and income since parental socioeconomic status is related to how parents discuss money with their children (Luhr 2018).

Data Analysis

Data were analyzed in two parts. We examined our first research question by testing how the three types of parental financial messages (messaging about savings, banking, and investing) varied by race. We then tested our second research question by considering how the association of these three messages with three financial outcomes (financial management, financial stress, and financial optimism) also varied by race. First, we completed summary statistics and Pearson's chi-square tests as a simple determination of whether individuals of different races reported receiving different messages. We used the chi-square test of independence since we considered three sets of associations: (1) race with whether or not the student received the saving message, (2) race with whether or not the student received the banking message, and (3) race with whether or not the student received the investing message. For each association, we examined the relationship of a categorical variable (race) with a categorical variable (whether or not the individual received the message) rather than variables that were approximately continuous and normally distributed. The chi-square test of independence is appropriate in this situation. Second, we completed multivariate analyses by fitting multiple general linear models on the three financial outcome scales to estimate the correlation between each message and the three financial outcome scales.

The formula for each model is

$$Y_{ijklmt} = \mu + \beta_1 x_{1t} + \beta_2 x_{2t} + \beta_3 x_{3t} + R_i + M_j + F_k + P_l + E_m + \beta_4 x_{4t} + \beta_5 x_{5t} + (SB)_{ij} + \epsilon_{ijklmt}$$

where Y_{ijklmt} is the outcome of financial management, optimism, or stress for the t^{th} respondent, μ is the value of the outcome at reference levels of the variables in the model, β_1 is the coefficient associated with the Save message, x_{1t} is an indicator variable for the Save message that is 0 if it was not reported and 1 if it was reported for the tth respondent, β_2 is the coefficient associated with the Bank message, x_{2t} is an indicator variable for the Bank message that is 0 if it was not reported and 1 if it was reported for the tth respondent, β_3 is the coefficient associated with the Invest message, x_{3t} is an indicator variable for the Invest message that is 0 if it was not reported and 1 if it was reported for the tth respondent, R_i is the effect of the ith level of Race (where $i=1,\ldots,6$),M_j is the effect of the jth level of Mother's Education (where $j=1,\ldots,9$), F_k is the effect of the kth level of Father's Education (where $k=1,\ldots,9$), P_l is the effect of the $l th$ level of Parent's Annual Income (where $l=1,\ldots,11$), E_m is the effect of the mth level of Employment Status (where $m=1,\ldots,3$),β_4 is the coefficient associated with GPA, x_{4t} is the GPA recorded for the tth respondent, and β_5 is the coefficient associated Age, and x_{5t} is the Age recorded for the tth respondent.

The regression model approach was appropriate to determine how race, messaging, and the interaction of race and messaging related to the outcomes of financial management, optimism, and stress while controlling for other factors known to affect these outcomes by including them as covariates. African American was used as the reference to compare African American students to each of the other racial/ethnic groups of students.

Table 3 Race/ethnicity by the message received from parents prior to college

	Saving			Banking			Investing		
Race	No	Yes	% Yes	No	Yes	% Yes	No	Yes	% Yes
White	1337	9184	87.3	1068	9453	89.80	7401	3117	29.60
Black	163	562	77.5	175	551	75.90	507	216	29.90
Hispanic	140	682	83.0	170	650	79.30	612	209	25.50
Asian	90	723	88.9	129	685	84.20	471	340	41.90
Multiracial	165	977	85.6	154	987	86.50	823	319	27.90
Other	96	509	84.1	101	503	83.30	399	204	33.80
χ^2		71.77			215.03			68.88	
df		5			5			5	
p		< 0.001			< 0.001			< 0.001	

Source: 2014 National Student Financial Wellness Survey

Observations with missing values were removed creating sample sizes of n = 16,628 for Saving, n = 16,626 for Banking, and n = 16,618 for Investing

Table 4 Summary statistics of scales

	Financial management	Financial stress	Financial optimism
Minimum	3.3	− 3.88	1.99
Maximum	13.2	10.43	7.96
Median	9.84	3.93	5.97
Mean	9.707	3.793	5.752
Standard deviation	2.000	3.489	1.188

Source: 2014 National Student Financial Wellness Survey

Results

We observed that African American students received the least saving and banking messages compared to other racial/ethnic groups. Hispanic students reported receiving the investing message the least of all groups. The small p-values from the chi-square tests suggest there were significant differences between the races/ethnicities with respect to the messages each received about money from their parents prior to college. The results are presented in Table 3.

After removing observations with missing values for items included in the scales and the demographic covariates, we were left with 12,306 observations for the multivariate analyses. Summary statistics for the three scales are presented in Table 4. The scales were calculated as the sum of item responses included in each scale. The minimum and maximum represent the lowest and highest that any individual student actually achieved. Based on the scores in the data set, the lowest and highest possible financial management scores were 3.3 and 13.2; the lowest and highest possible financial stress scores were − 3.88 and 10.43; and the lowest and highest possible financial optimism scores were 1.99 and 7.96. Note that two items in the financial stress scale were negative coded, so negative factor scores were possible on the scale. Also, financial optimism consisted of three items instead of five thus the total possible score will be lower than the other two scales.

Multivariate results are presented in Table 5. Among the main variables of interest, students encouraged to invest their money were associated with increases in higher financial management scores and higher financial optimism scores. There was also a significant inverse relationship with students being encouraged to invest their money and students experiencing financial stress. The students who received the message to invest demonstrated higher average financial management, lower average financial stress, and higher average financial optimism.

Differences existed by race/ethnicity with respect to the financial outcomes. African American students had a greater average decrease in financial management scores when compared to White students. African American students had a greater average increase in reports of financial stress when compared to Asian students. Hispanic students had the highest financial optimism scores, followed by African American students.

The interactions between messaging and race/ethnicity produced significant results. African American students that received the message to invest their money had a greater average increase in their financial management scores than both Asian students and Other students that were encouraged to invest their money. Additionally, African American students encouraged to invest their money had a greater average increase in their financial optimism than both Asian students and Other students encouraged to invest money. African American students encouraged to save their money had a greater average decrease in financial stress than Asian students encouraged to save money. However, the saving message had the opposite relationship for African American students with respect to financial optimism. African American students encouraged to save their money had lower average increases in optimism about their financial future than White students, Multiracial students, and students in the Other category.

There were other significant trends among other demographic variables in the multivariate results. Males had higher average financial management scores, lower average financial stress scores, and greater average financial optimism than females. As parents' income increased, students had lower average financial stress and greater average financial optimism scores. Students with full-time jobs reported higher average financial management scores. As GPA and age increased, students reported higher average financial management scores and financial optimism scores.

Discussion

This research study sought to understand 1) how the types of financial socialization messages given by parents to their children vary by race; and 2) how the relationships between particular financial socialization messages and financial outcomes vary by race. The results of this study show two things. First, the types of messages participants received did vary across racial groups. Second, the types of messages (banking, saving, and/or investing) participants received were related to their financial stress, optimism, and management with the investing message being the most influential. The results of this study support the claim that financial socialization is related to better outcomes, as individuals who discussed financial matters with their parents were more likely to experience better financial outcomes and improved

Table 5 Regression results

	Financial management			Financial stress			Financial optimism		
	β	SE	P	β	SE	p	B	SE	p
Messages									
Save	0.262	0.247	0.290	– 0.711	0.406	0.080	– 1.246	1.607	0.438
Bank	0.166	0.243	0.494	– 0.224	0.399	0.574	– 0.704	1.577	0.655
Invest	0.597	0.200	0.003	– 0.806	0.328	0.014	5.465	1.298	< 0.001
Race (black)									
White	0.525	0.208	0.012	0.100	0.341	0.769	– 3.797	1.348	0.005
Hispanic	0.464	0.285	0.103	0.399	0.467	0.393	1.721	1.846	0.351
Asian	– 0.390	0.335	0.244	– 1.560	0.549	0.005	– 6.086	2.173	0.005
Multiracial	0.229	0.276	0.405	0.052	0.452	0.908	– 6.040	1.788	< 0.001
Other	0.625	0.335	0.062	1.005	0.549	0.067	– 5.681	2.172	0.009
Gender (male)									
Female	– 0.113	0.039	0.003	0.906	0.064	< 0.001	– 3.845	0.251	< 0.001
Transgender	0.492	0.454	0.278	1.196	0.745	0.108	– 5.360	2.944	0.069
Self-defined	– 0.456	0.266	0.087	1.436	0.436	< 0.001	– 8.259	1.725	< 0.001
No answer	– 0.069	0.232	0.768	0.099	0.381	0.796	– 4.006	1.506	0.008
Mother's education (< H.S.)									
H.S. Diploma	0.015	0.094	0.872	0.052	0.154	0.734	– 0.874	0.609	0.152
Some College	– 0.111	0.099	0.261	– 0.002	0.163	0.991	– 0.017	0.643	0.979
Associates	– 0.108	0.101	0.288	– 0.104	0.166	0.531	0.168	0.657	0.798
Bachelor's	– 0.235	0.099	0.018	– 0.335	0.163	0.039	– 0.300	0.643	0.641
Master's	– 0.232	0.108	0.031	– 0.197	0.177	0.264	– 1.095	0.699	0.117
Professional	– 0.436	0.164	0.008	0.054	0.269	0.840	– 1.671	1.065	0.117
Doctorate	– 0.265	0.191	0.164	– 0.385	0.313	0.219	0.709	1.238	0.567
Don't Know	– 0.202	0.223	0.366	– 0.141	0.366	0.699	-1.803	1.446	0.213
Father's education (< H.S.)									
H.S. Diploma	– 0.111	0.085	0.191	0.178	0.139	0.200	– 1.489	0.550	0.007
Some College	– 0.076	0.092	0.411	– 0.002	0.151	0.991	– 0.805	0.597	0.178
Associates	– 0.057	0.097	0.555	– 0.048	0.159	0.765	– 1.419	0.630	0.024
Bachelor's	– 0.178	0.090	0.048	– 0.134	0.148	0.363	– 1.064	0.585	0.069
Master's	– 0.158	0.099	0.112	– 0.347	0.163	0.033	– 0.824	0.643	0.200
Professional	– 0.211	0.132	0.111	– 0.332	0.217	0.127	– 0.695	0.858	0.418
Doctorate	– 0.183	0.136	0.180	– 0.060	0.223	0.790	– 1.686	0.883	0.056
Don't Know	– 0.025	0.137	0.855	0.461	0.225	0.041	– 1.044	0.891	0.241
Parent's annual income (< $15,000)									
$15,000–29,999	– 0.052	0.109	0.636	– 0.091	0.179	0.610	– 0.142	0.708	0.841
$30,000–39,999	0.144	0.109	0.185	– 0.155	0.178	0.384	0.640	0.704	0.363
$40,000–59,999	0.167	0.102	0.102	– 0.273	0.168	0.103	– 0.339	0.663	0.609
$60,000–79,999	– 0.038	0.103	0.713	– 0.450	0.169	0.008	– 0.212	0.669	0.751
$80,000–99,999	– 0.001	0.106	0.992	– 0.581	0.173	< 0.001	0.361	0.685	0.598
$100,000–149,999	– 0.138	0.104	0.183	– 1.098	0.171	< 0.001	1.553	0.674	0.021
$150,000–199,999	– 0.215	0.126	0.088	– 1.826	0.207	< 0.001	3.467	0.819	< 0.001
$200,000 +	– 0.206	0.125	0.098	– 2.597	0.204	< 0.001	5.276	0.808	< 0.001
Don't Know	– 0.157	0.094	0.095	– 0.634	0.155	< 0.001	0.147	0.611	0.809
No Answer	0.072	0.105	0.493	– 1.312	0.172	< 0.001	0.589	0.680	0.386
Employment status (full-time)									
Part-time	– 0.315	0.053	< 0.001	0.058	0.087	0.503	– 0.673	0.345	0.051
Not employed	– 0.471	0.058	< 0.001	– 0.297	0.096	0.002	– 0.638	0.379	0.092
GPA	0.001	0.000	< 0.001	– 0.005	0.000	< 0.001	0.014	0.001	< 0.001

Table 5 (continued)

	Financial management			Financial stress			Financial optimism		
	β	SE	P	β	SE	p	B	SE	p
Age	0.015	0.003	< 0.001	0.008	0.005	0.082	0.167	0.018	< 0.001
Messages and race/ethnicity interactions (black)									
Save*White	− 0.179	0.258	0.488	0.256	0.424	0.546	2.690	1.675	0.108
Save*Hispanic	0.158	0.336	0.637	− 0.142	0.551	0.796	1.988	2.177	0.361
Save*Asian	0.439	0.375	0.242	1.561	0.615	0.011	2.374	2.431	0.329
Save*Multiracial	0.352	0.325	0.278	− 0.244	0.532	0.646	4.119	2.105	0.050
Save*Other	0.190	0.380	0.617	0.049	0.623	0.937	5.035	2.462	0.041
Bank*White	− 0.059	0.256	0.819	− 0.055	0.420	0.896	1.753	1.660	0.291
Bank*Hispanic	− 0.259	0.326	0.426	0.261	0.534	0.625	− 2.027	2.113	0.337
Bank*Asian	0.371	0.341	0.276	− 0.034	0.559	0.952	3.668	2.209	0.097
Bank*Multiracial	− 0.195	0.327	0.551	0.686	0.537	0.201	0.777	2.122	0.714
Bank*Other	− 0.193	0.376	0.608	− 0.335	0.617	0.587	0.938	2.439	0.701
Invest*White	− 0.264	0.206	0.199	− 0.041	0.337	0.903	− 2.295	1.333	0.085
Invest*Hispanic	− 0.002	0.272	0.995	0.248	0.446	0.579	− 3.479	1.763	0.048
Invest*Asian	− 0.511	0.259	0.049	0.479	0.425	0.259	− 4.189	1.680	0.013
Invest*Multiracial	− 0.261	0.248	0.292	0.249	0.406	0.539	− 0.299	1.606	0.852
Invest*Other	− 0.609	0.289	0.035	0.019	0.475	0.968	− 4.767	1.877	0.011

Source: 2014 National Student Financial Wellness Survey

financial well-being (Fan and Chatterjee 2019; Gudmunson and Danes 2011; Kim and Chatterjee 2013; Kim and Torquati 2019; Serido et al. 2010; Shim et al. 2015).

Findings from this study are also consistent with the Family Financial Socialization Theory (Gudmunson and Danes 2011) which states that race may affect how family members interact and communicate with each other based on the values and norms family members hold regarding personal finances. The findings provide evidence that engaging in explicit financial socialization and the actual message received are each important, while the individual's race/ethnicity may also be a contributing factor. For all racial/ethnic groups, the investing message was significantly associated with higher financial management scores, higher financial optimism, and lower financial stress.

Of all groups, Hispanic students were least likely to receive the investment message. According to Porto (2016), Hispanics may differ from other groups because of many internal and/or external reasons related to cultural beliefs and attitudes when dealing with financial institutions. For example, although not measured here, immigration factors such as non-citizenship could impact investment messages provided by Hispanic parents. Personal finance stakeholders should amend curricula that were created to be a cultural "one size fit all" plan. Instead, an emphasis should be placed on creating inclusive financial education curricula that are not only specific to families of color, but also tailored to the needs of people from different ethnicities and cultures (Hudson et al. 2017; Williams et al. 2011). Integrating culture into family-based financial interventions could result in positive financial changes, e,g., increased savings and investing for households.

Furthermore, the findings suggest that race may also play a role in understanding how a specific financial message affects a person's financial behaviors and attitudes. Previous research has found differences in financial management behaviors across racial groups (Danes et al. 2008; Gutter et al. 2014); however, what has not been examined are the differences in the reception of messages and the effects that specific financial messages have across racial groups as they relate to financial behaviors, attitudes, and stress. For example, the current study found that White and Asian students were more likely to report receiving messages related to savings and banking than their African American peers. One reason for this could be that many African Americans lack trust in traditional banks. Research has found that African American households have disproportionately experienced discrimination with traditional financial services as it relates to their savings and banking needs (Goering and Wienk 2018; Hunter 2019) which has led to a historical and present distrust of banks for many of these households.

Implications

This study contributes to the Family Financial Socialization Theory and the financial socialization literature in two ways. First, it provides support for the idea that the financial discussions and related outcomes of these discussions do indeed vary by race. Second, it provides evidence that the type of financial message is related to several financial outcomes. More specifically, the financial message related to investing had the most significant association with financial outcomes such as financial management, financial optimism, and financial stress. Since this message had the most significant association, it is imperative that parents not only focus on messages related to concepts such as banking and saving, but also discuss concepts related to investing to increase the likelihood of better financial outcomes for their children. This is especially true and important for African American parents and their children.

Finally, given that many families may feel ill-equipped (e.g., low financial literacy, low financial self-efficacy) to provide the explicit financial socialization their children need in order to thrive, financial educators serve a critical role in filling in the gaps. Increased funding for financial education is necessary at the federal, state, and local levels. Legislators could support the efforts of personal finance professionals by passing legislation that would increase funding for financial education interventions for parents and children. Additionally, funding could encourage research that further investigates cultural differences as it relates to individuals' financial management outcomes.

These programs should aim to increase the financial management skills of parents in the home, which could lead to the emergence of better financial legacies for subsequent generations. As parents become more intentional in their teaching of financial principles, a strong foundation is more likely to be laid for their children's financial wellness. Thus, financial professionals and educators can engage parents on how to have conversations with their children to decrease racial and ethnic disparities in the type of messaging being discussed in the home. Additionally, teaching children investing concepts involving more comprehensive lessons with discussions on risk, time value of money, and financial goal setting may have a positive spillover effect on other financial behaviors.

Limitations

Financial optimism poses one limitation in the current study due to its lower Cronbach's alpha that places it in the questionable range of reliability as a dependent variable. However, the authors chose to include financial optimism as a dependent variable for three reasons: (1) there is a paucity of research exploring financial optimism, (2) although optimism is difficult to measure, its relationship with financial decision making provides evidence that it should be studied (Dawson 2017; Puri and Robinson 2007), and (3) Cronbach's alpha has been known to underestimate true reliability (Peterson and Kim 2013). As such, data containing better measures of financial optimism are needed for future analyses in order to add to the literature.

Although the study uses data from a large, nationally representative dataset, the analyses were constrained due to the cross-sectional and self-report nature of the NSFWS dataset. Future studies should use longitudinal data to identify potential causes for the associations found in this study. In addition, although differences were found in the messages received and their associations with financial outcomes across race, findings from this study do not explain why the differences exist. Additional studies should examine why financial messages vary across racial groups to better inform families and personal finance stakeholders about how these messages are chosen and delivered in households and the potential long-term effects of these conversations on financial behaviors.

Conclusion

Demographic factors like race and ethnicity are often overlooked when considering how financial messages shape financial management behaviors and attitudes. Financial researchers and clinicians have emphasized the importance and need for this work to be represented in the field. The current study has provided evidence of the nuances that may exist across racial and ethnic groups as they navigate their financial behaviors and attitudes. More work is needed to explore the differences that exist between racial and ethnic groups to provide an in-depth understanding of how specific financial messages can influence one's financial well-being.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

Research Involving Human and Animal Rights This article does not contain any studies with human participants or animals performed by any of the authors. The submission does not include images that may identify any person.

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Addressing Market Access (Part 1 - Research)
Friday, October 22
12:30 p.m. – 1:15 p.m.

This session presents current research examining the role of financial services in diversity and inclusion in capital markets, including advances in technology, advertising and the availability of financial advice.

Moderator:

Lori Walsh
Vice President, Office of the Chief Economist
FINRA Office of the Chief Economist

Panelists:

Christopher Clifford
Chair, Department of Finance and Quantitative Methods; Phillip Morris Associate of Finance
University of Kentucky

Will Gerken
Real Estate Endowed Associate Professor of Finance
University of Kentucky

Stanislav Sokolinski
Assistant Professor with the Finance and Economics Department
Rutgers Business School

Addressing Market Access (Part 1 - Research) Panelist Bios:

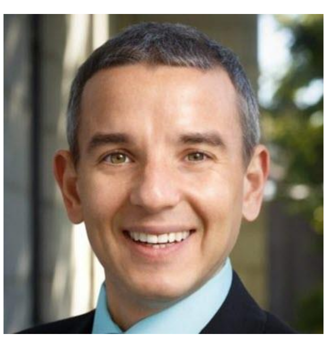
Moderator:

Lori Walsh is Vice President and Deputy Chief Economist and is responsible for management of national strategic and tactical initiatives by providing high quality research, analysis and advice on the economics of securities regulation and policy in support of the Office of the Chief Economist (OCE) and FINRA's mission. The work product informs current rulemaking initiatives, instantiated rules and potential areas of future regulatory actions through analysis of the economic impacts of existing and potential rulemakings. Ms. Walsh has been with FINRA since 2017. In addition to standing in for the Chief Economist in his absence, Ms. Walsh has been leading OCE's efforts to provide strategic and tactical support to FINRA's settlement and litigation activities. Ms. Walsh is also actively involved in several advanced R&D initiatives with Technology and other business units to ensure that FINRA stays a on the cutting edge of technological innovations in the financial markets. Ms. Walsh holds a B.S. in Accounting, an MBA and a PhD in Finance from the Pennsylvania State University. She is also a graduate of FINRA's Leadership Wharton program.

Panelists:

Dr. Chris Clifford is Chair of the Finance and Quantitative Methods department at the University of Kentucky and the Phillip Morris Associate Professor of Finance. His academic research interests focus primarily on non-bank intermediaries such as hedge funds, mutual funds, and investment advisors. His papers have been published at the *Review of Financial Studies*, the *Journal of Financial Economics*, and the *Journal of Finance*. His work has been mentioned in media outlets such as the *Financial Times*, *The Economist*, and *The Wall Street Journal*.

Will Gerken is the Real Estate Endowed Associate Professor of Finance. He has a PhD in Finance from Michigan State University, MS and MBA degrees from Georgia Tech, and BS degrees from West Virginia University. He is a CFA charter holder and serves as the principal contact for the CFA Institute University Affiliation Programs (BS & MSF). Prior to joining the Gatton College of Business, he was an Assistant Professor at Auburn University. His research focuses on financial advisors, financial misconduct, and governance. He has published his research in leading finance journals such as: *Journal of Finance*, *Journal of Financial Economics*, *Journal of Financial and Quantitative Analysis* and *Review of Finance*. He is an associate editor of the *Journal of Corporate Finance*. His research has won best paper awards at leading international conferences. His research has also been featured in the international media such as *The Wall Street Journal*, *Financial Times*, and *NPR* and cited by Securities Exchange Commission.



Stanislav Sokolinski is Assistant Professor of Finance and Economics at the Rutgers Business School in Newark and New Brunswick. His current research interests are in financial intermediation and asset management, with a specific emphasis on industrial organization to understand the benefits for investors and market efficiency. He studies the effects of financial advice, the determinants of competition and incentives in the mutual fund industry and explores how new financial technologies affect wealth inequality. Dr. Sokolinski holds a Ph.D. in Economics from Harvard University, a B.A. in Economics and Accounting and M.A. in Financial Economics from Hebrew University. Prior to pursuing his academic career, he advised the Director General of Israeli Ministry of Finance on economic policy and capital market reforms.

Addressing Market Access (Part 1 - Research)

Panelists

- **Moderator**
  - Lori Walsh, Vice President, Office of the Chief Economist, FINRA Office of the Chief Economist
- **Panelists**
  - Christopher Clifford, Chair, Department of Finance and Quantitative Methods; Phillip Morris Associate of Finance, University of Kentucky
  - Will Gerken, Real Estate Endowed Associate Professor of Finance, University of Kentucky
  - Stanislav Sokolinski, Assistant Professor with the Finance and Economics Department, Rutgers Business School

Trust and Race:
Evidence From the Market for Financial Advice

Christopher Clifford, University of Kentucky

Research Question

- Many households do not participate in equity markets
- Financial advisers are overwhelmingly white (and male)
- Trust in financial advisers plays a role in equity market participation

How does racial homophily between adviser and client relate to stock market participation?

Methodology

- FINRA data
  - Track geographic location (branch) of 1.5MM advisors over their career
  - NamePrism Linguistic surname algorithm to determine adviser race
- IRS data
  - Equity market participation at the zip code-income-year level
- Census data (ACS survey)
  - Zip code level demographic and socioeconomic data

Main Takeaways

- **Where a racial match exists e.g.,(at least one black advisor in a predominately black zip code)**
  - Equity market participation rates are 12% higher
    - Control for zip code income and population
    - Effect holds within-zip code changes
  - These effects predominately exist among middle income households ($50k-200k)
    - Relative to their own unconditional participation rates, middle income households are 25% more likely to invest when there is racial homophily
    - Low vs. high income levels?

Implications

- Non-monetary costs can affect participation
- Disparate impact can exacerbate wealth gaps
- Need to consider when hiring and developing programs to establish cross-cultural trust

Gauging the Participation of Diverse Communities in the Capital Markets

2021 ACCESS & IMPACT CONFERENCE

Where is the Intersection of Madison Avenue and Wall Street?

Advertisement, Local Access to Investment Advice, and Stock Market Participation

Joe Farizo, Will Gerken, and Ge Wu

Research Questions

What are the effects of advertising on stock market participation?

How do these effects interact with disparate levels of income, access to financial advice, and trust?

Methodology

- Data: *Advertising* (Kantar Media), *Advisors*, (SEC Form ADV & FINRA's BrokerCheck), & *Participation* (IRS Statistics of Income)

Main Takeaways

- **Investment advisory firm advertising elasticities are significant**
  - but somewhat smaller in magnitude than those found in other industries (Shapiro, Hitsch, and Tuchman, 2021)

- **Significant income effects**

- **Complementary nature of local access and trust building**

Implications

- Access and awareness of local finance matters

- Under-served neighborhoods may not be able to reap the benefits of promotional campaigns that help encourage broader participation in the markets

Automation and Inequality in Wealth Management

Michael Reher (UCSD) and Stanislav Sokolinski (Rutgers)

Research Question

- Professional wealth managers historically catered to the wealthy.

- Automated wealth managers (i.e. robo advisors) promote the idea of democratizing wealth management
  - Low account minimums and management costs.

- Is this view correct?
  - Do less wealthy participate in robo advice when it becomes more accessible?
  - What are the benefits from access to automated wealth management?

Methodology

Data and Setting

- Novel datasets from a major U.S. robo advisor, Wealthfront.
- Account-level data with demographics and investment activity.
- <u>Experiment:</u> the 2015 reduction in account minimum from $5000 to $500.

Analysis

- Differences in participation with robo advisor across wealth groups.
- Economic model to examine what drives demand for asset management.
- Quantify benefits to investors.

Main Takeaways

- **The reduction mostly affects middle-class households.**
  - Participation with robo advisor increases by 110%.
  - Especially strong effects for lower middle-class.
  - Participation among upper/lower class is unaffected.

- **Investors participate because they struggle to diversify on their own.**
  - Robo-portfolios have Sharpe Ratio of 0.75 against 0.45 for self-managed.
  - Higher expected returns and lower volatility.

- **Welfare gain equates to gain from 4pp higher equity premium.**

Implications

- Robo advice democratizes asset management.
  - Large benefits to investors from improved diversification.

- Why we don't observe even more participation with robo advisors?
  - The robo advice market is still relatively new and it keeps on expanding.
  - Why do some investors keep investing on their own if access to professional wealth management has been improving?
  - Financial education? Lack of information?

Does Automation Democratize Asset Management?*

Michael Reher† and Stanislav Sokolinski‡

February 2021

Abstract

We show that automation affects wealth inequality by giving middle-class households access to asset management. Using novel microdata from a major U.S. automated asset manager (i.e., robo advisor), we study a quasi-experiment in which the advisor suddenly reduces its account minimum by 90%. The reduction relaxes investment constraints on middle-class households and increases the number who participate with the advisor by 110%. Consequently, their expected return on liquid wealth rises by 1-2 pps relative to upper-class households, reflecting a sustained increase in compensated risk. However, automation may not reduce overall wealth inequality, as the reduction does not affect lower-class households.

Keywords: FinTech, Financial Advice, Portfolio Delegation, Inequality

JEL Classification: G11, G24, D3, O3

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1 Introduction

Wealth inequality has soared over the past four decades, in part because the wealthy earn higher financial returns than other households (e.g., Piketty 2014). Wealthy households also have access to a much wider range of investment opportunities, including accounts managed by professional asset managers. Opening such an account typically requires a minimum investment of at least $100,000 (e.g., Pilon 2011), far exceeding the median U.S. household's wealth of $17,000. Against this backdrop, a new class of asset managers that rely on automation (i.e., robo advisors) have promoted the idea of accessible asset management, and they have grown roughly tenfold over the past half-decade.[1]

Whether robo advisors actually improve the financial condition of non-wealthy households is unclear for two reasons. First, it is unclear whether robo advisors even give the non-wealthy access to asset management, versus simply competing with traditional asset managers for the wealthy. Second, even if robo advisors do "democratize" asset management, it is unclear whether this benefits non-wealthy households. For example, participating with a robo advisor may reduce household welfare if, like many asset managers, robo advisors charge high fees, project their own preferences, or face conflicts of interest (e.g., Fama and French 2010; Foerster et al. 2017; Chalmers and Reuter 2020) or if, like other FinTech intermediaries that democratize financial markets, they amplify households' own behavioral biases.[2] On the other hand, automation may enable robo advisors to circumvent these issues and, thus, improve welfare by providing low-fee, diversified, and personalized portfolios (e.g., D'Acunto, Prabhala and Rossi 2019; Loos et al. 2020; Rossi and Utkus 2020).

In this paper, we find that robo advising democratizes professional asset management, and, consequently, it affects inequality in financial returns to the benefit of the middle class (i.e., the moderately wealthy). Our research hypothesis begins with the observation that automation lowers robo advisors' fixed costs relative to traditional asset managers (e.g., Philippon 2019). Therefore, robo advisors can profitably manage smaller portfolios and,

[1]Quoting the financial press: "The wealth-management industry stratifies customers in a manner rather similar to airlines. High-net-worth clients fly business class, picking stocks and chatting in person with named advisors. Cattle class gets no service at all. Technology is conspiring to change that" (The Economist 2019). The top five robo advisors managed $283 billion in 2020 versus $30.4 billion in 2015 (Appendix Table A1).

[2]The surge in retail trading on the online brokerage Robinhood Markets during the COVID-19 pandemic exemplifies the latter case (e.g., Ben-David et al. 2021; Welch 2020; Barber et al. 2020).

thus, require lower accounts minimums. A lower minimum relaxes investment constraints on middle-class households and, thus, disproportionately increases their participation relative to both the wealthy, who were never constrained, and the poor, who remain constrained. As a consequence of this "asymmetric democratization", financial returns increase for the middle class relative to other households.

Two econometric hurdles make it challenging to test this hypothesis. The first hurdle is limited data: regulatory filings, industry reports, and other readily available sources of data about asset managers do not contain information about the *composition* of households who participate with them, which is central for our research hypothesis. We overcome this challenge by obtaining novel microdata directly from a major U.S. robo advisor. Our dataset includes information on the demographic background, investment activity, and liquid assets, inclusive of retirement accounts, of households who participate with the advisor. This information enables our main investigation into the distributional effects of automation in asset management. Additionally, since our dataset covers a period when the number of robo participants was small, we can examine whether shifts in the composition of robo participants at that time helped spur robo advisors' subsequent growth.

The second econometric hurdle is omitted variables bias. It would be naive to attribute differences in wealth between clients of robo advisors vs. traditional asset managers to lower account minimums, since robo advisors may attract households who vary in other dimensions that correlate with wealth (e.g., technological savviness). We overcome this challenge by studying a quasi-experiment in which the same robo advisor unexpectedly reduces its account minimum from \$5,000 to \$500 in July 2015. This \$4,500 reduction constitutes a large shock for most U.S. households, as it equals 26% of the median U.S. household's liquid assets of \$17,000 at the time. Moreover, it generates a clean source of variation with which to test our research hypothesis because it occurs within the same asset manager, thereby allowing us to hold manager-specific effects fixed.

Our main result is that the reduction democratizes the market for automated asset management by relaxing investment constraints on middle-class households. Graphically, the wealth distribution of robo participants shifts sharply leftward after the reduction, as shown in Figures 1 and 2, while showing no pre-trend in the months leading up to it, as shown in Figure 3. In particular, the share of robo participants from the second and third U.S. wealth quintiles (i.e., "middle class") increases by 107% (16 pps), reflecting a sharp break from trend that is not present among participants from the wealthiest two quintiles (i.e., "upper class"). However, the democratization is asymmetric, in that there is no change in participation among the poorest quintile (i.e., "lower class").

We formalize this graphical intuition through a difference-in-difference analysis that compares the probability of participating with the robo advisor after vs. before the reduction between middle vs. upper-class households. Intuitively, the middle class represents the "treated" group in that it experiences a relaxation of investment constraints due to the reduction. Accordingly, we find that middle-class households are 14 pps more likely to participate with the robo advisor after the reduction, relative to the upper class. Since the middle class was previously underrepresented, this estimate implies that the reduction increases the total number of middle-class robo participants by 110%. These findings do not confound the effect of household demographic characteristics or risk attitude, which we control for in our regressions. Neither do they stem from measurement error in liquid assets, since we obtain the same results from four different measures of middle-class wealth status.

The internal validity of this research design depends on whether the middle class experiences a relaxation of investment constraints. Consistent with this view, the majority of middle-class households who became robo participants prior to the reduction "bunched" their investment right at the previous minimum of $5,000, suggesting that they were constrained by it. After the reduction, however, such bunching immediately disappears, and most new middle-class participants make a previously infeasible investment of less than $5,000. These new middle-class participants were also previously inactive in many financial markets, and, for example, were 43 pps less likely to have participated in the stock market before the reduction, relative to new upper-class participants. This finding again suggests that the previous account minimum imposed a binding constraint on middle-class households' set of investment opportunities.

Based on a wide variety of robustness tests, we find no evidence that the results are driven by channels distinct from a relaxation of constraints, such as targeted advertising, media attention, business stealing from competitors, effects specific to the millennial generation, or gambling motives. For example, we obtain the same results from a panel regression that explicitly allows the middle class to respond differently to the advisor's advertising efforts and media attention, which implies that our research design disentangles the effect of investment constraints from the well-documented impact of visibility on retail investors' behavior (e.g., Kaniel and Parham 2017). Moreover, we find similar results from an aggregated difference-in-difference analysis where observational units are bins of the U.S. population.

Turning to inequality in financial returns, we follow Calvet, Campbell and Sodini (2007) and estimate the reduction's effect on middle-class households' total portfolio return, defined as the expected annual return on liquid assets. We find that the reduction increases the middle class' total return by 1.1 pps relative to the upper class, and this effect is driven by a 13 pps increase in risky share. The increase is strongest among households from the second quintile of the U.S. wealth distribution, as their total return grows by 2.1 pps. These results are robust to a placebo test on existing participants, and we check that they are not driven by various forms of measurement error in risky share or expected return. Neither are our results biased by the possibility that new middle-class robo participants invest more efficiently than other households, since the robo advisor chooses portfolio allocations algorithmically with little room for discretion by participants themselves.

While we cannot make definitive welfare statements without imposing a specific utility function or observing the entirety of households' assets and liabilities, three pieces of evidence suggest that the reduction benefits middle-class households. First, their increase in risky share can be rationalized with plausible coefficients of relative risk aversion (e.g., 7), suggesting that these households do not take excessive risk. Second, the risk they do take is well-compensated, in that 96% of the variance in their robo portfolio returns is spanned by well-known risk factors (e.g., Fama and French 1993). Third, these households hold their positions long enough to realize gains from automated asset management, as only 6% make a withdrawal over our sample period. Moreover, 70% make a subsequent deposit, consistent with the dollar cost averaging approach advocated by practitioners and inconsistent with silent attrition or inertia (e.g., Agnew, Balduzzi and Sunden 2003; Bilias, Georgarakos and Haliassos 2010). Collectively, therefore, we interpret the reduction as a Pareto-improving technological innovation that, by favoring the middle class over both the wealthy and the poor, has an ambiguous effect on overall inequality in financial returns.

In policy terms, governments in both the U.S. and the U.K. have developed retirement plans that aim to increase investing by non-wealthy households (e.g., myRA, OregonSaves, NEST). However, these plans typically offer a limited set of investment options, charge high fees, and provide little personalization.[3] Our results suggest that private asset management can accomplish similar objectives as these programs by using automation to provide portfolios that are both sophisticated and accessible. However, this conclusion comes with two caveats related to external validity. First, aggregating our estimates may overstate the effects of an industry-wide reduction in account minimums, since asset managers compete for the same clients in general equilibrium. That said, we observe little reallocation across robo advisors in our setting, suggesting that such an overstatement may be modest. Second, our quasi-experiment occurs against the backdrop of a rapidly growing market for robo advising (e.g., D'Acunto and Rossi 2020), and so the same research design may yield weaker estimates in, say, an aging economy.

The rest of the paper proceeds as follows. We conclude this section by situating our contribution within the related literature. Section 2 presents an organizing theoretical framework. Section 3 provides institutional background and describes our quasi-experiment. Section 4 describes our data. Section 5 estimates the effect of the reduction on the democratization of the robo market, and Section 6 assesses the robustness of this effect. Section 7 studies the effect on inequality in financial returns. Section 8 studies welfare implications. Section 9 concludes. The online appendix contains additional material.

Related Literature

This paper makes three contributions to the literature. First, we contribute to a nascent literature on robo advisors by showing how automation democratizes professional asset management. Our focus on how robo advisors expand accessibility complements existing research on how they improve diversification, reduce behavioral biases, and increase risky investment

[3]For example, the recently phased-out myRA program only offered investments in U.S. government bonds. OregonSaves charges a management fee of 1%. The U.K.'s NEST pension scheme charges a load of 1.8%, a 0.3% management fee, and can require a minimum contribution.

among investors who already have access to investment professionals (e.g., D'Acunto, Prabhala and Rossi 2019; Loos et al. 2020; D'Hondt et al. 2020; Bianchi and Briére 2020; Rossi and Utkus 2020; Reher and Sun 2019). Like the existing research, our findings contrast with the high fees, underperformance, and misaligned incentives associated with traditional asset managers and financial advisors (e.g., French 2008; Bailey, Kumar and Ng 2011; Christoffersen, Evans and Musto 2013; Del Guercio and Reuter 2014; Linnainmaa, Melzer and Previtero 2021). However, we draw a parallel between robo and traditional advisors, in that both increase stock market participation (e.g., Linnainmaa et al. 2020).

Second, we contribute to a broader literature on new financial technologies (i.e., FinTech) by proposing robo advice as an example of how FinTech affects financial inclusion and wealth inequality. In terms of financial inclusion, this finding complements analogous results in the contexts of app-based payments (e.g., Hong, Lu and Pan 2020), bank deposits (e.g., Bachas et al. 2018; Bachas et al. 2020; Higgins 2020), and mortgage markets (e.g., Fuster et al. 2019; Bartlett et al. 2021; Fuster et al. 2021). In terms of inequality, our empirical results confirm the theoretical prediction of Philippon (2019) that robo advising favors the middle class over both the upper and lower classes. More broadly, this finding exemplifies how FinTech can affect well-documented inequality in financial returns (e.g., Lusardi, Michaud and Mitchell 2017; Campbell, Ramadorai and Ranish 2019; Bach, Calvet and Sodini 2020; Fagereng et al. 2020).

Third, we contribute to a large literature on household finance by empirically characterizing a novel friction that constrains household investment in risky asset markets: account minimums required by asset managers. This friction arises from the supply side and does not directly depend on household characteristics such as preferences (e.g., Barberis, Huang and Thaler 2006), sophistication (e.g., Grinblatt, Keloharju and Linnainmaa 2011; Christelis, Jappelli and Padula 2010), socialization (e.g., Hong, Kubik and Stein 2004), or education (e.g., Cole, Paulson and Shastry 2014; Van Rooij, Lusardi and Alessie 2011).[4]

[4] Based on a calibration, Haliassos and Bertaut (1995) conclude that account minimums may have a quantitatively small effect on household investment, but they do not actually use data on such minimums. Separately, a number of asset pricing models have studied how limited stock market participation may contribute to the equity premium puzzle (e.g., Mankiw and Zeldes 1991, Gomes and Michaelides 2008, or Malloy, Moskowitz and Vissing-Jørgensen 2009). A common parameter in these models is a fixed cost of participation (e.g., Vissing-Jørgensen 2002), and our results show how account minimums can be used to micro-found this parameter. Lastly, the asymmetric democratization that we document provides an

2 Theoretical Framework

We organize our empirical analysis around a framework of delegated risky investment with constraints, which we sketch below. Given our empirical focus, we defer a more formal theoretical treatment to Appendix B.

Setup

1. *Delegated Risky Investment*: Households solve a portfolio optimization problem in which they delegate their risky portfolio to asset managers. This strong preference for delegation is a simplification, but it does match the empirical observation that 70% of stock market participants rely on professional advice, as shown in Appendix Table A3 and corroborated by Guiso and Sodini (2013).[5] The intuition would be the same if, instead, households delegate a fraction ρ of their risky portfolio to asset managers because, say, they do not fully trust them. For the sake of exposition, we discuss the case where ρ approaches one.

2. *Account Minimum*: Asset managers offer a portfolio with risky, net-of-fee return R. However, they can only manage portfolios larger than some account minimum M because they incur a fixed cost of management per portfolio.

3. *Constrained-Optimal Portfolio Choice*: Absent the account minimum, a household would delegate a share $\tilde{\omega}$ of her wealth to the asset manager and receive expected utility $U(\tilde{\omega})$. However, if $\tilde{\omega} < \frac{M}{W}$, then she cannot invest this optimal share, since doing so would result in an investment smaller than the minimum. Instead, she would need to invest the exact share $\frac{M}{W}$ to participate, which she may not do for one of two reasons. First, she may simply lack enough wealth to invest without borrowing (i.e., $W < M$). Second, she may have enough wealth, but participating would require investing such a large share of her wealth that she prefers not to invest at all (i.e.,

alternative perspective to models that predict a positive relationship between FinTech and inequality (e.g., Begenau, Farboodi and Veldkamp 2018; Kacperczyk, Nosal and Stevens 2019; Mihet 2020).

[5] Various theories exist for why households exhibit such a strong preference for delegation (e.g., Gennaioli, Shleifer and Vishny 2015; Gârleanu and Pedersen 2018), but we simply take it as given. According to Guiso and Sodini (2013), only 12% of retail investors make financial decisions without professional assistance.

$U(0) > U\left(\frac{M}{W}\right)$). Thus, the minimum can still constrain households whose wealth exceeds it, as we find empirically.

Effects of Automation

4. *Reduction in Account Minimum*: Technological innovation enables asset managers to automate portfolio management. Automation lowers their fixed per-portfolio costs, and, consequently, they can substantially reduce their account minimum to $M' < M$.

5. *Asymmetric Democratization*: The automation-enabled reduction in account minimum removes constraints on moderately wealthy households, for whom $\frac{M'}{\tilde{\omega}} \leq W < \frac{M}{\tilde{\omega}}$. It does not affect wealthier households, since they were never constrained. Neither does it affect poorer households, since they remain constrained. Thus, the reduction democratizes asset management by enabling middle-class households to participate in it, but this democratization is asymmetric because the poor are unaffected.

6. *Lower Inequality in Returns and Higher Welfare*: Participating in asset management increases moderately wealthy households' risky share, and, therefore, raises their expected financial return relative to the wealthy. By revealed preference, the reduction makes fully-optimizing households better off relative to a counterfactual of holding cash (i.e., $\tilde{\omega} = 0$). In reality, households may not realize these theoretical welfare gains by taking excessive risk, not diversifying their risk, or prematurely liquidating their portfolios. However, our evidence in Section 8 suggests that the automated nature of robo portfolios prevents households from making such mistakes.

7. *General Equilibrium*: In a competitive equilibrium, asset managers innovate to attract moderately wealthy households. Therefore, we interpret the reduction as the result of a productivity "shock" that, in the Romer (1990) sense, is not exogenous in general equilibrium. However, the reduction constitutes an exogenous shock within the portfolio optimization problem described above, and so we can identify its effect on household choice. In particular, the fixed effects in our regressions absorb general equilibrium effects, as we discuss in Section 5.2. Thus, general equilibrium considerations (e.g.,

industry competition) do not affect the results' internal validity, although they may impact external validity in ways outlined our conclusion.

3 Institutional Background

To test the theory outlined above, we study a quasi-experiment in which a major U.S. robo advisor reduces its account minimum. We now describe the U.S. robo advising market, the business model of the particular robo advisor we study, and the reduction implemented by this advisor.

3.1 The U.S. Robo Advising Market

As summarized by D'Acunto and Rossi (2020), robo advisors emerged in the mid-2000s in response to the limitations of traditional asset managers. They are distinguished by relying on algorithms to select and maintain an allocation for their clients. This automated approach features lower per-portfolio management costs relative to the traditional approach of manually constructing and managing a client's portfolio. In practice, several robo advisors also incorporate human judgment on a portfolio-by-portfolio basis, much as a traditional manager would. Others rely purely on algorithm, including our data provider, Wealthfront.

At the time of our analysis, Wealthfront managed roughly $3 billion and was the largest standalone robo advisor in the U.S. market, with Betterment and Personal Capital as its nearest competitors. Two traditional asset managers, Vanguard and Charles Schwab, launched robo advising services early in 2015. Both of these services managed more than Wealthfront because they transferred assets from existing, non-robo services. Appendix Table A1 summarizes the largest robo advisors in the U.S. as of July 2015, including their account minimums, assets under management, fees, and provision of traditional, human-based management. Note that Wealthfront stands out as the only robo advisor that relies purely on automation, with no option for a human advisor.

3.2 Robo Portfolio Allocations

Wealthfront, henceforth "the robo advisor", has offered many services throughout its history, including tax loss harvesting, long term financial planning, portfolio lines of credit, and a risk parity fund. Its baseline product, which is most relevant for this paper, is an automatically rebalanced portfolio of 10 ETFs corresponding to 10 asset classes.[6] The portfolio weights are determined by a questionnaire that asks the client several questions about age, liquid assets, income, demographic background, and response to hypothetical investment decisions. The client is then assigned to one of 20 possible risk tolerance scores, which range from 0.5 to 10 in increments of 0.5. Each risk tolerance score uniquely determines a robo portfolio. The portfolio weights solve a problem of optimal asset allocation across the 10 ETFs, taking this score as a parameter. As summarized in Appendix Table A2, portfolios associated with higher risk tolerance scores exhibit higher betas, higher expected returns, and higher proportions of wealth invested in stocks.

Summarizing, the robo portfolios we study conform to most "textbook" recommendations for retail investors (e.g., Malkiel 2015), in that they provide well-diversified risk exposure with more personalization than a generic "60/40" portfolio, but without the complexity often associated with active management. Importantly, robo portfolios are not recommendations, but, rather, they are directly managed by the robo advisor. Consequently, households have little discretion over their portfolio allocations, and so their robo performance will not depend on sophistication (e.g., Grinblatt, Keloharju and Linnainmaa 2011; Christelis, Jappelli and Padula 2010), ability to diversify (e.g., Calvet, Campbell and Sodini 2007), willingness to follow advice (e.g., Bhattacharya et al. 2012), or reluctance to rebalance (e.g., Calvet, Campbell and Sodini 2009).

[6]Strictly speaking, each asset class has a primary ETF and multiple secondary ETFs. The robo advisor will rebalance toward the secondary ETF if doing so yields a capital loss and, thus, reduces the client's tax liability. The 10 primary ETFs are chosen to track stock market indices (VIG, VTI, VEA, VW), bond market indices (LQD, EMB, MUB, TIPS), and other asset classes, namely real estate (VNQ) and commodities (XLE).

3.3 The 2015 Reduction in Account Minimum

On July 7, 2015, the robo advisor unexpectedly reduced its account minimum from \$5,000 to \$500, which represents a sizeable decline from the standpoint of most U.S. households. For reference, \$5,000 equals 30% of the median household's liquid assets (\$17,000), and it defines the 37$^{\text{th}}$ percentile of the U.S. wealth distribution, according to the 2016 Survey of Consumer Finances. Prior to the reduction, therefore, half of U.S. households could not participate with the advisor without investing at least 30% of their wealth, while 37% could not participate at all without borrowing. The reduction was motivated by the advisor's philosophy of inclusive investment and belief that non-wealthy households will eventually accumulate enough assets to become high-revenue customers.[7] Indeed, given the advisor's management fee of zero for accounts under \$10,000 or 0.25 pps for larger accounts, the reduction was not intended to increase short-term revenue.

At the time of the reduction, all of the largest five U.S. robo advisors required an account minimum of at least \$5,000 except for one, Betterment, which had no account minimum but maintained a fee structure that discouraged setting up small accounts.[8] Importantly, the month of the reduction does not coincide with any other product launches by the robo advisor, any changes in its fee, or any significant developments in the overall robo advising market. This effectively idiosyncratic timing allows us to identify the reduction's effect on household participation in automated asset management, as we describe in Section 5.

4 Data

Our core analysis relies on two datasets: a panel dataset covering deposit activity by households who participate with the robo advisor; and a cross-sectional dataset covering all U.S. households. We describe the key features of each dataset here and defer additional

[7] In the words of the robo advisor's then-CEO: "Unlike the many banks and brokerage firms that came before us, [we] refuse to build our business by preying on clients with small accounts. ... We believe that, given a fair shake, people bold enough to scrape together the savings for their first investment account will build those accounts over time."

[8] This advisor charged a \$3 service fee on accounts under \$10,000 for customers who do not auto-invest \$100 monthly in their accounts. This fee structure implies a 7.2% annual management fee for a \$500 account and a 36% management fee for a \$100 account (Thomson Reuters 2015).

details to Appendix A. For the rest of the paper, we use the term “robo participant” to describe households who have invested money with the robo advisor, Wealthfront.

4.1 Robo Advising Dataset

The first core dataset contains a weekly time series of deposits with the robo advisor from December 1, 2014 through February 29, 2016. This window straddles the reduction in account minimum, and it marks a formative period in the history of the robo advising market when the number of participating households was still small. We obtained this dataset through a direct query of the robo advisor’s internal server, and so we observe the same information as would an analyst working for the advisor. Specifically, we observe the date and size of the deposit, whether the deposit comes from a new participant with the robo advisor, and the following demographic variables about the participating household: annual income; state of residence; householder age; and liquid assets, defined as “cash, savings accounts, certificates of deposit, mutual funds, IRAs, 401ks, and public stocks”. The demographic variables are self-reported via the robo advisor’s questionnaire and static. Thus, liquid assets may be subject to measurement error from misreporting, but the battery of tests in Section 5.3.1 suggest any such measurement error does not bias our results.

Studying a company-specific dataset has two advantages over publicly available datasets such as the SEC’s Form ADV filings, which serve as the basis for many industry reports about the robo market. First, estimates of robo participation growth derived from Form ADV data would be highly imprecise because they can include both inactive clients and “clients” who create a username but never provide the robo advisor with any money.[9] Second, unlike public data, our dataset includes information about a robo participant’s wealth. This feature allows us to study investment activity across the wealth distribution, which lies at the heart of our research hypothesis.

[9]For example, we observe 9,702 participants in our dataset, in contrast to the 61,000 reported in publicly available SEC filings. This discrepancy reflects how: “The definition of ‘client’ for Form ADV states that advisors must count clients who do not compensate the advisor” (SEC 2017).

4.2 Survey of Consumer Finances (SCF)

The second core dataset is the 2016 Survey of Consumer Finances (SCF), which includes financial and demographic information about a representative cross-section of U.S. households. The SCF dataset fulfills two purposes in our setting. First, it allows us to benchmark a household's wealth in our robo advising dataset against the U.S. population and, thus, to estimate the shock's effect on the democratization of the robo market. We respectively use the terms "lower class", "middle class", and "upper class" to describe households from the first, second or third, and fourth or fifth quintiles of the overall U.S. distribution of liquid assets, where liquid assets are calculated to match the definition in our robo advising dataset as closely as possible. The corresponding boundary between the lower vs. middle class is \$1,000 in liquid assets, and the boundary between the middle vs. upper class is \$42,000. The second purpose of the SCF dataset is to impute participation in asset management, the stock market, and homeownership, which we do not observe in our robo advising dataset. Section 6.1.3 describes our imputation methodology at a high level, and Appendix C provides complete details. Appendix Tables A3 and A7-A10 summarize the SCF dataset.

4.3 Summary Statistics

Table 1 compares households who become robo participants after the reduction in account minimum with existing participants. The upper panel shows how these new participants are significantly less wealthy, earn lower incomes, make smaller initial deposits, and are 16 pps more likely to belong to the middle class. The lower panel restricts the comparison to middle-class households, and it conveys a similar pattern. In particular, the median new middle-class participant's initial deposit of \$2,000 would have been infeasible under the previous account minimum of \$5,000. Indeed, over half of existing middle-class participants invested exactly \$5,000 for their initial deposit, suggesting that they were constrained by the previous account minimum. Interestingly, new middle-class participants are not significantly younger than existing ones, providing suggestive evidence that the reduction works through a relaxation of constraints rather than through, say, technological savviness or other generation-specific effects.

5 Democratization of the Robo Market

We now test our main research hypothesis that the reduction in account minimum increases robo participation by constrained, middle-class households (i.e., "democratization"), which is a necessary first step toward understanding the effect of automation on such households' financial condition. After first providing graphical evidence, we then formalize our identification strategy, report our main results, and assess the magnitude of the effect.

5.1 Graphical Evidence

Three pieces of graphical evidence support the prediction that the reduction democratizes the robo market. First, Figure 1 shows how the wealth distribution of robo participants shifts left after the reduction. This shift reflects how new robo participants are significantly less wealthy than existing ones, as already documented in Table 1.

Second, Figure 2 shows how the leftward shift documented in Figure 1 makes the robo wealth distribution more representative of the overall U.S. wealth distribution (i.e., more "democratic"). Notably, the share of robo participants from the second and third quintiles of the U.S. wealth distribution grows by 107% (16 pps), while the share from the upper two quintiles falls by 18% (16 pps). However, there is a non-monotonic relationship between robo participation growth and wealth, since lower-class households remain nonparticipants. Therefore, consistent with the prediction from Section 2, the reduction asymmetrically democratizes the robo market. Appendix Figure A1a reproduces this pattern using an alternative measure of middle-class status.

Third, Figure 3 shows how the increase in middle-class households' robo participation occurs strikingly and immediately after the reduction, and Appendix Figure A1b confirms its statistical significance. In particular, the sharp jump and absence of a pre-trend in middle-class participation strongly suggests that this increase does not reflect reverse causality. Otherwise, an exogenous shock to middle-class robo participation coinciding exactly with the month of the reduction would have prompted the advisor to reduce its minimum at exactly that time, which seems implausible. More likely, the advisor accurately judged that reducing its minimum would induce such an increase in middle-class participation.

Collectively, these three pieces of graphical evidence show that a leftward shift in the robo wealth distribution occurs immediately after the reduction, making the distribution more representative of the U.S. population. In the remainder of this section, we test whether the reduction causally induces this shift by relaxing constraints on middle-class households.

5.2 Identification

Begin with the following flexible model of robo participation in period T,

$$Participant_{i,T} = \beta \left(Middle_i \times Post_T \right) + \delta \left(X_i \times Post_T \right) + \mu_i + \tau Post_T + \upsilon_{i,T}, \tag{1}$$

where i indexes household; T indexes the pre-reduction period (i.e., $T = 0$) vs. the post-reduction period (i.e., $T = 1$); $Participant_{i,T}$ indicates if household i participates with the robo advisor at some point in period T; $Middle_i$ indicates if i belongs to the second or third U.S. wealth quintile, in contrast to the fourth or fifth quintiles that comprise the reference group; μ_i is a household fixed effect; and X_i is a vector of household characteristics: age, log income, state of residence fixed effects, and an indicator for whether the household chooses a higher risk tolerance score than that recommended by the advisor's algorithm.

Our framework in Section 2 predicts that the reduction affects robo participation among households with moderate levels of wealth because it relaxes constraints on their ability to invest. Equation (1) measures "moderate wealth" using the indicator $Middle_i$. Therefore, under an identification assumption described shortly, the parameter β equals the effect of the reduction on middle-class households' probability of robo participation. Explicitly, β equals the double difference in the probability of becoming a robo participant after vs. before the reduction between middle-class vs. upper-class households.

Two other terms in equation (1) merit discussion. First, μ_i captures time-invariant or otherwise slow-moving characteristics that predispose households to participating with the advisor, such as a certain level of sophistication or trust (e.g., Guiso, Sapienza and Zingales 2008). Since such "affinity" to the advisor increases the probability of participation in any period, we can separately identify the effect of investment constraints because the account minimum changes over time. Second, the interaction between X_i and $Post_T$ captures heterogeneous trends by observed household characteristics. If, for example, younger households are more likely to become robo participants after the reduction for reasons apart from a relaxation of investment constraints, then this effect would be separately captured by the parameter δ. Thus, both of the additional terms in equation (1) capture channels distinct from the investment constraints channel, and they also define how strong the latter must be to induce a change in robo participation. In particular, relaxing constraints increases the probability of robo participation by β, and this effect can push a household over the threshold to eventually participating if the other two channels are strong enough.

Estimating equation (1) is equivalent to estimating the first-differenced equation,

$$\Delta Participant_i \equiv New\ Participant_i = \beta Middle_i + \delta X_i + \tau + u_i, \tag{2}$$

where $New\ Participant_i$ indicates if household i becomes a robo participant after the reduction; and $u_i \equiv \Delta v_i$. We estimate equation (2) on the set of eventual robo participants, and, therefore, β equals the reduction's effect on the probability of robo participation conditional on eventually participating. This statistic is relevant because, as we formalize in Section 5.4, it directly maps to the mass of participants whom the reduction brings into the robo market and, thus, quantifies the democratization of the robo market.

The following identification assumption allows us to interpret β as the effect of the reduction on middle-class households' probability of robo participation:

$$0 = \mathbb{E}\left[Middle_i \times u_i \middle| X_i \right]. \tag{3}$$

In words, equation (3) states that unobserved determinants of a *change* in robo participation, u_i, do not systematically vary across the middle and upper classes, which implies that the difference in the change in robo participation between the middle and upper classes reflects the effect of a lower account minimum. This assumption is conditional on the household's observable characteristics, X_i.

Apart from measurement error in self-reported liquid assets, which we discuss at length below, there are two other ways in which equation (3) could be violated. First, u_i may capture changes in middle-class households' robo participation that coincide with the reduction, but which are not caused by the reduction. One such confounding change could be trend growth in middle-class households' robo participation. However, the strong parallel trends shown in Figure 3 make this form of bias unlikely. Another potentially confounding factor could be contemporaneous developments in the robo industry, such as the launching of new robo products by Vanguard and Charles Schwab. However, these new products were not targeted toward the middle class, and they were launched at least two months prior to the reduction, comfortably before the strong divergence in middle-class households' behavior in Figure 3.

Second, equation (3) could be violated if u_i captures changes in middle-class households' robo participation that are themselves side effects of the reduction, the leading examples of which are media attention and advertising. If middle-class households are more exposed to such media attention or advertising, then the results may confound the effects of these alternative shocks, which work through heightened visibility (e.g., Kaniel and Parham 2017), with the effect of the reduction, which works through a relaxation of investment constraints. We assess the scope for bias from heterogeneous visibility in Section 6.2, and the evidence suggests that such heterogeneity does not bias the estimates.

5.3 Baseline Results

Table 2 reports the results. The estimate in column (1) implies that middle-class households are 22 pps more likely to become robo participants after the reduction in account minimum, relative to upper-class households. After we add household-level control variables and state fixed effects in column (3), the estimated effect equals 14 pps, which we take as our baseline estimate. We reserve Section 5.4 for assessing the magnitude of this effect.

5.3.1 Measurement Error

Our treatment exposure variable, $Middle_i$, may be subject to additive measurement error due to self-reporting. On the one hand, such measurement error introduces attenuation bias, which would tend to bias the estimates toward zero. Similarly, the estimates are biased toward zero if new robo participants overreport their wealth more than existing participants do. On the other hand, measurement error biases the estimates away from zero if new participants underreport their wealth relative to existing participants.[10]

We mitigate this concern by remeasuring $Middle_i$ in three ways, all of which plausibly provide a more precise measure. First, we redefine the middle class exclusively as the second quintile of the U.S. wealth distribution and omit households from the third quintile from the sample. Under this definition, upper-class households would need to underreport liquid assets by at least \$36,000 to be misclassified as middle-class. Second, we exclude households whose liquid assets are within a 10% buffer of the boundary between the third and fourth quintiles. This approach removes all cases of mismeasurement that exceed \$8,400 ($2 \times 0.1 \times 42,000$). Third, we remove households whose reported wealth class differs from their imputed wealth class, based on the imputation procedure described in Appendix C applied to the SCF dataset. The remaining 61% of households have a well-measured wealth class, in that it accords with what one would predict based on a nationally representative dataset. Note that self-reported wealth class is equally well-measured for middle and upper-class robo participants, as shown in Appendix Table A10, which suggests that the measure of liquid assets in our robo advising dataset is not systematically biased.

The estimates based on these alternative measures of $Middle_i$ all lie between 0.1 and 0.17, as shown in columns (4), (5) and (6) of Table 2. This range straddles our baseline estimate of 0.14, suggesting that it is not biased because of measurement error.

5.4 Magnitude of Effect

We use the estimates in Table 2 to decompose the observed growth rate in the total number of robo participants into the component due to the reduction vs. that due to other forces. The observed growth rate can be directly calculated from the data as

$$g = \frac{New\ Participants}{Existing\ Participants}, \tag{4}$$

[10]Formally, if we mismeasure $Middle_i$ as $\widehat{Middle}_i = Middle_i + \varepsilon_i$, then the estimator for β in a specification of equation (2) without controls is: $\widehat{\beta} = \beta \left(1 - \frac{\mathrm{Var}[\varepsilon_i] + \mathbb{E}[Middle_i \times \epsilon_i]}{\mathrm{Var}\left[\widehat{Middle}_i\right]}\right) + \frac{\mathbb{E}[u_i \times \varepsilon_i]}{\mathrm{Var}\left[\widehat{Middle}_i\right]}$. The term in parentheses captures the effect of attenuation bias. The second term captures bias from differences in misreporting between new and existing participants.

where *New Participants* is the number of households who become robo participants after the reduction; and, analogously, *Existing Participants* is the number who participated beforehand. It will be helpful to rewrite the numerator of equation (4) as

$$\textit{New Participants} = \mathbb{E}\left[\textit{New Participant}_i\right] \times \textit{All Participants}, \tag{5}$$

where *All Participants* = *New Participants* + *Existing Participants* is the sum of new and existing robo participants; and $\mathbb{E}\left[\textit{New Participant}_i\right]$ is the share of all such robo participants who are new. Substituting equations (5) and (2) into equation (4) allows us to express g as

$$g = \frac{\mathbb{E}\left[\textit{New Participant}_i\right]}{1 - \mathbb{E}\left[\textit{New Participant}_i\right]} = \frac{\beta \mathbb{E}\left[\textit{Middle}_i\right] + \delta \mathbb{E}\left[X_i\right] + \tau}{1 - \left(\beta \mathbb{E}\left[\textit{Middle}_i\right] + \delta \mathbb{E}\left[X_i\right] + \tau\right)}, \tag{6}$$

which, by definition, is numerically equivalent to the expression in equation (4).

Consider a counterfactual without the reduction, in which middle-class households do not experience a relaxation of investment constraints and, thus, $\beta = 0$. Under this counterfactual, the overall number of robo participants grows at the rate

$$g^C = \frac{\delta \mathbb{E}\left[X_i\right] + \tau}{1 - \left(\delta \mathbb{E}\left[X_i\right] + \tau\right)} = \frac{\mathbb{E}\left[\textit{New Participant}_i\right] - \beta \mathbb{E}\left[\textit{Middle}_i\right]}{1 - \left(\mathbb{E}\left[\textit{New Participant}_i\right] - \beta \mathbb{E}\left[\textit{Middle}_i\right]\right)}, \tag{7}$$

where the two expressions on the right side of equation (7) are equivalent. The first expression highlights how the counterfactual growth rate only depends on factors distinct from the reduction, captured by δ and τ. In particular, the effect of the reduction, β, has been removed, as the second expression makes clear. Our statistic of interest is

$$\eta \equiv g - g^C, \tag{8}$$

which, in words, equals the component of the observed growth in the total number of robo participants that is due to the reduction.

Table 3 summarizes various calculations of η and of the analogous statistic for growth in middle-class households' robo participation.[11] Interpreting the first row, the baseline

[11]The analogous expression for g^C is: $g^C = \frac{\mathbb{E}[\textit{New Participant}_i | \textit{Middle}_i = 1] - \beta}{1 - (\mathbb{E}[\textit{New Participant}_i | \textit{Middle}_i = 1] - \beta)}$.

estimates from Table 2 imply that the reduction increases the overall number of robo participants by 14%, which is driven by a 110% increase in the number of middle-class participants. These values quantify the democratization of the robo market, that is, the mass of all robo participants and middle-class participants brought into the market by the reduction, respectively. In relation to Table 2, the 110% increase in the number of middle-class participants follows from the estimated 14 pps increase in their probability of participation because the middle class was underrepresented before the reduction. The additional estimates in Table 3 imply an increase in the number of middle-class participants between 56% and 129%. While we emphasize distributional rather than aggregate effects in this paper, these results nevertheless suggest that an industry-wide adoption of automation could significantly increase the total number of middle-class households participating in asset management.

6 Robustness

We assess the internal validity of the baseline results in Table 2, which is important given that we will again use our baseline setup to assess the reduction's effect on middle-class households' financial condition in Section 7. Specifically, we: directly assess the investment constraints channel (6.1); evaluate dynamic confounding channels, such as media attention (6.2); evaluate a variety of other specific confounding channels (6.3); and perform a complementary analysis where observational units are aggregates (6.4). The results of all these tests support the baseline results' validity.

6.1 Testing the Constraints Channel

According to the theory from Section 2, the reduction increases middle-class households' robo participation because it relaxes investment constraints imposed by the previous minimum. We test this channel in four ways.

6.1.1 Constrained Investment Behavior: Graphical Evidence

We first graphically inspect whether middle-class robo participants invest in a way consistent with binding investment constraints imposed by the previous account minimum, relative to upper-class participants who constitute our control group. Consistent with this hypothesis, 65% of new middle-class robo participants invest under the previous minimum of $5,000, as shown in panel (a) of Figure 4. Such a small investment would have been infeasible under the previous minimum, and so this behavior suggests that many middle-class households would have preferred to invest under $5,000 prior to the reduction but were constrained.

Indeed, panel (b) shows how 52% of middle-class households who became participants before the reduction invest right at the minimum, a hallmark of constrained behavior. However, this bunching behavior dissipates after the reduction, consistent with a relaxation of constraints. Notably, these patterns are much less pronounced among upper-class households, supporting our difference-in-difference assumption (3) that the change in behavior between the middle vs. upper classes represents the effect of investment constraints.

6.1.2 Constrained Investment Behavior: Regression Evidence

Building on the previous exercise, Table 4 reports the results of regressions that complement Figure 4. The estimate in column (1) implies that new middle-class participants are 30 pps more likely to invest under $5,000 than new upper-class participants, which matches the graphical evidence from Figure 4a. Column (2) implies that middle-class households who became participants prior to the reduction were 25 pps more likely to invest right at the minimum than upper-class participants, but their propensity to do so falls by 32 pps afterward. This finding matches the pre-reduction bunching behavior shown in Figure 4b, which then dissipates after the reduction. These results again support our definition of middle-class households as the "treated" group, in that they experience a relaxation of constraints relative to the upper class.

6.1.3 Financial Inclusion Measures

We next test the investment constraints channel by examining new middle-class robo participants' rate of participation in other financial markets (i.e., financial inclusion). If these households did not own enough assets to overcome the previous account minimum, then they presumably could not have participated in other markets that require a minimum investment or, more generally, a fixed cost. Asset management stands out as a classic example of such a market. Similarly, participating in the stock market without outside assistance involves a fixed cost of acquiring financial knowledge (e.g., Lusardi, Michaud and Mitchell 2017). In real estate, accessing the mortgage market to become a homeowner requires a down payment. If the rate of participation in these other markets is the same for new middle-class robo participants as for new upper-class ones, it suggests that new middle-class robo participants were unconstrained by the previous minimum.

Since we do not observe participation in other financial markets in our robo advising dataset, we use the SCF dataset to impute our three measures of financial inclusion: participation in asset management, in the stock market, and in homeownership. Our imputation methodology is standard, as described in great detail in Appendix C. Summarizing, we predict a given measure of financial inclusion for each household in our robo advising dataset using the subset of variables observed in both the SCF and robo advising datasets and a prediction model. Since we take no prior stance on which prediction model to use, we perform this exercise separately for four different conventional and machine learning models, letting the data inform which model is most appropriate based on out-of-sample performance. Among these models, the best out-of-sample performance comes from a tree-based algorithm called "boosted trees". Therefore, after training and testing the boosted trees algorithm on the SCF dataset, we use it to impute the unobserved variables in our robo advising dataset. We obtain similar results from less-accurate models, like logistic regression.[12]

The results in columns (3)-(5) of Table 4 show that new middle-class robo participants are 18 pps less likely to have participated in asset management, 43 pps less likely to have participated in the stock market more generally, and 15 pps less likely to own their home, relative to their counterparts in the upper class.[13] To alleviate concerns about the use of imputed variables, column (6) of Table 4 measures financial inclusion as the probability of

[12]We test four main predictive models: basic logistic regression, logistic regression with regularization, random forest, and boosted regression trees. For each model, we first train the model and optimally choose the model's hyperparameters using a 10-fold cross-validation procedure. We use 80% of the sample for training and cross-validation purposes, and we choose hyperparameters to maximize the ROC-AUC performance metric. We finally test the performance of the model with the optimal hyperparameter set, using the remaining 20% of the data as a test set.

[13]The difference between estimates in columns (3) and (4) reflects how participation in asset management is uncommon among both the middle and upper classes, as shown in Appendix Tables A7 and A8.

living in a zip code where the share of households receiving dividend income exceeds the median share, and we again estimate a negative coefficient. Together, the results in columns (3)-(6) suggest that new middle-class robo participants demonstrate lower levels of financial inclusion and, thus, are likely to have been constrained by the previous minimum.

6.1.4 Participants from Financially Developed Regions

Lastly, we visually inspect the change in the share of robo participants from each U.S. state to assess whether new robo participants come from less financially developed regions. The result in Figure 5 shows how new robo participants do not live in states associated with strong financial services sectors (e.g., New York), but, rather, in states associated with less financial development (e.g., southern states). This observation further supports the role of the investment constraints channel, albeit suggestively.

6.2 Dynamic Confounding Channels

Our data's panel structure allows us to rigorously evaluate whether heterogeneous media attention, targeted advertising, pre-trends across wealth quintiles, or other higher-frequency dynamic effects bias our baseline results. We estimate the following regression equation

$$New\ Participant_{i,t} = \beta\,(Middle_i \times Post_t) + \alpha_i + \tau_t + u_{i,t}, \tag{9}$$

where i and t index household and week; $Post_t$ indicates if t is greater than the week of the reduction; $New\ Participant_{i,t}$ indicates if i becomes a robo participant in week t, as opposed to the other weeks in our observation window; α_i is a household fixed effect; and τ_t is a month fixed effect. The parameter β now equals the effect of the reduction on middle-class households' probability of robo participation in any given week. This interpretation differs from its counterpart in equation (2), where it equals the cumulative effect over the post-reduction period.

As a first step, we estimate equation (9) as-is and report the results in column (1) of Table 5. The reduction increases the weekly probability of becoming a robo participant by 0.7 pps, or, cumulatively, 22 pps over the 32-week post-reduction period (32×0.007), which is on par with the estimated effect in Table 2. The remainder of this subsection augments equation (9) with additional terms to assess the scope for more specific forms of bias.

6.2.1 Media Attention and Targeted Advertising

We examine whether media attention, advertising, or other changes in visibility bias our results by collecting additional data on news articles from Google News and on blog posts written by the robo advisor itself. Then, we create two variables: $\textit{Monthly News Articles}_t$, defined as the number of news articles about the advisor published in the month of week t, which proxies for media attention; and $\textit{Monthly Advisor Blogs}_t$, defined as the number of blog posts written by the advisor in the month of week t, which proxies for advertising.

Our primary concern is that media attention and advertising around the reduction disproportionately influence middle-class households. We address this concern by interacting $Middle_i$ with the previous two proxies, thus allowing middle-class households to respond differentially to changes in the robo advisor's visibility. The corresponding coefficient of interest in columns (2) and (3) of Table 5 is unchanged. This finding suggests that the baseline results do not confound changes in visibility that disproportionately influence the middle class.

6.2.2 Pre-Trends and Other Dynamic Effects

More generally, our baseline results may confound any dynamic effect that occurs over our observation window and disproportionately affects the middle class. Examples of such effects include a secular trend in middle-class households' demand for automated asset management or changes in industry competition for the middle class.

We address this concern by replacing $\textit{Post}_t$ in equation (9) with a set of indicator variables that equal one if the month of week t is k months before the reduction, denoted $\textit{Months Before}_{t,k}$, or after it, denoted $\textit{Months After}_{t,k}$. The coefficients on the interaction between $Middle_i$ and these indicator variables represent the weekly probability that a middle-class household becomes a robo participant during the indicated month, relative to the reference month of June 2015 (i.e., $\textit{Months Before}_{t,1}$). If the increase in middle-class robo participation coincides exactly with the month of the reduction, then unobserved changes in household demand or industry competition can only bias our results it they, too, coincide exactly with that month, imposing a high hurdle for these alternative explanations.

The results in column (4) of Table 5 show that the probability of becoming a robo participant increases sharply and significantly for middle-class households exactly in the month of the reduction, July 2015, consistent with Figure 3. By contrast, the middle and upper classes remain on parallel trends over the preceding months, as implied by the insignificant coefficients on the interactions with $Months\ Before_{t,k}$. The precise timing of this increase makes it unlikely that pre-trends in middle-class households' robo participation or other dynamic effects bias the baseline results.

6.2.3 Dynamic Response by Millennials

Commentators often portray automated asset management as the investment of choice for millennials, defined as being born between 1981 and 1996. On the one hand, millennials may have not yet accumulated enough wealth to participate with traditional asset managers, and so they instead participate with automated ones. This margin would support the investment constraints channel, although it would imply that the reduction relaxes temporary, life-cycle constraints. However, it is unlikely that the reduction exclusively relaxes such temporary constraints, since new middle-class robo participants would otherwise be significantly younger than existing ones, which is inconsistent with Table 1.

On the other hand, millennials may respond more strongly to any increase in the robo advisor's visibility because of, say, technological savviness. This alternative margin would bias our baseline results. We assess the scope for such bias by interacting $Post_t$ with an indicator for whether household i is a millennial, denoted $Millennial_i$. The highly insignificant coefficient on this interaction term in column (5) of Table 5 implies that millennials do not respond to the reduction for reasons apart from belonging to the middle class. This finding supports the baseline results' validity.

6.3 Other Confounding Channels

6.3.1 Business Stealing

New middle-class robo participants may have planned to invest with a competitor robo advisor during the post-reduction period, but the reduction prompted them to invest with Wealthfront instead. In this case, our results would reflect business stealing rather than democratization of automated asset management. We assess this possibility by using data from the SEC's Form ADV to plot new participants at other standalone robo advisors, namely Betterment and Personal Capital. While the Form ADV data have limitations described in Section 4, they are the best source of data for this exercise, short of having microdata from each major U.S. robo advisor. The results in Figure 6 show very little decline in new participation at Wealthfront's competitors, measured by log change in number of clients, from the pre-reduction to the post-reduction periods. This observation suggests that the reduction indeed expands access to asset management, rather than simply reallocating participants across robo advisors.

6.3.2 Gambling Motives

Experimental evidence suggests that households exhibit lower risk aversion in the context of small lotteries (e.g., Bombardini and Trebbi 2012). Therefore, the baseline results are unlikely to confound gambling motives, since such motives would be stronger among upper-class households, for whom an investment under $5,000 is relatively small. If anything, such a gambling channel would imply negative estimates, which is not in line with the results.

6.4 Aggregated Measure of Democratization

As described in Section 5.4, estimating equation (2) on the set of eventual robo participants quantifies the share of such participants who were brought into the robo market by the reduction and, thus, the extent to which the market itself becomes more democratic. A separate but related question is whether the reduction increases the share of households eligible to become robo participants who indeed participate. In Appendix D, we estimate an aggregated version of equation (9) in which observational units are population segments and, thus, not restricted to eventual participants. The estimates from this aggregated analysis are consistent with our main results, as they imply that the reduction increases the probability that any household eligible to become a robo participant does so.

7 Inequality in Returns

As discussed in our introduction, automated asset management does not necessarily improve middle-class household's financial condition, which we measure using the expected annual return on liquid assets. The answer depends on both the quantity of risk that middle-class robo participants take and their compensation for taking that risk. Accordingly, we first estimate the reduction's effect on risky share and then turn to its effect on returns. We assess the welfare content of these effects in Section 8.

7.1 Measuring Risky Share

Let $\textit{Risky Share}_{i,0}$ denote the unobserved risky share during the pre-reduction period (i.e., $T = 0$). If a household's robo investment is financed by cash-on-hand and we ignore the effects of compounding over our relatively short sample period, then liquid assets before the reduction are approximately equal to liquid assets after the reduction. Therefore, the household's risky share after the reduction equals

$$\textit{Risky Share}_{i,1} = \textit{Risky Share}_{i,0} + \frac{\textit{Robo Investment}_{i,1}}{\textit{Liquid Assets}_{i,1}}, \tag{10}$$

where $\textit{Robo Investment}_{i,1}$ is the value of net deposits by i in the post-reduction period (i.e., $T = 1$). We can then express the change in risky share from the pre-reduction to the post-reduction periods as

$$\Delta \textit{Risky Share}_{i} = \frac{\textit{Robo Investment}_{i,1}}{\textit{Liquid Assets}_{i,1}}. \tag{11}$$

Equation (11) may be subject to two sources of measurement error, but, importantly, such measurement error would tend to bias our results toward zero. First, equation (11) would overstate the increase in risky share if robo investments are financed by liquidating an outside risky position. This scenario is unlikely because liquidation would trigger potentially costly capital gains taxes. Avoiding liquidation through a direct transfer would be infeasible because, by design, the robo advisor can only manage a restricted set of ETFs. More importantly, however, our imputations of stock market participation in Appendix Table A7 imply that any such outside liquidation would be especially unlikely for middle-class robo participants, the bulk of whom were formerly nonparticipants in the stock market. Therefore, the measurement error is negatively correlated with the treatment exposure variable, $Middle_i$, leading to conservative bias.

Second, equation (11) would overstate the increase in risky share if robo investments are financed through an increase in saving. However, as we show in Appendix Table A5, the implied increase in the savings rate is smaller for middle-class households, consistent with the fact that such households spend a larger share of their income on necessities (e.g., Aguiar and Bils 2015). Like in the previous case, the corresponding measurement error in equation (11) is negatively correlated with $Middle_i$, again leading to conservative bias.

7.2 Measuring Total Return

Given the change in risky share in equation (11), we can calculate the change in a household's total portfolio return, defined as the expected annual return on liquid assets. Explicitly,

$$\Delta \mathit{Total\ Return}_i = \Delta \mathit{Risky\ Share}_i \times \mathit{Risky\ Return}_i \tag{12}$$

where $\mathit{Risky\ Return}_i$ is a measure of the expected return on household i's robo portfolio.

Using historical averages to measure expected returns is subject to well-known challenges, and so, following Calvet, Campbell and Sodini (2007), we propose an asset pricing model to estimate the expected return for securities in the robo portfolio. Appendix E describes our methodology in detail. Briefly, for each security k, we estimate

$$\mathit{Return}_{k,t} = \beta_k^F F_t + \epsilon_{k,t}^F, \tag{13}$$

where F_t denotes a column vector of pricing factors in month t; β_k^F denotes the respective row vector of loadings; and $Return_{k,t}$ denotes the monthly return on security k in excess of the risk-free return. Our baseline model is the standard CAPM, which we later augment with other well-known models (e.g., Fama-French Three Factor). Given a vector of factor risk prices for model F, a vector of portfolio weights across securities k, and a vector of estimated loadings $\hat{\beta}_k^F$, it is straightforward to compute the expected return on household i's robo portfolio under model F, which we denote by $Risky\ Return_i^F$. This return is net of all fees, including the advisor's management fee, if applicable.

7.3 Effect on Risky Share and Total Return

We estimate the effect on new robo participants' risky share and total return using a similar difference-in-difference setup as in equation (2), the validity of which is strongly supported by the robustness exercises in Section 6. The results in column (1) of Table 6 imply that the reduction increases new middle-class robo participants' risky share by 15 pps. Columns (2) and (3) show how this finding is robust to the inclusion of controls and fixed effects. In column (4), we find evidence of substantial heterogeneity within the middle class. In particular, the increase in risky share is 26 pps for households from the second quintile of the U.S. wealth distribution (i.e., "lower middle class"). Appendix Table A6 verifies the canonical intuition that the increase in risky share is greater for households with a higher subjective risk tolerance.

Turning to the effect on inequality in returns, column (5) shows that middle-class robo participants experience a 1.2 pps increase in total return, relative to the upper class. As with risky share, this average effect masks substantial heterogeneity within the middle class, since total return increases by 2.1 pps for the lower middle class, shown in column (8). This effect is quantitatively large given that many of these households were formerly nonparticipants in the stock market, per Table 4. As a back-of-envelope calculation, a 2 pps increase in total return for a former stock market nonparticipant translates to an 800% higher return, given the risk-free rate of 0.25 pps in 2016 ($\frac{2.25-0.25}{0.25}$). Compounding this increase over time implies a potentially large impact on wealth accumulation, given the persistent investment behavior of new middle-class participants that we document in Section 8.3.

7.3.1 Robustness of Effect on Risky Share and Total Return

Table 7 reports the results of a variety robustness tests. Columns (1)-(3) show that the baseline results are robust to the choice of asset pricing model F used to estimate expected return and to using realized return over a three-year period, as in column (4). Column (5) performs a placebo test on the set of households who participated with the advisor before the reduction, which yields insignificant estimates and, thus, supports the baseline results. Column (6) restricts the sample to former nonparticipants in the stock market. The estimates are similar to the baseline ones, supporting the previous claim that the reduction has a large relative effect on such households' total return. Columns (7) and (8) respectively report results based on the subsamples of households with no deposit outflows and with nontaxable, retirement accounts (e.g., IRAs). We interpret both sets of households as long-term investors: in the first case, they do not withdraw funds; and, in the second case, they face high liquidation costs from early withdrawal penalties. The similar estimates suggest that the baseline effect persists over a long horizon, which we corroborate in Section 8.3.

8 Welfare Implications

Before concluding, we examine how the reduction affects households' welfare, relative to a counterfactual of holding their robo investment in cash. To make progress on this question, we evaluate three aspects of new middle-class robo participants' portfolios: the quantity of risk taken; the share of that risk that is compensated; and the length of time over which they can realize the gains from taking compensated risk.

8.1 Excessive Risk

First, we examine whether new robo participants take on an "excessive" quantity of risk by benchmarking their risky share against the optimal share recommended by the classic Merton (1969) formula. This Merton-optimal risky share equals, using our notation,

$$\textit{Risky Share}_i^* = \frac{1}{\gamma} \frac{\textit{Total Return}_i}{\textit{Variance of Return}_i}, \tag{14}$$

where, as in Section 7.2, $\textit{Total Return}_i$ is the expected return on the household's robo portfolio, net of fees and the risk-free rate; $\textit{Variance of Return}_i$ is the variance of this return; and γ is the household's coefficient of relative risk aversion. We then define a household's excessive risky share as

$$\textit{Excessive Risky Share}_i = \textit{Risky Share}_i - \textit{Risky Share}_i^*, \tag{15}$$

where $\textit{Risky Share}_i$ is defined as in equation (10), after omitting time subscripts because all variables correspond to the post-reduction period.[14]

The upper panel of Table 8 summarizes new robo participants' excessive risky share. Focusing on middle-class participants in column (1), the median household's risky share falls 10 pps short of the level recommended by equation (14) when parameterizing $\gamma = 5$, as in many life cycle models (e.g., Campbell et al. 2001). In fact, the median risky share matches the Merton-optimal share under a higher coefficient of relative risk aversion of $\gamma = 7$, which lies toward the upper end of reasonable parameter values (Mehra and Prescott 1985). Therefore, new middle-class robo participants do not appear to be taking excessive risk. If anything, they appear to underinvest relative to the recommendations of benchmark models. An even stronger statement holds for the small minority of upper-class robo participants who enter the stock market, based on the results in column (2).

8.2 Underdiversification

Second, the Merton (1969) model assumes households diversify away uncompensated risk, and so the results from the previous subsection may be misleading if new middle-class robo participants are not compensated for the risk they take (i.e., underdiversified). We assess this possibility by calculating the share of variance in a household's robo portfolio that is compensated according to asset pricing model F, denoted $\textit{Compensated Risk Share}_i^F$ and defined explicitly in Appendix E.

The middle panel of Table 8 summarizes the results. For new middle-class robo partic-

[14]We can only calculate equation (15) for new robo participants who are imputed to have not participated in the stock market beforehand since, for such households, the change in risky share from equation (11) also equals the level of risky share from equation (10). Appendix Table A7 summarizes stock market participation.

ipants, the share of risk that is compensated ranges from 0.64 based on the CAPM to above 0.95 when expanding the set of factors to include the three Fama-French factors, and, in the bottom row, two additional U.S. and global bond factors. This observation implies that robo portfolios do not contain substantial idiosyncratic risk but, rather, expose households to priced risk factors.[15] Notably, behavioral biases do not inhibit diversification because robo portfolio allocations are determined solely by algorithm.

8.3 Persistence of Investment

Third, we evaluate whether new robo participants hold their positions long enough to realize the gains from their robo investment. We are particularly concerned that our findings are driven by a "novelty" effect, where households initially experiment with a new financial service but eventually choose to abandon it. We address this concern by calculating the probability that new middle-class robo participants close their account, withdraw funds, or, on the contrary, make a subsequent deposit.

The results in the bottom panel of Table 8 suggest that new middle-class robo participants exhibit remarkably persistent investment behavior. For example, 97% do not close their account over our sample period. This rate mirrors the 98% non-closure rate among new upper-class participants. Moreover, 94% of new middle-class robo participants make no subsequent withdrawals, and 98% make no withdrawal larger than 20% of their initial deposit. We can also measure persistence by subsequent deposit behavior. Accordingly, 70% of new middle-class robo participants make a subsequent deposit. Such subsequent deposit-making resembles the "dollar cost averaging" strategy commonly advocated by practitioners, which Brennan, Li and Torous (2005) show is optimal for risk averse investors.

[15]We cannot directly rule out correlation between a household's robo portfolio return and nonfinancial income. However, the broad exposure provided by the ETFs in robo portfolios shown in Appendix Table A2 makes it unlikely that households are overexposed to, say, specific labor markets or local business cycles (e.g., Ivković and Weisbenner 2005). Moreover, since the advisor assigns older households a lower risk tolerance score, Appendix Table A2 implies that the allocation to equities decreases in age, consistent with portfolio choice models featuring labor income risk (e.g., Viceira 2002).

8.4 Discussion

The results in Table 8 suggest that the reduction improves welfare for new middle-class robo participants through a non-excessive, sustained increase in compensated risk and, thus, total return. This conclusion is surprising in light of the well-documented underperformance and high fees associated with traditional asset managers and investment mistakes made by retail investors, as referenced in the introduction. However, not all forms of FinTech that democratize financial markets necessarily improve welfare. For example, access to discount brokerage accounts or fractional shares may harm households if they subsequently make poor investment decisions, per footnote 2. In another example, automated advice that is decoupled from asset management may not improve long-term welfare if households do not heed it (e.g., Bhattacharya et al. 2012). Our setting is unique relative to these two examples because the advisor uses automation to both construct and manage a household's portfolio.

The analysis in this section also comes with the caveat that we have specified welfare relative to the particular counterfactual of holding one's robo investment in cash. Alternatively, households may have financed their robo investment by reducing consumption or by borrowing. In the former case, we would tend to understate the welfare implications of the reduction insofar as households do not over-save (e.g., Lusardi and Mitchell 2011; Scholz, Seshadri and Khitatrakun 2006). The latter case is theoretically possible but empirically unlikely given recent evidence that households do not increase borrowing in response to expanded savings opportunities (e.g., Medina and Pagel 2020). Lastly, our organizing theory from Section 2 begins with the idea that households strongly prefer to delegate their portfolio, and we do not account for any nonpecuniary gains from delegation (e.g., peace-of-mind).

9 Conclusion

We found that automation affects inequality in financial returns by bringing middle-class households into the market for asset management. To do so, we studied a large and unexpected reduction in the required account minimum by a major U.S. automated asset manager (i.e., robo advisor). By relaxing constraints on their ability to invest with a professional asset manager, the reduction increases the number of robo participants from the middle segments of the U.S. wealth distribution by 110%. Consequently, these households' expected return on liquid wealth increases by 1-2 pps relative to wealthier households. This increase in return does not reflect excessive or uncompensated risk-taking, nor does it appear to be short-lived. However, the reduction has no impact on the poorest fifth of U.S. households. Therefore, we interpret the reduction as a Pareto-improving technological innovation with ambiguous effects on overall wealth inequality.

From the policy perspective, a number of governments have developed retirement plans for non-wealthy households, with mixed rates of success (e.g., myRA, OregonSaves, NEST). Our results suggest that private asset managers can themselves provide the non-wealthy with retirement plans using automation, without the need for government intervention. However, this conclusion comes with two caveats related to external validity. First, we hold general equilibrium effects fixed in our research design. Accounting for such effects may attenuate the impact of a competitive, industry-wide reduction in account minimums. Second, we study a period of rapid growth in the robo market, and the impact of automated asset management may be weaker in, say, aging or developing economies. Future research may make progress on these questions of external validity by studying automated asset management in a quantitative model. Such a model may also inform how robo advising might be designed to benefit the poorest.

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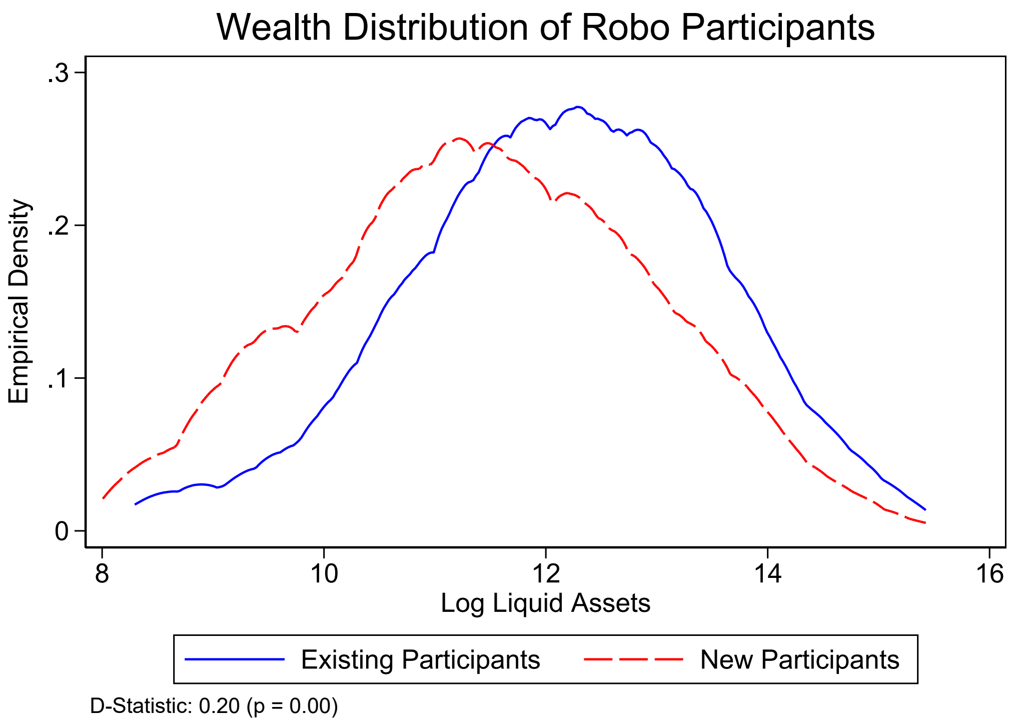
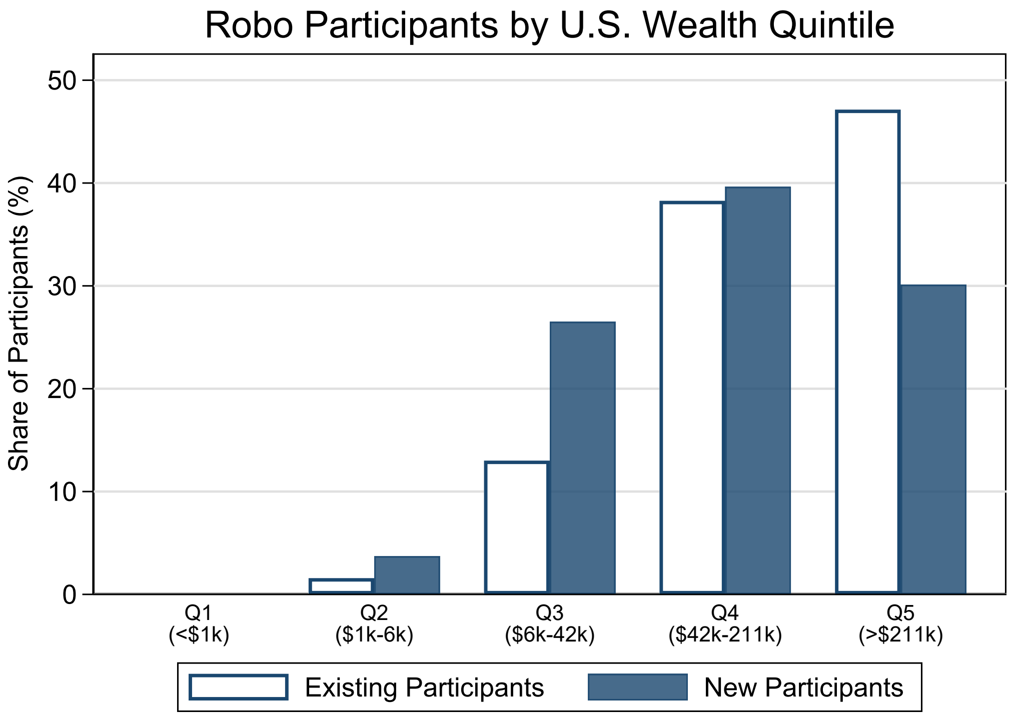
Figures and Tables

Figure 1: Shift in Wealth Distribution of Robo Participants



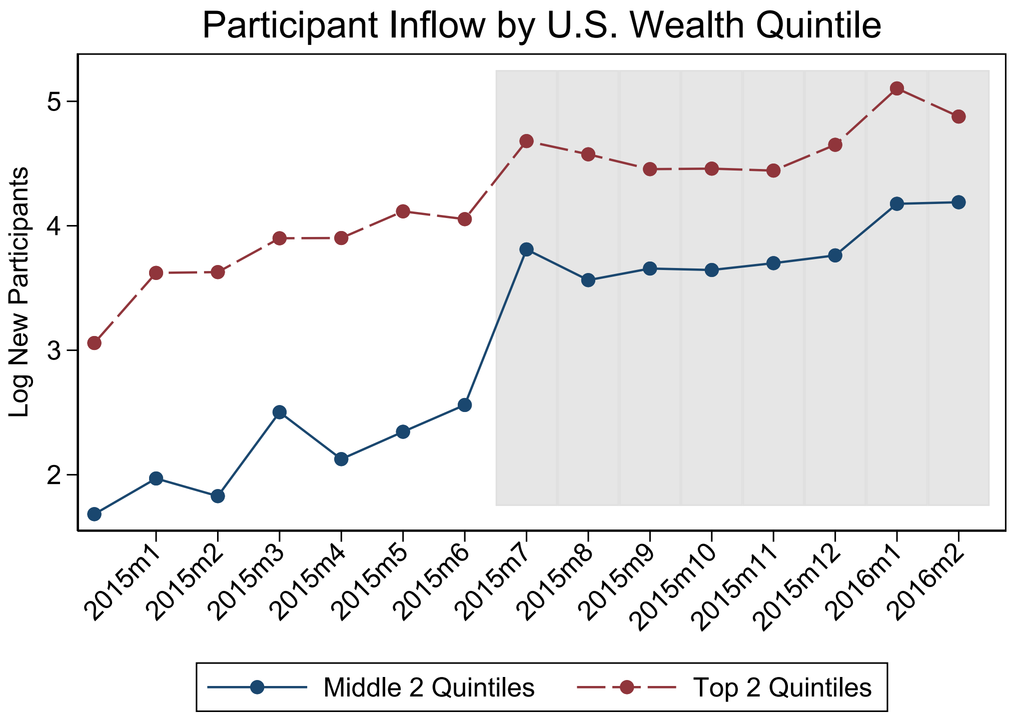
Note: This figure plots the distribution of log liquid assets among households who participated with the robo advisor before the reduction in account minimum (Existing Participants) and who become robo participants after the reduction (New Participants). Liquid assets are defined in Table 1. The distribution is calculated using a kernel density. The D-statistic is based on the Kolmogorov-Smirnov test for equality of distributions.

Figure 2: Change in Representativeness of Robo Wealth Distribution



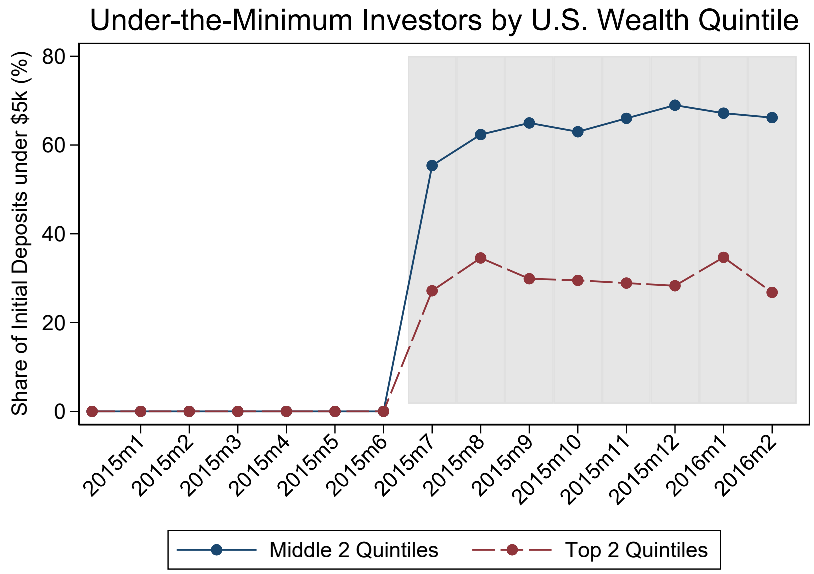
Note: This figure plots the share of robo participants from each quintile of the U.S. wealth distribution. The share is calculated separately for households who participated before the reduction in account minimum (Existing Participants) and who become participants after the reduction (New Participants). Wealth consists of liquid assets, defined in Table 1. Wealth quintiles are calculated using the Survey of Consumer Finances (SCF) dataset.

Figure 3: Pre-Trends in Robo Participation by the Middle Class

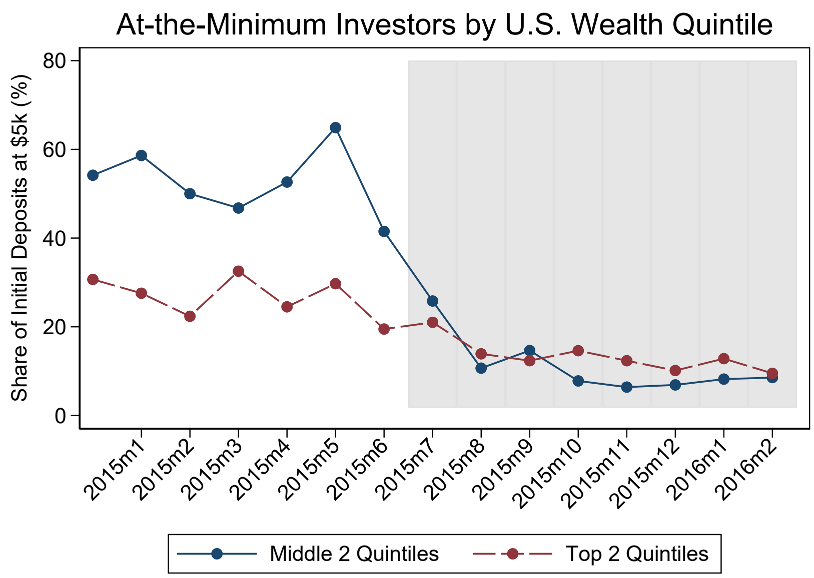


Note: This figure plots the log number of new robo participants from the second and third quintiles (Middle 2) and fourth and fifth quintiles (Top 2) of the U.S. wealth distribution, averaged across weeks in each month. Wealth consists of liquid assets, defined in Table 1. Wealth quintiles are calculated using the Survey of Consumer Finances (SCF) dataset. The shaded region corresponds to the period after the reduction in account minimum.

Figure 4: Constrained Investment Behavior by the Middle Class



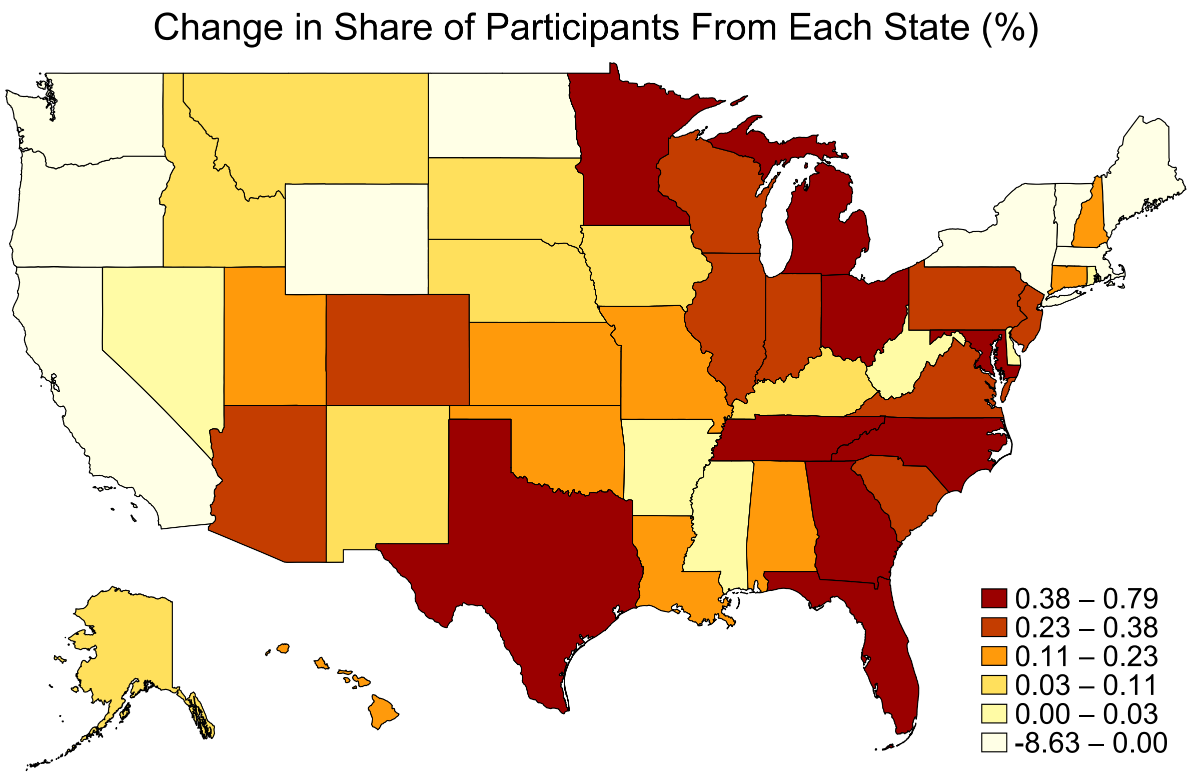
(a) Initial Deposits under $5,000



(b) Initial Deposits at $5,000

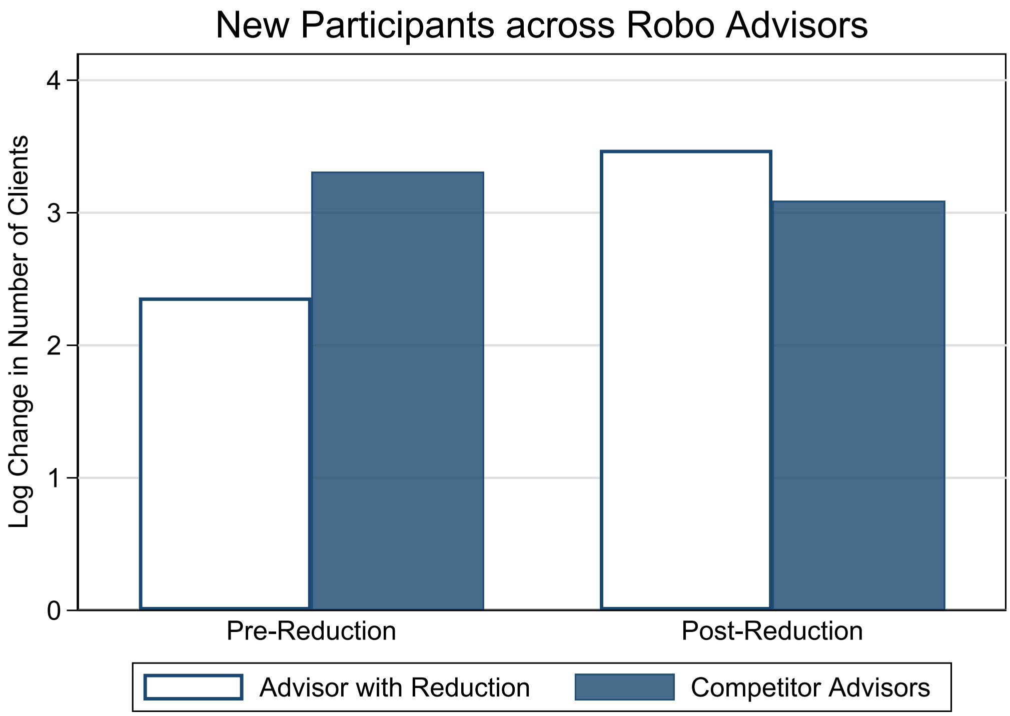
Note: Panel (a) plots the share of new robo participants whose initial deposit is less than the previous account minimum ($5,000) separately for participants from the second and third quintiles (Middle 2) and fourth and fifth quintiles (Top 2) of the U.S. wealth distribution. Panel (b) plots the share whose initial deposit equals the previous account minimum or is no more than 5% higher. Wealth consists of liquid assets, defined in Table 1. Wealth quintiles are calculated using the Survey of Consumer Finances (SCF) dataset. The shaded region corresponds to the period after the reduction in account minimum.

Figure 5: Change in the Geographic Distribution of Robo Participants



Note: This figure plots the change in the share of robo participants from each U.S. state. The change is from the pre-reduction period (December 1, 2014 to July 7, 2015) to the post-reduction period (July 7, 2015 to February 29, 2016).

Figure 6: Reallocation of Participants across Robo Advisors



Note: This figure plots the log change in the number of clients across robo advisors, in thousands, which assesses whether the reduction increases robo participation or simply reallocates robo participants across advisors. The change is calculated separately for the robo advisor that reduced its account minimum, Wealthfront, and for its competitors combined. The left two columns plot this change over the pre-reduction period (Q4, 2014 to Q2, 2015), and the right two columns plot this change over the post-reduction period (Q2, 2015 to Q1, 2016). Data are from the SEC's Form ADV. Competitors are defined as Betterment and Personal Capital, since Schwab's and Vanguard's robo advising services do not file a separate Form ADV. The SEC defines clients to include investors who have not compensated their advisor. Advisors do not file a Form ADV every quarter, and so we use the nearest available observation when the advisor does not file a form ADV in a quarter.

Table 1: Summary of Robo Participants

	Existing Participants			New Participants			
	Mean	Standard Deviation	Median	Mean	Standard Deviation	Median	Difference in Mean
All Households:							
Liquid Assets$_i$ (‘000)	436.44	660.82	200	265.21	480.25	100	-171.22
							(0.000)
Income$_i$ (‘000)	157.36	110.67	130	116.17	95.9	90	-41.18
							(0.000)
Initial Deposit$_i$ (‘000)	33.68	94.54	10	22.56	72.61	5	-11.12
							(0.041)
Age$_i$	35.79	8.72	34	35.4	9.97	33	-0.39
							(0.000)
High Risk Tolerance$_i$	0.15	0.35	0	0.14	0.34	0	-0.01
							(0.146)
Middle$_i$	0.15	0.35	0	0.3	0.46	0	0.156
							(0.000)
Middle Class:							
Liquid Assets$_i$ (‘000)	23.23	11.68	25	19.71	11.36	18	-3.527
							(0.000)
Income$_i$ (‘000)	92.86	62.21	80	67.14	42.52	60	-25.720
							(0.000)
Initial Deposit$_i$ (‘000)	7.6	5.34	5	4.95	12.58	2	-2.652
							(0.000)
Age$_i$	30.33	6.33	29	30.04	7.07	28	-0.293
							(0.339)
High Risk Tolerance$_i$	0.13	0.34	0	0.12	0.32	0	-0.012
							(0.446)
Number of Existing Participants: 4,366							
Number of New Participants: 5,336							

Note: P-values are in parentheses. This table summarizes households who participated with the robo advisor before the reduction in account minimum (Existing Participants) and who become participants after the reduction (New Participants). Subscript i indexes household. *Liquid Assets*$_i$ is the sum of cash, savings accounts, certificates of deposit, mutual funds, IRAs, 401ks, and public stocks, in thousands of dollars. *Income*$_i$ is annual household income, in thousands of dollars. *Initial Deposit*$_i$ is the value of the household's initial deposit, in thousands of dollars. *Age*$_i$ is the householder's age. *High Risk Tolerance*$_i$ indicates if the household chooses a higher risk tolerance score than that recommended by the robo advisor. *Middle*$_i$ indicates if i belongs to the second ($1k-$6k) or third U.S. wealth quintile ($6k-$42k). Wealth consists of liquid assets, and wealth quintiles are calculated using the Survey of Consumer Finances (SCF) dataset. The sample consists of households who participate with the robo advisor and make a deposit over the period from December 2014 through February 2016. The upper panel summarizes all households in the sample, and lower panel summarizes households from the second or third U.S. wealth quintile. Appendix A contains additional variable descriptions.

Table 2: Democratization of the Robo Market after the Reduction

Outcome:	*New Participant$_i$*					
	(1)	(2)	(3)	(4)	(5)	(6)
$Middle_i$	0.219	0.154	0.141	0.101	0.159	0.166
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Controls						
Age_i		0.004	0.003	0.001	0.003	0.004
		(0.000)	(0.000)	(0.038)	(0.000)	(0.000)
$\log(Income_i)$		-0.128	-0.111	-0.133	-0.108	-0.116
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$High\ Risk\ Tolerance_i$		-0.030	-0.027	-0.025	-0.025	-0.025
		(0.036)	(0.059)	(0.083)	(0.084)	(0.167)
Measure of Middle	Second or Third Quintile			Second Quintile	Middle with Buffer	Imputed Middle
State FE	No	No	Yes	Yes	Yes	Yes
R-squared	0.033	0.065	0.094	0.085	0.096	0.107
Number of Observations	9,349	9,349	9,349	9,349	8,982	5,728

Note: P-values are in parentheses. This table estimates equation (2), which assesses whether the reduction in account minimum brings middle-class households into the market for automated asset management. Subscript i indexes household. The regression equation is of the form

$$New\ Participant_i = \beta Middle_i + \delta X_i + \tau + u_i,$$

where $Middle_i$ indicates if i belongs to the second (\$1k-\$6k) or third U.S. wealth quintile (\$6k-\$42k), as opposed to the fourth or fifth quintile (>\$42k) that together constitute the reference group; and $New\ Participant_i$ indicates if i becomes a robo participant after the reduction, as opposed to before it. Columns (4)-(6) assess the scope for measurement error by remeasuring $Middle_i$ using alternative measures: an indicator for whether i belongs to the second U.S. wealth quintile (Second Wealth Quintile), which we later denote in Table 6 as $Lower\ Middle_i$; an indicator for whether i belongs to the second or third U.S. wealth quintile, after assigning a missing value to households whose liquid assets are within a 10% buffer of the third U.S. wealth quintile (Middle with Buffer); and an indicator for whether i belongs to the second or third U.S. wealth quintile, after assigning a missing value to households whose reported wealth quintile does not equal their imputed wealth quintile based on the boosted trees imputation methodology described in Section 6.1 applied to the SCF dataset. The sample consists all robo participants in the Wealthfront dataset. Wealth consists of liquid assets, defined in Table 1. Wealth quintiles are calculated using the Survey of Consumer Finances (SCF) dataset. Household controls are $\log(Income_i)$, Age_i, and $High\ Risk\ Tolerance_i$, defined in Table 1. Standard errors are clustered by household.

Table 3: Magnitude of Effect on Robo Participation

	Growth in Number of Robo Participants					
	All Participants			Middle-Class Participants		
	Observed (g) (1)	Counterfactual (g^C) (2)	Effect (η) (3)	Observed (g) (4)	Counterfactual (g^C) (5)	Effect (η) (6)
Baseline Estimates:						
Table 2, Column (3)	119.4%	105.7%	13.7%	239.4%	129.8%	109.6%
Additional Estimates:						
Table 2, Column (4)	119.4%	118.4%	1%	165.3%	109.3%	55.9%
Table 2, Column (5)	119.4%	105.3%	14.1%	256.2%	127.6%	128.6%
Table 2, Column (6)	119.4%	104.0%	15.4%	242.2%	118.2%	124.0%

Note: This table summarizes the observed and counterfactual growth rates in the number of robo participants around the reduction, which assesses the magnitude of the results in Table 2. Column (1) summarizes the observed growth rate in the total number of robo participants, denoted g, and column (2) summarizes the counterfactual growth rate in the absence of the reduction, denoted g^C and defined in equation (7) as

$$g^C = \frac{\mathbb{E}\left[New\ Participant_i\right] - \beta\mathbb{E}\left[Middle_i\right]}{1 - \left(\mathbb{E}\left[New\ Participant_i\right] - \beta\mathbb{E}\left[Middle_i\right]\right)}.$$

Column (3) summarizes the effect of the reduction, defined as the difference between g and g^C, that is, $\eta = g - g^C$. Columns (4)-(5) summarize the analogous observed and counterfactual growth rates in the number of middle-class robo participants, and column (6) summarizes the analogous value of η. The counterfactual growth rate in the number of middle-class robo participants in column (5) is defined as

$$g^C = \frac{\mathbb{E}\left[New\ Participant_i | Middle_i = 1\right] - \beta}{1 - \left(\mathbb{E}\left[New\ Participant_i | Middle_i = 1\right] - \beta\right)}.$$

Each row calculates these statistics using the estimated β and definition of $Middle_i$ from the indicated specification in Table 2. The observed growth rate in the number of middle-class participants differs across specifications in column (4) because the definition of $Middle_i$ varies across specifications. The remaining notes are the same as in Table 2.

Table 4: Robustness of Investment Constraints as the Channel

	Constrained Investment Measures		Financial Inclusion Measures			
Outcome:	*Under Minimum*$_i$	*At Minimum*$_i$	*Asset Management*$_i$	*Stock Market Participant*$_i$	*Homeowner*$_i$	*High Dividend Zip Code*$_i$
	(1)	(2)	(3)	(4)	(5)	(6)
Middle$_i$	0.295	0.253	-0.180	-0.429	-0.152	-0.056
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Middle$_i$ × *New Participant*$_i$		-0.317				
		(0.000)				
New Participant$_i$		-0.149				
		(0.000)				
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.155	0.022	0.213	0.328	0.406	0.540
Number of Observations	5,088	6,890	5,088	5,088	5,088	4,998

Note: P-values are in parentheses. This table estimates variants of equation (2), which assess the robustness of interpreting households from the second or third U.S. wealth quintiles as constrained by the previous account minimum. Subscript i indexes household. The regression equation is of the form

$$Y_i = \lambda_0 Middle_i + \lambda_1 X_i + \lambda_2 + \nu_i,$$

where Y_i is a measure of constraints imposed on i by the previous account minimum. Columns (1)-(2) consider measures based on the household's investment behavior: *Under Minimum*$_i$ indicates if i's initial deposit is less than the previous account minimum ($5k); and *At Minimum*$_i$ indicates if i's initial deposit equals the previous account minimum or is no more than 5% higher. Column (2) tests for a change in bunching behavior by middle-class participants by including the interaction between *Middle*$_i$ and *New Participant*$_i$. Columns (3)-(6) consider measures based on the household's financial inclusion before the reduction: *Asset Management*$_i$ indicates if i is imputed to have participated in asset management before the reduction, based on the boosted trees imputation described in Section 6.1 applied to the SCF dataset; *Stock Market Participant*$_i$ indicates if i is imputed to have participated in the stock market before the reduction; *Homeowner*$_i$ indicates if i is imputed be a homeowner; and *High Dividend Zip Code*$_i$ indicates if the zip code associated with i's income bracket and state of residence has an above-median share of households reporting dividend income, based on the IRS SOI Tax Stats dataset. Lower values of the financial inclusion measures proxy for greater constraints imposed by the previous account minimum. The sample consists of households who become robo participants after the reduction, except in column (2) where households who became robo participants before the reduction are also included. The remaining notes are the same as in Table 2.

Table 5: Robustness to Media Attention, Advertising, and Other Dynamic Effects

Outcome:	*New Participant*$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
$Middle_i \times Post_t$	0.007	0.007	0.007		
	(0.000)	(0.000)	(0.000)		
$Middle_i \times Monthly\ News\ Articles_t$		-0.000			
		(0.186)			
$Middle_i \times Monthly\ Advisor\ Blogs_t$			-0.000		
			(0.101)		
$Middle_i \times Months\ Before_{t,3+}$				0.000	0.000
				(0.920)	(0.920)
$Middle_i \times Months\ Before_{t,2}$				-0.002	-0.002
				(0.279)	(0.279)
$Middle_i \times Months\ After_{t,0}$				0.007	0.007
				(0.000)	(0.000)
$Middle_i \times Months\ After_{t,1}$				0.005	0.005
				(0.015)	(0.014)
$Middle_i \times Months\ After_{t,2+}$				0.008	0.008
				(0.000)	(0.000)
$Millennial_i \times Post_t$					-0.000
					(0.689)
Household FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.011	0.011	0.011	0.011	0.011
Number of Observations	504,504	504,504	504,504	504,504	504,504

Note: P-values are in parentheses. This table estimates equation (9), which assesses the robustness of the baseline results to a dynamic specification that accounts for various time-varying factors that may disproportionately affect middle-class households. Subscripts i and t index household and week. The regression equation in columns 1-3 is of the form

$$New\ Participant_{i,t} = \beta\,(Middle_i \times Post_t) + \alpha_i + \tau_t + u_{i,t},$$

where $Post_t$ indicates if t is greater than the week of the reduction; and $New\ Participant_{i,t}$ indexes if i becomes a robo participant in week t, as opposed to the other weeks in our observation window. Columns (2)-(3) include the interaction between $Middle_i$ and a measure of the robo advisor's visibility: $Monthly\ News\ Articles_t$ is the number of news articles about the robo advisor published in the month of week t, a proxy for media attention; and $Monthly\ Advisor\ Blogs_t$ is the number of blog posts written by the robo advisor in the month of week t, a proxy for advertising. Columns (4)-(5) replace $Post_t$ with an indicator for whether t is k months before or after the reduction, respectively denoted $Months\ Before_{t,k}$ and $Months\ After_{t,k}$, where the reference group consists of the month before the reduction ($Months\ Before_{t,1}$). Column 5 includes the interaction between $Post_t$ and an indicator for whether i is under 35 years old, denoted $Millennial_i$. The set of news articles used to construct $News\ Articles_t$ are the top 150 articles, sorted by relevance, from a Google News search of the advisor's name ("Wealthfront") among articles published in 2015. Standard errors are two-way clustered by household and week. The remaining notes are the same as in Table 2.

Table 6: Implications for Inequality in Total Portfolio Returns

Outcome:		$\Delta Risky\ Share_i$				$\Delta Total\ Return_i$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Middle_i$	0.145	0.132	0.133		1.223	1.044	1.056	
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	
$Lower\ Middle_i$				0.262				2.084
				(0.000)				(0.000)
$Upper\ Middle_i$				0.121				0.959
				(0.000)				(0.000)
Household Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes	Yes
R-squared	0.076	0.078	0.092	0.100	0.102	0.111	0.122	0.133
Number of Observations	4,679	4,679	4,679	4,679	4,668	4,668	4,668	4,668

Note: P-values are in parentheses. This table estimates variants of equation (2), which assess the effect of reducing the account minimum on new robo participants' risky share and total portfolio return. Subscript i indexes household. The regression equation is of the form

$$\Delta Y_i = \beta Middle_i + \delta X_i + \tau + u_i.$$

The outcomes ΔY_i are: the ratio of robo investment over the post-reduction period to the household's liquid assets, denoted $\Delta Risky\ Share_i$; and the change in total portfolio return, denoted $\Delta Total\ Return_i$ and defined in equation (12) as

$$\Delta Total\ Return_i \equiv \Delta Risky\ Share_i \times Risky\ Return_i,$$

where $Risky\ Return_i$ is a measure of the expected return on the robo portfolio. The baseline measure, used in this table, is the expected return implied by the CAPM. Columns (4) and (8) decompose $Middle_i$ into households from the second U.S. wealth quintile ($1k-$6k), denoted $Lower\ Middle_i$, and the third quintile ($6k-$42k), denoted $Upper\ Middle_i$. Returns are excess of the risk-free return and net of all fees, including the advisor's management fee. The sample consists of households who become robo participants after the reduction. The remaining notes are the same as in Table 2.

Table 7: Robustness of Implications for Inequality in Returns

Outcome:	Δ *Total Return*$_i$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Middle_i$	1.056	1.168	1.273	0.999	-0.080	1.066	1.071	1.047
	(0.000)	(0.000)	(0.000)	(0.000)	(0.763)	(0.000)	(0.000)	(0.000)
Measure of Return	CAPM	Fama-French	Fama-French with Bond	3-Year Realized	CAPM	CAPM	CAPM	CAPM
Participants in Sample	New	New	New	New	Existing (Placebo)	Stock Market Nonparticipant	No Outflow	Retirement
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.122	0.120	0.106	0.113	0.007	0.107	0.122	0.158
Number of Observations	4,668	4,668	4,668	4,679	3,721	1,698	4,481	566

Note: P-values are in parentheses. This table assesses the robustness of the effect of reducing the account minimum on new robo participants' total portfolio return. Subscript i indexes household. The specification is the same as in columns (5)-(7) of Table 6. Columns (1)-(4) assess robustness to the measure of expected return on the robo portfolio: the expected return implied by the CAPM (CAPM); the expected return implied by the Fama-French Three Factor Model (Fama-French); the expected return implied by the Fama-French Three Factor Model augmented with U.S. and global bond returns (Fama-French with Bond); and the portfolio's realized return over the 3-year period ending in 2018 (3-Year Realized). The sample in columns (1)-(4) consists of households who become robo participants after the reduction (New). Columns (5)-(8) assess robustness to various other subsamples: households who participated with the robo advisor before the reduction (Existing), which serves as a placebo sample; new robo participants who are imputed to be first-time stock market participants, based on the boosted trees imputation described in Section 6.1 applied to the SCF dataset (Stock Market Nonparticipant); new robo participants who do not withdraw any money over the post-reduction period (No Outflow), defined as July 7, 2015 to February 29, 2016; and new robo participants who open a nontaxable, retirement portfolio (Retirement). The remaining notes are the same as in Table 6.

Table 8: Welfare Implications for New Middle-Class Robo Participants

	Median across Robo Participants	
	New Middle-Class (1)	New Upper-Class (2)
Excessive Risky Share$_i$		
Baseline Risk Aversion ($\gamma = 5$)	-0.1	-0.22
Higher Risk Aversion ($\gamma = 7$)	0	-0.12
Compensated Risk Share$_i$		
CAPM	0.64	0.63
Fama-French	0.95	0.95
Fama-French with Bond	0.96	0.96
Probability of Persistence$_i$		
No Account Closure	0.97	0.98
No Subsequent Outflow	0.94	0.96
No Large Subsequent Outflow	0.98	0.98
Subsequent Inflow	0.70	0.71

Note: This table summarizes various measures related to the welfare of households who become robo participants after the reduction. Subscript i indexes household. The upper panel summarizes *Excessive Risky Share$_i$*, defined in equation (15) as the difference between the household's actual risky share and the risky share recommended by the Merton (1969) formula, based on coefficients of relative risk aversion (γ) of 5 or 7. The risky share for former nonparticipants in the stock market equals Δ*Risky Share$_i$*, defined in equation (11) as the ratio of robo investment over the post-reduction period to the household's liquid assets. The risky share for stock market participants cannot be calculated because *Risky Share$_{i,0}$* is unobserved in equation (10). Stock market participation is based on the boosted trees imputation described in Section 6.1 applied to the SCF dataset. The middle panel summarizes *Compensated Risk Share$_i$*, defined as the share of variance in the household's robo portfolio that is compensated according to the asset pricing model used to calculate *Risky Return$_i$*. The three models used are: the CAPM; the Fama-French Three Factor Model (Fama-French); and the Fama-French Three Factor Model augmented with U.S. and global bond returns (Fama-French with Bond). The lower panel summarizes *Probability of Persistence$_i$*, defined as the probability of exhibiting persistent investment behavior and calculated as the share of new robo participants who, over the post-reduction period (July 7, 2015 to February 29, 2016): do not close their account (No Account Closure); do not withdraw any money (No Subsequent Outflow); do not withdraw more than 20% of their initial deposit (No Large Subsequent Outflow); or make a subsequent deposit (Subsequent Inflow). The first column summarizes new robo participants from the second and third quintiles of the U.S. wealth distribution (\$1k-\$42k), and the second column summarizes new robo participants from the fourth and fifth quintiles (>\$42k). The remaining notes are the same as in Table 2.

Online Appendix

This document contains additional material referenced in the text. Appendix A builds on Section 4 by describing our data in greater detail. Appendix B characterizes a stylized model grounded in the framework sketched in Section 2. Appendix C describes how we impute variables not observed in our robo advising dataset. Appendix D performs an aggregated analysis referenced in Section 6.4. Appendix E describes how we estimate expected risky return as used in Section 7.2.

A Additional Data Description

We provide additional details on the paper's two principal datasets: a weekly panel of deposit activity by robo participants (A.1); and a cross-section of all U.S. households (A.2). We also provide a catalog of the paper's key variables (A.3).

A.1 Robo Advising Dataset

Our robo advising dataset contains a weekly time series of deposits with the robo advisor, Wealthfront. We obtain this information directly through a query of Wealthfront's internal server. The query merges two internal subdatasets. The first subdataset includes demographic information about Wealthfront participants. The second subdataset contains the date and size of each deposit made by a Wealthfront participant from December 1, 2014 through February 29, 2016. The internal query then merges these two subdatasets together based on username and tax status of the portfolio associated with the username. Each merged observation defines a "robo participant". As implied by Table 1, the merged dataset includes information on 9,702 Wealthfront participants who made at least one deposit during the sample period, 4,366 of whom became participants before the July 2015 reduction and 5,336 of whom become participants afterward.

Summarizing the discussion in the text, we observe the date and size of the deposit and whether the deposit comes from a new participant. In addition, we observe the participating household's annual income, state of residence, liquid assets, recommended and selected risk tolerance score, and householder age. Per the language of the questionnaire, liquid assets are defined as "cash, savings accounts, certificates of deposit, mutual funds, IRAs, 401ks, and public stocks".

The risk tolerance score defines the portfolio allocation received by the participant, as shown in Table A2. The recommended risk tolerance score is a function of the household's demographic information and answers to several questions about financial goals and response to market downturns. The selected risk tolerance score equals the recommended score for 64% of Wealthfront participants, and the remaining participants select a different score. We use this difference to calculate a measure of high subjective risk tolerance, denoted *High Risk Tolerance*$_i$ in the text. Only 3% of households who select a different risk tolerance score deviate from their recommended score by more than 3 points, corresponding to a shift in CAPM beta of around 15 pps.

We cross-referenced our robo advising dataset against publicly available SEC ADV filings. According to these filings, Wealthfront reported 18,800 participants (i.e., clients) in December 2014 and 61,000 participants in February 2016. As described in the text, the discrepancy between the SEC ADV filings and our dataset is explained by the SEC's filing requirements. Specifically, the SEC states: "The definition of 'client' for Form ADV states that advisors must count clients who do not compensate the advisor" (SEC 2017). Thus, the number of participants reported to the SEC by Wealthfront or any other robo advisor includes participants who did not make any deposits over the sample period as well as "participants" who created a username but never funded a Wealthfront account.

A.2 Survey of Consumer Finances (SCF)

The Survey of Consumer Finances (SCF) is a publicly available dataset administered by the Federal Reserve Board every three years, and we rely on the 2016 dataset. The SCF contains financial and demographic information about a representative cross-section of U.S. households. The SCF is one of the most commonly used datasets in the literature, and Bricker et al. (2017) provide a thorough overview of it.

We calculate two sets of variables using the SCF dataset. First, we calculate quintiles of the overall U.S. distribution of liquid assets. To maximize comparability with our robo advising dataset, we define liquid assets in the SCF as the sum of checking accounts, savings accounts, certificates of deposit, cash, stocks, bonds, savings bonds, mutual funds, annuities, trusts, IRAs, and employer-provided retirement plans. This definition of liquid assets most closely matches the definition in our robo advising dataset, although the two are not equivalent. For example, we include bonds and savings bonds in the SCF definition, although they are not explicitly mentioned as a liquid asset in the robo advisor's questionnaire. Removing bonds and savings bonds from the SCF definition has little impact because it only changes the boundary between the middle and upper classes by 1%. We carefully examine how measurement error might affect our results in Sections 5.3.1 and 7.1 of the text. Table A3 reports the boundaries that define the five quintiles.

The second set of variables that we calculate are measures of participation in asset management, the stock market, and homeownership. Participation in asset management is not directly observed in the SCF, and we proxy for it using the intersection of stock market participation and consulting with a broker, financial planner, banker, accountant or lawyer regarding investment. Participation in the stock market is defined as ownership of stocks, mutual funds, a trust, or an IRA. Participation in homeownership is defined as owning owner-occupied residential real estate. We calculate these variables using the SCF dataset because we do not observe them in our robo advising dataset. We then impute each variable for the households in our robo advising dataset using demographic characteristics observed in both the SCF and robo advising datasets and a boosted trees prediction model, as described in Appendix C.

A.3 Description of Variables

- *Liquid Assets*$_i$: This variable is the sum of cash, savings accounts, certificates of deposit, mutual funds, IRAs, 401ks, and public stocks for household i, based on the robo advising dataset.

- *Middle*$_i$: This variable indicates if household i's liquid assets fall within the second or third U.S. quintile of liquid assets. Household i's liquid assets are calculated using the robo advising dataset. Quintiles of liquid assets are calculated using the SCF dataset.

- *New Participant*$_i$: This variable indicates if household i becomes a participant with the robo advisor over the period from July 7, 2015 through February 29, 2016. Explicitly, it equals 1 for such individuals and equals 0 for households who participated before July 7, 2015.

- *Initial Deposit*$_i$: This variable is the initial deposit with the robo advisor made by household i, based on the robo advising dataset.

- *Income*$_i$: This variable is annual income for household i, based on the robo advising dataset.

- *Age*$_i$: This variable is the age of the householder for household i, based on the robo advising dataset.

- *High Risk Tolerance*$_i$: This variable indicates if household i chooses a higher risk tolerance score than recommended by the robo advisor, based on the robo advising dataset.

- *Under Minimum*$_i$: This variable indicates if household i's initial deposit with the robo advisor is less than \$5,000, based on the robo advising dataset.

- *At Minimum*$_i$: This variable indicates if household i's initial deposit with the robo advisor is between \$5,000 and \$5,250, based on the robo advising dataset.

- *Asset Management*$_i$: This variable indicates if household i is imputed to participate in asset management. The imputation is based on the boosted trees algorithm described in Appendix C. This algorithm is trained using the SCF dataset and applied to the robo advising dataset. Participation in asset management is defined based on the SCF dataset as both: (a) owning stocks, mutual funds, a trust, or an IRA; and (b) consulting with a broker, financial planner, banker, accountant or lawyer regarding investment.

- *Stock Market Participant*$_i$: This variable indicates if household i is imputed to participate in the stock market. The imputation is based on the boosted trees algorithm described in Appendix C. This algorithm is trained using the SCF dataset and applied to the robo advising dataset. Participation in the stock market is defined as owning stocks, mutual funds, a trust, or an IRA, based on the SCF dataset.

- *$Homeowner_i$*: This variable indicates if household i is imputed to own owner-occupied residential real estate. The imputation is based on the boosted trees algorithm described in Appendix C. This algorithm is trained using the SCF dataset and applied to the robo advising dataset. Ownership of owner-occupied residential real estate is based on the SCF dataset.

- *High Dividend Zip $Code_i$*: This variable indicates if the zip code associated with i's bracket of annual income and state of residence has a share of households reporting dividend income in 2015 that is greater than or equal to the median share. Data on annual income are from the robo advising dataset, and annual income brackets are defined by the following boundaries: $25,000; $50,000; $100,000; and $125,000. Data on state of residence are from the robo advising dataset. Data on the share of households in a zip code reporting dividend income are from the IRS SOI Tax Stats dataset, which is available at the zip code level. Zip codes are assigned to an annual income bracket based on the zip code's average adjusted gross income across tax returns. For each income bracket by state bin, we calculate the average zip code-level share of households reporting dividend income. Then, we calculate the median of this share across bins.

- Δ*Risky $Share_i$*: This variable is the ratio of household i's deposits with the robo advisor over the post-reduction period (i.e., July 7, 2015 through February 29, 2016) to the household's liquid assets, based on the robo advising dataset.

- Δ*Total $Return_i$*: This variable is the product of Δ*Risky $Share_i$* and *Risky $Return_i$*, defined as a measure of the expected return on the portfolio that the robo advisor manages for household i. The baseline measure of expected return is the expected return implied by the CAPM. Appendix E describes additional measures. Robo portfolios are indexed by risk tolerance score and tax status. Data on Δ*Risky $Share_i$* are from the robo advising dataset. Data used to calculate *Risky $Return_i$* for a given portfolio are from the Center for Research in Security Prices (CRSP) and Ken French's website.

B Stylized Model

We propose a stylized model that exemplifies the theory sketched in Section 2. As in Section 2, households solve a portfolio optimization problem in which they delegate a share ρ of their risky portfolio to asset managers. We take the limiting case as ρ approaches one. Asset managers offer a portfolio with risky, net-of-fee return R. Alternatively, households can invest in a riskless asset that delivers return R^f, where, to minimize notation, $R^f = 0$.

Asset managers have a cost structure such that they require an account minimum M. Therefore, given investable assets W, the household solves the following version of the traditional mean-variance optimization problem,

$$\max_{\omega} \quad U(\omega) = \left\{ \omega \mathbb{E}\left[R\right] - \frac{1}{2}\gamma\omega^2 \mathrm{Var}\left[R\right] \right\} \tag{B1}$$

$$s.t.$$

$$\omega W \geq M, \tag{B2}$$

where ω denotes the share of investable assets allocated to the advisor. One can motivate the problem in (B1) by supposing R is normally distributed and uncorrelated with nonfinancial income, and the household has a constant coefficient of absolute risk aversion γ, not to be confused with the use of γ to denote the coefficient of relative risk aversion in the text.

Absent the constraint in (B2), households invest in the risky portfolio and allocate a share

$$\tilde{\omega} \equiv \frac{1}{\gamma} \frac{\mathbb{E}\left[R\right]}{\mathrm{Var}\left[R\right]} \tag{B3}$$

of their investable wealth W to the robo advisor. Under the account minimum M, this optimal allocation may no longer be feasible, and so the household's participation status depends on wealth. In particular, the solution to problem (B1) is

$$\omega^* = \begin{cases} 0, & W \leq \max\left\{M, \frac{M}{2\tilde{\omega}}\right\} \\ \\ \frac{M}{W}, & \max\left\{M, \frac{M}{2\tilde{\omega}}\right\} < W \leq \frac{M}{\tilde{\omega}} \\ \\ \tilde{\omega}, & \frac{M}{\tilde{\omega}} < W \end{cases}, \tag{B4}$$

and the household's participation status is given by

$$p^* = \begin{cases} 0, & W \leq \max\left\{M, \frac{M}{2\tilde{\omega}}\right\} \\ \\ 1, & \max\left\{M, \frac{M}{2\tilde{\omega}}\right\} < W \end{cases}. \tag{B5}$$

The wealth cutoff for participation in equation (B5) does not necessarily equal the account minimum, M, and it is likely to be larger than M if $\tilde{\omega}$ is reasonably low. Intuitively, if the household's wealth lies below the cutoff, it would either need to invest such a large fraction of its wealth in the risky portfolio that it optimally chooses not to participate, in which case the cutoff equals $\frac{M}{2\tilde{\omega}}$, or it simply does not have enough assets to overcome the minimum without borrowing, in which case the cutoff equals M.

Now consider a reduction in the account minimum from M to M'. It is straightforward to show that the household responds by becoming a participant if and only if

$$\underline{W} \equiv \max\left\{M', \frac{M'}{2\tilde{\omega}}\right\} < W \leq \max\left\{M, \frac{M}{2\tilde{\omega}}\right\} \equiv \overline{W}. \tag{B6}$$

Therefore, the framework predicts that the effects of the reduction will be concentrated among households with intermediate levels of wealth (i.e., "middle class"). Households with low levels of wealth such that $W < \underline{W}$ (i.e., "lower class") are predicted to remain nonparticipants, while households with high levels of wealth such that $W > \overline{W}$ (i.e., "upper class") remain participants. As discussed in Section 4.2 of the text, the empirical analogues to the lower, middle, and upper classes are households from the first, second or third, and fourth or fifth quintiles of the U.S. distribution of liquid assets, respectively.

Turning to the wealth distribution across participants, let ΔP_m and ΔP_u respectively denote the changes in the total number of middle-class and upper-class participants caused by the reduction. According to the framework,

$$\Delta P_m = \int_{\underline{W}}^{\overline{W}} \left[p^*(W, M') - p^*(W, M)\right] dW, \tag{B7}$$

$$\Delta P_u = \int_{\overline{W}}^{\infty} \left[p^*(W, M') - p^*(W, M)\right] dW, \tag{B8}$$

which implies the following difference-in-difference equation

$$\Delta P_m - \Delta P_u = \int_{\underline{W}}^{\overline{W}} \left[p^*(W, M') - p^*(W, M)\right] dW > 0. \tag{B9}$$

In words, equation (B9) says that the predicted increase in participation by the middle class exceeds that of the upper class. The results in Tables 2, 5, and A4 all support this prediction.

Letting $\bar{R} \equiv \omega\mathbb{E}\left[R\right]$ denote a household's total portfolio return, the difference-in-difference between a new middle-class participant's total portfolio return, $\bar{R}_m$, and a new upper-class participant's total portfolio return, $\bar{R}_u$, is

$$\Delta\bar{R}_m - \Delta\bar{R}_u = \Delta\omega_m^*\mathbb{E}\left[R\right] > 0, \tag{B10}$$

where

$$\Delta\omega_m^* = \begin{cases} \frac{M'}{W}, & \max\left\{M', \frac{M'}{2\tilde{\omega}}\right\} < W \leq \frac{M'}{\tilde{\omega}} \\ \\ \tilde{\omega}, & \frac{M'}{\tilde{\omega}} < W \leq \max\left\{M, \frac{M}{2\tilde{\omega}}\right\} \end{cases}. \tag{B11}$$

Equation (B10) shows how inequality in total return falls as middle-class households experience an increase in total return. As shown in Table 8, this increase in total return primarily reflects greater compensated risk.

Relative to the discussion in Section 2 of the text, equation (B9) summarizes our prediction of "asymmetric diversification" using a closed-form expression. We find strong support for this prediction in Figure 2 and Table 2. Moreover, Table 6 supports the prediction from equation (B10) that inequality in total return falls. Lastly, our model implies that, by revealed preference, middle-class households benefit from this increase in total return. In reality, households may take excessive risk, not diversify away uncompensated risk, withdraw their investment prematurely, or make other mistakes that cannot be captured by our stylized model. While we cannot rule out any of these possibilities, the analysis in Section 8 suggests that middle-class households with conventional utility functions do indeed benefit from automated asset management.

C Imputation Methodology

As described in Section 6.1.3, we use the SCF dataset impute various measures of financial inclusion for households in our robo advising dataset, namely, a household's participation in the stock market, professional asset management, and homeownership. Imputation of these variables is necessary because we do not observe them in our robo advising dataset. We also impute a household's wealth class to assess the scope for bias due to measurement error in Section 5.3.1. Our imputation procedure involves predicting a variable's value for each household in our robo advising dataset using a prediction model applied to the set of variables observed in both our robo advising dataset and the SCF dataset. Accordingly, we first estimate, cross-validate, and test each model on the SCF dataset. A priori, we take no stance on which model to use. Instead, we let the data inform which model to use, based on performance in out-of-sample tests.

In this appendix, we describe the candidate prediction models (C.1), the process for imputing measures of financial inclusion (C.2), and the process for imputing a household's wealth class (C.3)

C.1 Prediction Models

We consider four parametric prediction models: standard logistic regression, lasso logistic regression, ridge logistic regression, and elastic net logistic regression. The latter three models all involve regularizations applied to the standard logistic regression model, and so we collectively refer to the lasso, ridge, and elastic net logistic regression models as logistic regression with regularizations. We also consider two nonparametric, tree-based models: random forest and boosted trees. We now describe each model and its hyperparameters, that is, a set of model-specific parameters that govern how the estimation is performed but have no economic interpretation themselves.

C.1.1 Standard Logistic Regression Model

Logistic regression models assume that the relationship between the dependent variable and independent variables takes a particular functional form. To estimate a standard logistic regression model, we minimize the following negative log-likelihood function across the sample of N observations:

$$L(y, \zeta, \psi, x) = -\sum_{i=1}^{N} \left(y_i \log\left(\xi_i\right) + (1 - y_i) \log\left[1 - \xi_i\right] \right), \tag{C1}$$

with

$$\xi_i \equiv \frac{1}{1 + \exp(-(x_i \psi + \zeta))}, \tag{C2}$$

where $y_i \in \{0, 1\}$; the model parameters are given by $\psi = (\psi_1, \ldots, \psi_q)'$ and ζ; and the set of predictors is given by $x = (x_1, \ldots, x_q)$.

C.1.2 Logistic Regression Models with Regularizations

Ridge, lasso, and elastic net are all classic shrinkage methods employing techniques that optimally shrink the coefficient estimates. We augment the baseline logistic regression with three regularizations to improve the model's performance.

First, we introduce a ridge regularization. The objective function to be minimized is

$$\kappa \sum_{j=1}^{q} \psi_j^2 + L(y, \zeta, \psi, x). \tag{C3}$$

The penalty term is $\kappa \sum_{j=1}^{q} \psi_j^2$, which is called the l_2 penalty, and $\kappa > 0$ is a hyperparameter that controls the model's complexity. By increasing κ, the level of shrinkage becomes higher, which limits on the size of the coefficients. The predictors need to be standardized before running a ridge regression. When predictors are highly correlated with each other (e.g., wealth and income), the ridge penalty enforces similarity in their coefficient estimates.

Second, we introduce a lasso regularization, which constrains the absolute values of the estimated coefficients. The objective function for lasso is

$$\kappa \sum_{j=1}^{q} |\psi_j| + L(y, \zeta, \psi, x). \tag{C4}$$

The penalty term in lasso regression is $\kappa \sum_{j=1}^{q} |\psi_j|$, which is named the l_1 penalty, and κ is the hyperparameter. This penalty term could drive some coefficients to zero if κ is large enough. As in ridge regression, we need to standardize the independent variables before running the regression. The main difference between ridge and lasso regressions is that coefficient estimates in ridge regression rarely equal zero exactly, while lasso regression coefficient estimates are more likely to equal zero. This feature gives lasso regression a natural advantage when the true model is sparse and there are many redundant predictors. The limitation of lasso is that it may only select one variable out of a group of highly correlated variables.

Third, we introduce an elastic net regularization. Under this regularization, the estimated coefficients are values that minimize the objective function

$$\kappa \sum_{j=1}^{q} \left(\varrho \psi_j^2 + (1 - \varrho)|\psi_j| \right) + L(y, \zeta, \psi, x). \tag{C5}$$

The penalty term for elastic net is $\kappa \sum_{j=1}^{q} (\varrho \psi_j^2 + (1 - \varrho)|\psi_j|)$ and there are two hyperparameters, κ and ϱ. The elastic net penalty is a linear combination of the lasso and the ridge penalties: it is able to select a subset of predictors as in the lasso, and it drives the coefficients of correlated predictors down simultaneously as in the ridge.

C.1.3 Nonparametric Models

We next describe nonparametric, tree-based models. While linear regularization-based models could perform better than the baseline logistic regression, especially when there are many correlated variables, these models still impose a parametric relationship between the predictors and the target variable. Random forest and boosted trees are both tree-based models, which allow for the inclusion of complex interactions among the predictors.

The family of tree-based models divides the space of predictors into an assortment of rectangles S_j and then fits a simple model (e.g., a constant ϕ_j) within each rectangle partition. The formal expression of a tree is

$$T(x;\Theta) = \sum_{j=1}^{J} \phi_j \mathbb{1}\left[x \in S_j\right] \tag{C6}$$

where $\Theta = \{S_j, \phi_j\}_1^J$ encodes how the sample is partitioned into rectangles.

To make equation (C6) more concrete, consider an example of predicting a household's stock market participation status using the household's age and income as independent variables, so that $x = (Age, Income)$. In this example, one such rectangle S_j may be the subsample of households with age between the boundaries $\underline{Age}$ and $\overline{Age}$ and annual income between the boundaries $\underline{Income}$ and $\overline{Income}$. The corresponding value of ϕ_j would be the stock market participation rate among households whose age and income place them within rectangle S_j.

The partition Θ associated with tree T is found by minimizing some loss function

$$\hat{\Theta} = arg\, min_{\Theta} \sum_{j=1}^{J} \sum_{x_i \epsilon S_j} L(S_j). \tag{C7}$$

In our procedure, the loss function $L(S_j)$ is the Gini index within region S_j, defined as

$$L(R_j) = 1 - \left[\hat{\phi}_j^2 + (1-\hat{\phi}_j)^2\right]. \tag{C8}$$

In the context of the previous example, $\hat{\phi}_j$ would be the stock market participation rate among households in rectangle S_j, based on the subsample of the SCF dataset used to estimate the model. Intuitively, the loss function in equation (C8) rewards rectangles where the share of stock market participants is close to either zero or one.

An optimization routine called recursive binary splitting is used to optimally divide the set of independent variables into space into J rectangles. Again making use of the previous concrete example, this optimization routine would select the values of $\underline{Age}$, $\overline{Age}$, $\underline{Income}$, and $\overline{Income}$ that minimize equation (C8). When there are many independent variables, recursive binary splitting selects not only the cut-points that define each rectangle S_j but also the set of independent variables used to partition the sample. The splitting process ends after a certain number of splits, called, the "tree size". Once the tree is "grown", the predictions are formed based on the prevailing values within the rectangles: if most households from the training set in the rectangle are stock market participants, a household from the test set who falls into the same rectangle is also predicted to be a stock market participant.

In any tree-based model, the number of sample splits (i.e., tree size) is an important hyperparameter. A large tree with many splits may lead to overfitting, while a small tree with relatively few splits may lead to inaccurate predictions. A single-tree model produces approximately unbiased estimates, but these estimates can be inefficient, that is, have a large variance. Two variants of the single-tree model that offer substantially more efficient estimates are a random forest model and a boosted regression trees model. We discuss the intuition behind these models below and defer complete methodological details to James et al. (2013).

The random forest model introduces a technique called "bagging", or bootstrap aggregation. The bagging process reduces the variance through averaging predictions from many trees. In particular, a random forest is a collection of uncorrelated trees, which is created by growing trees with a certain degree of randomization. The model first draws multiple bootstrap samples from the training data, and fits a tree for each sample with a random subset of the predictors at each split. Specifically, random forests only consider a subset m of all available predictors q at each split, typically $m = \sqrt{q}$. Next, the predictions are obtained by averaging the results across the fitted trees from each sample. The random forest's hyperparameters are the number of trees and the number of splits for each tree.

The boosted trees method creates a tree ensemble using the idea of boosting. Boosting techniques seek to improve the prediction power by training a sequence of "weak" models, each compensating the weakness of its predecessors. Specifically, a "boosted trees" algorithm grows the trees in a sequential way such that each new tree is constructed using information about the residuals from the previous tree. In the stock market participation example, the boosting algorithm would optimize equation (C8) after disproportionately penalizing prediction errors in the current tree for households whose prediction errors in the previous tree were larger. The degree of penalty is governed by a shrinkage hyperparameter.

There are three key hyperparameters for models that incorporate boosting: the number of trees, the shrinkage parameter, and the number of splits. In general, a boosted trees model features shallow trees with relatively few splits (i.e., "weak"). The number of splits d in each tree controls the model's complexity. A higher value of d implies more complex interactions among the predictors. The shrinkage parameter controls the speed with which the algorithm learns from previous prediction errors, and a very small shrinkage parameter should be combined with a very large number of trees for better prediction accuracy.

C.1.4 Hyperparameters

Based on the previous model descriptions, each model has a set of hyperparameters that govern how the estimation is performed. Typically, hyperparameter values are chosen to optimize a predetermined performance metric on a subset of the full dataset, called the validation set. This validation set is distinct from the subset used to train the prediction model, called the training set. The final subset of the data, called the testing set, is used to evaluate the out-of-sample performance of the model with the optimally chosen hyperparameter values. The process of optimizing hyperparameter values is called hyperparameter tuning.

We implement a grid search procedure, which involves an exhaustive search through a predetermined grid of hyperparameter values and is the traditional method for hyperparameter optimization (Murphy 2012). To choose among various sets of hyperparameter values, we use a 10-fold cross-validation procedure.

C.2 Imputing Financial Inclusion Measures

We use the following procedure to impute participation in the stock market, professional asset management, and homeownership. To avoid overfitting, we first split the sample following a standard 80/20 sample split. In particular, we use 80% of the data as a training/cross-validation sample to tune each model's hyperparameters, and we test the model using the remaining 20% of the data as a testing sample. All of the models are estimated using *scikit-learn* library in Python.

As mentioned above, we start by estimating each model on the SCF training sample to later impute the measures of financial inclusion that are unobserved in our robo advising dataset. We apply each model to the independent variables that are jointly observed across the two datasets: liquid assets, income, and age. Then, we use a 10-fold cross-validation procedure to choose the hyperparameters. The hyperparameter optimization is based on the receiver operating characteristic (i.e., ROC) curve, and we choose hyperparameters to maximize the area under this curve (AUC).

We first estimate a standard logistic regression model and use it as a baseline to compare with other models. We next turn to logistic regression models with regularizations. For these three models, we use the cross-validation procedure to jointly choose the optimal regularization and the hyperparameters for that regularization. Finally, we separately fit random forest and boosted trees models, using cross-validation to optimize the hyperparameters. As a result, we effectively have a choice among four models: the baseline logistic regression, the optimally chosen logistic regression model with regularization, and the two tree-based models. Across all the models, we report the average ROC-AUC across 10 validation sets as well as the ROC-AUC in the test set. We also report the accuracy in the test set as an additional performance metric.

C.2.1 Results

The results for stock market participation are reported in Table A7. The tree-based models perform better than the parametric models, suggesting that the relationship between predictors and stock market participation status is highly non-linear. In the case of boosted trees, the ROC-AUC equals 99% in the average validation set and 96% in the test set, and the model's accuracy equals 97%. The random forest model exhibits slightly lower performance metrics: a 95% validation set ROC-AUC, an 87% test set ROC-AUC, and an accuracy of 87%. While we find that lasso is the preferred logistic regression model with regularization, its performance metrics are not very different from the standard logistic regression. They are also significantly lower than among the tree-based models. The results on participation in professional asset management are reported in Table A8. The comparable performance metrics suggest that the boosted trees model performs best. Finally, Table A9 reports the results for homeownership status and, again, the boosted trees model performs best.

Since the boosted trees model exhibits slightly higher performance metrics than the random forest model and substantially higher performance than the parametric models for all three financial inclusion measures, we impute these measures for each household in our robo advising dataset using the boosted trees model. We use these imputed values in Tables 4 and 7.

C.3 Imputing Wealth Class

We follow a similar procedure for imputing the wealth class for households in our robo advising dataset. Explicitly, we first predict wealth class (i.e., lower, middle, or upper class) using the two other independent variables observed in both the robo advising and SCF datasets: age and income. Then, we assess the quality of self-reporting by comparing a household's predicted wealth class and the wealth class associated with the household's self-reported liquid assets (i.e., self-reported wealth class). Given that wealth class is non-binary, we modify the baseline imputation procedure in two ways. First, we do not use parametric models and instead rely only on non-parametric models. Additionally, we do not use the loss function based on ROC-AUC and instead rely on prediction accuracy as the main performance metric in our 10-fold cross-validation procedure.

C.3.1 Results

Table A10 reports the results. The boosted trees prediction model suggests that 58% and 62% of robo participants who self-report as middle-class and upper-class, respectively, are predicted to indeed belong to their self-reported wealth class. We obtain similar results from the random forest model. Thus, according to the imputation procedure, roughly 60% of robo participants are "telling the truth". The similar truth-telling rates among middle and upper-class robo participants suggests that the definition of liquid assets in our robo advising dataset is not systematically biased downward relative to the SCF definition. Otherwise, we would observe a much lower truth-telling rate among the middle class, since, in the case of such systematic downward bias, robo participants who self-report as middle-class in our robo advising dataset would be imputed to belong to the upper class. More likely, the fact that truth-telling rates fall short of 100% reflects a combination of prediction error, which, per the bottom row in Table A10, would apply to 15% of the sample, as well as classical measurement error in self-reported liquid assets. As discussed in Section 5.3.1, classical measurement error in middle-class wealth status would bias the estimates toward zero through attenuation.

D Aggregated Measure of Democratization

As mentioned in the text, the baseline regression equation (2) is estimated on the set of eventual robo participants, which is appropriate given our interest in the democratization of the market for automated asset management. In particular, this regression quantifies the share of robo participants who were brought into the market by the reduction. We now estimate the effects of the reduction on a related statistic: the share of eligible middle-class households who participate with the robo advisor.

Our procedure has two steps. In the first step, we partition the U.S. population into cohorts based on observable characteristics, as described below, and calculate the total number of new robo participants within each cohort and week. Using notation similar to that in Appendix B, the empirical probability that a household in cohort c becomes a robo participant in week t is

$$p_{c,t} = \frac{\textit{New Participants}_{c,t}}{\textit{Eligible Participants}_{c}}, \tag{D1}$$

where c and t index cohort and week; $\textit{New Participants}_{c,t}$ is the number of new robo participants from cohort c in week t; and $\textit{Eligible Participants}_{c}$ is the number of households from cohort c eligible to become robo participants, in that they are both aware of the robo advisor and satisfy the demographic requirements needed to participate (e.g., U.S. resident over 18 years old). Similarly, the probability that any eligible household becomes a robo participant over all weeks t in our sample period is

$$P = \sum_{t} \sum_{c} w_c p_{c,t}, \tag{D2}$$

where w_c is the share of all eligible households in cohort c. We assume that the total number of eligible participants from any given cohort is approximately constant over our sample period.

In the second step, we estimate the effect of the reduction on the percent change in the probability of participation for households in cohort c. Taking logs of equation (D1) and incorporating cohort-level controls and fixed effects, we estimate the following regression equation

$$\log\left(\textit{New Participants}_{c,t}\right) = \beta\left(\textit{Middle}_c \times \textit{Post}_t\right) + \alpha_c + \tau_t + \lambda X_{c,t} + u_{c,t}, \tag{D3}$$

where $\textit{Middle}_c$ indicates if c belongs to the second or third U.S. wealth quintile, in contrast to the fourth or fifth quintiles that comprise the reference group; and

$$\alpha_c \equiv \log\left(\textit{Eligible Participants}_c\right) + \tilde{\alpha}_c \tag{D4}$$

is a composite cohort fixed effect. Like with the household-level analogue in equation (9), middle-class cohorts constitute the treated group in equation (D3), since they experience a relaxation of investment constraints because of the reduction. Thus, the parameter β equals the effect of the reduction on the percent change in $p_{c,t}$, as distinct from the percentage point change. The percentage point change in the overall probability of robo participation, P, is

$$\Delta P = \sum_t \sum_c w_c p_{c,t} \left[e^{\beta(Middle_c \times Post_t)} - 1 \right], \tag{D5}$$

which follows from equation (D2).

In terms of implementation, we partition households into cohorts according to a set of sorting variables. Adding new sorting variables reduces intra-cohort heterogeneity such that we can better isolate variation in wealth, but it also introduces noisy idiosyncratic variation. In light of this tradeoff, we construct three separate partitions that progressively increase the number of sorting variables. First, we define cohorts by sorting the U.S. population into a maximum of 10 bins based on decile of liquid assets, where deciles are calculated using the SCF dataset. Second, we introduce a three-way sort into a maximum of 1,000 bins based on deciles of liquid assets, age, and income, such that there are 10 possible groups for each variable. In our final approach, cohorts are defined by sorting the U.S. population into a maximum of 6,250 bins based on state of residence, of which there are 50 groups, and quintiles of liquid assets, age, and income, of which there are 5 groups each.

The results of cohort-level panel regression are reported in Table A4. The first two columns estimate the effect of the reduction after sorting the U.S. population only by liquid assets. The results in column (2) suggest that the reduction in account minimum increases the number of middle-class robo participants by 29%. The estimated effect equals 9% when estimated from the three-way sort based on liquid assets, age and income, as shown in column (4), and it equals 2% after additionally sorting by state of residence, as shown in column (6). The lower point estimates reflect the fact that more granular bins can contain fewer robo participants, and so, to recover the increase in the overall probability of robo participation, we must aggregate the effects across all cohorts belonging to the middle class, according to equation (D5).

Quantitatively, we can back out the percent change in the overall probability of robo participation when the product $w_c p_{c,t}$ is uniform. In that case, the reduction's effect on the overall probability of participation implied by the estimate in column (4) is 109%, or, to match the statement in Section 6.4, the reduction roughly doubles the baseline probability. Depending on the covariance between w_c and $p_{c,t}$, this estimate may either overstate or understate the true effect.

Qualitatively, our cohort-level results imply a similar conclusion as our baseline results in Table 2: the reduction increases robo participation by middle-class households who, as we find in Section 6.1, were constrained by the previous account minimum. In particular, this core conclusion continues to hold even when observational units are cohorts and, thus, not restricted to eventual robo participants.

E Estimating Expected Return

This appendix describes the method for estimating the expected return on robo portfolios in Section 7. As mentioned in Section 7.2, using a historical average to measure expected return is subject to well-known issues related to limited time horizons, and especially so in our setting given the relatively-short history of many ETFs managed by our data provider. Therefore, we follow Calvet, Campbell and Sodini (2007) and propose an asset pricing model to estimate the expected returns for the securities in our sample.

While imposing a model improves the efficiency of expected return estimates relative to directly measuring them from historical returns, it leads to some bias by imposing an imperfect model of the return structure. Since the choice of model is somewhat arbitrary and the degree of bias will depend on the characteristics of the portfolio in question, we estimate expected return across a variety of common asset pricing models, indexed by their vector of factors F.

For each security k (i.e., ETF k), we estimate the following pricing kernel

$$Return_{k,t} = \beta_k^F F_t + \epsilon_{k,t}^F, \tag{E1}$$

where F_t denotes a column vector of pricing factors in month t; β_k^F denotes the respective row vector of loadings; $Return_{k,t}$ denotes the monthly return on security k in excess of the risk-free return, measured by the one-month Treasury yield, and net of expense ratios and other fees; and $\epsilon_{k,t}^F$ is an idiosyncratic, zero-mean shock to security k with standard deviation σ_k^F. We estimate equation (E1) using the longest available time series of monthly returns for each security k and factor vector F dating back to January 1975.

Given the estimated loadings $\hat{\beta}_k^F$ from estimating equation (E1) for model F, it is straightforward to compute the expected return on household i's robo portfolio, denoted $Risky\ Return_i^F$. Explicitly, if there are K securities and N factors, then

$$Risky\ Return_i^F = w_i \boldsymbol{\beta}^F \pi^F, \tag{E2}$$

where w_i is a $1 \times K$ row vector of weights across securities in household i's robo portfolio; $\boldsymbol{\beta}^F$ is a $K \times N$ matrix of factor loadings; and π^F is an $N \times 1$ column vector of factor risk prices.

We estimate equation (E1) for the following asset pricing models,

$$F_t^{CAPM} = [R_t^m]', \tag{E3}$$

$$F_t^{FF} = \left[R_t^m, \quad R_t^{HML}, \quad R_t^{SMB}\right]', \tag{E4}$$

$$F_t^{FF+} = \left[R_t^m, \quad R_t^{HML}, \quad R_t^{SMB}, \quad R_t^{USB}, \quad R_t^{GLB}\right]', \tag{E5}$$

where R_t^m is the monthly market return based on the global Morgan Stanley Capital International Index (MSCII), net of the one-month Treasury yield; R_t^{HML} is the spread in monthly return between high book-to-market stocks and low book-to-market stocks; R_t^{SMB} denotes the spread in monthly return between stocks with a small market capitalization and a big market capitalization; R_t^{USB} is the monthly return on the Barclays Aggregate U.S. Bond Index Unhedged, net of the one-month Treasury yield; and R_t^{GLB} is the monthly return on the Barclays Global Aggregate Bond Index Unhedged, net of the one-month Treasury yield.

In words, equations (E3)-(E5) are: the standard capital asset pricing model (CAPM), the Fama-French Three Factor Model, and a five-factor model augmenting the Fama-French model with U.S. and global bond returns. Our data on monthly returns come from the Center for Research in Security Prices (CRSP) and Ken French's website, as described in Appendix A. We use the sample mean to calibrate the factor risk prices, multiplied by 12 to obtain an approximate annual value. The corresponding risk prices for the models in equations (E5)-(E5) are

$$\pi^{CAPM} = [0.068]', \tag{E6}$$

$$\pi^{FF} = [0.068, \quad 0.036, \quad 0.004]', \tag{E7}$$

$$\pi^{FF+} = [0.068, \quad 0.036, \quad 0.004, \quad 0.062, \quad 0.060]'. \tag{E8}$$

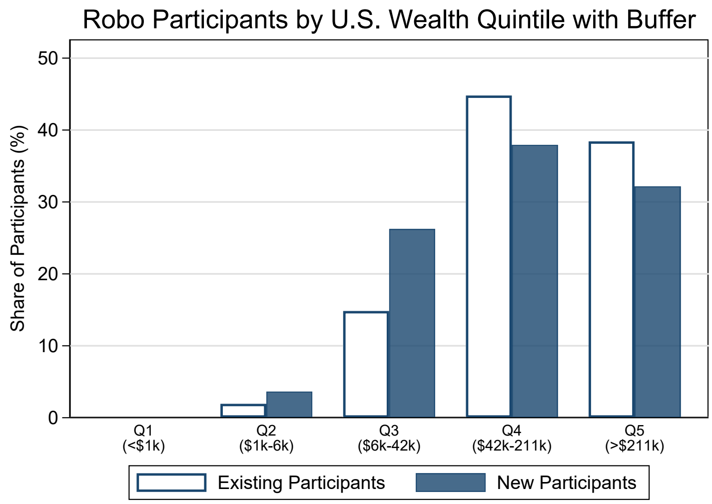
Similarly, we use the sample covariance matrix to calculate the share of risk that is compensated according to a given asset pricing model, studied in Section 8.2. Explicitly, this share equals

$$\textit{Compensated Risk Share}_i^F = \frac{\left(w_i\boldsymbol{\beta}^F\right)\Sigma^F\left(w_i\boldsymbol{\beta}^F\right)'}{\left(w_i\boldsymbol{\beta}^F\right)\Sigma^F\left(w_i\boldsymbol{\beta}^F\right)' + w_i\Sigma_\epsilon^F w_i'}, \tag{E9}$$

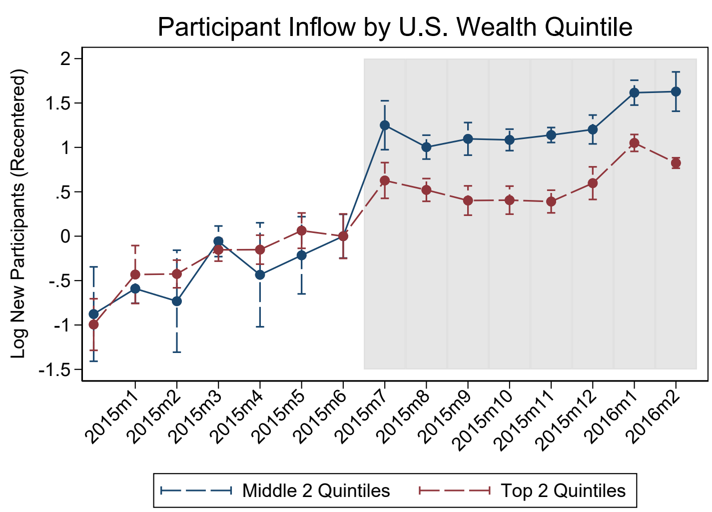
where Σ^F is an $N \times N$ covariance matrix of factor returns under asset pricing model F; and Σ_ϵ^F is an analogous $K \times K$ covariance matrix of idiosyncratic returns, $\epsilon_{k,t}^F$.

Additional Figures and Tables

Figure A1: Robustness of Graphical Evidence



(a) Robo Participants by Buffered Wealth Quintile



(b) Significance of Pre-Trends in Robo Participation

Note: This figure assesses the robustness of Figures 2 and 3. Panel (a) is analogous to Figure 2 after dropping households whose liquid assets are within a 10% buffer of each U.S. wealth quintile, which assesses robustness to measurement error in liquid assets. Panel (b) is analogous to Figure 3 after demeaning the log number of new participants by its value the month prior to the reduction (June 2015) for each set of wealth quintiles and plotting 95% confidence intervals.

Table A1: Summary of the U.S. Robo Advising Market around the Reduction

Robo advisor	AUM ($bil)	Fees by Account Size	Account Minimum	Presence of Human Advisor
Wealthfront	2.43	0% (under $10k) 0.25% (over $10k)	$500	No
Betterment	2.33	0.35% or $36 (under $10k) 0.25% ($10k to $100k) 0.15 % (over $100k)	$0	Yes (2017)
Personal Capital	1.44	0.89% (under $1mil) 0.49% to 0.89% (over $1mil)	$100k	Yes (2009)
Charles Schwab, Intelligent Portfolios	3	0% (see note)	$5k	Yes (2017)
Vanguard, Personal Advisor Services	21.2	0.3%	$50k	Yes (2015)

Note: This table presents information about the five largest robo advisors in the U.S. market around the time of Wealthfront's reduction in account minimum in July 2015. AUM denotes assets under management around July 2015, which we obtain from the Q2, 2015 Form 13-F for Wealthfront, Betterment, and Personal Capital and from company press releases for Schwab and Vanguard. Fees denotes annual management fees in July 2015, which we obtain from company press releases and contemporaneous industry publications. Fees do not include expense ratios on ETFs in the robo portfolio. Betterment charged 0.35% on accounts under $10,000 which auto-invest at least $100 per month, or $3 monthly (i.e., $36 annually) if they do not auto-invest. Schwab's robo advising service does not charge a management fee, and it instead monetizes by holding 8-10% of clients' portfolios in cash. Account Minimum denotes the minimum investment required to open an account in July 2015, which we obtain from company press releases and contemporaneous industry publications. Presence of Human Advisor denotes whether the advisor offers the option to speak with a human advisor, which we obtain from company websites, industry publications, and phone calls with company representatives. The year when the option to speak with a human became available is listed in parentheses. Wealthfront, Betterment, Personal Capital, Schwab, and Vanguard respectively held $23, $22, $13, $45.9, and $179.7 billion in June 2020. Collectively, these five advisors held $283.6 billion in AUM in June 2020, compared to $30.4 billion in July 2015.

Table A2: Summary of Robo Portfolios

Risk Tolerance (0.5 to 10)	Beta	Expected Return (%)	Stocks (%)	Bonds (%)	Other (%)	Percent of Households (%)
0.50	0.32	4.15	33.00	60.00	7.00	0.67
2.00	0.45	5.15	47.00	48.00	5.00	0.39
2.50	0.49	5.40	50.00	44.00	6.00	0.20
3.00	0.52	5.55	53.00	41.00	6.00	0.89
3.50	0.57	5.95	59.00	35.00	6.00	0.86
4.00	0.58	6.02	59.00	35.00	6.00	1.56
4.50	0.61	6.28	62.00	33.00	5.00	1.14
5.00	0.64	6.51	66.00	29.00	5.00	1.68
5.50	0.67	6.73	69.00	26.00	5.00	1.21
6.00	0.70	6.94	72.00	23.00	5.00	2.27
6.50	0.72	7.10	74.00	21.00	5.00	2.32
7.00	0.75	7.26	77.00	18.00	5.00	6.41
7.50	0.77	7.44	80.00	15.00	5.00	8.06
8.00	0.79	7.61	82.00	13.00	5.00	14.39
8.50	0.82	7.84	86.00	9.00	5.00	16.50
9.00	0.85	8.03	89.00	6.00	5.00	16.30
9.50	0.88	8.26	90.00	5.00	5.00	5.43
10.00	0.91	8.45	90.00	5.00	5.00	19.72

Note: This table summarizes robo portfolios assigned to households in our sample. Portfolios are indexed by risk tolerance score, which ranges from 0.5 to 10 in increments of 0.5, and tax status. Each portfolio has a unique vector of weights across 10 possible ETFs, which are chosen to represent exposure to different asset classes. Stocks, Bonds, and Other respectively denote the sum of weights for ETFs that track stock market indices (VIG, VTI, VEA, VW), bond market indices (LQD, EMB, MUB, SCHP), and other asset classes, namely real estate (VNQ) and commodities (XLE). Expected Return and Beta are based on the CAPM, as described in Section 7.2. The rightmost column shows the percent of robo participants with the indicated portfolio. The table only shows taxable portfolios to emphasize how the allocation varies across risk scores, rather than tax status.

Table A3: Summary of U.S. Wealth Quintiles

Wealth Quintile:	First	Second	Third	Fourth	Fifth
Participation in the Stock Market	0.003	0.064	0.314	0.579	0.87
Participation in Asset Management	0.002	0.041	0.207	0.418	0.693
Conditional Participation in Asset Management	0.66	0.64	0.66	0.72	0.8
Range of Liquid Assets ($000)	[0, 0.6]	[0.6, 6.3]	[6.3, 42]	[42, 211]	> 211

Note: This table summarizes the share of U.S. households who participate in the stock market and in asset management by wealth quintile in 2016, based on the SCF dataset. The first row summarizes participation in the stock market, defined as owning stocks, mutual funds, a trust, or an IRA. The second row summarizes participation in professional asset management, defined as both participating in the stock market and consulting with a broker, financial planner, banker, accountant or lawyer regarding investment. The third row summarizes participation in professional asset management conditional on participation in the stock market. The bottom row summarizes the range of liquid assets that define each U.S. wealth quintile, in thousands of dollars. Wealth consists of liquid assets, defined as the sum of checking accounts, savings accounts, certificates of deposit, cash, stocks, bonds, savings bonds, mutual funds, annuities, trusts, IRAs, and employer-provided retirement plans. The sample consists of all households in the SCF dataset.

Table A4: Robustness to Aggregated Measure of Democratization

Outcome:	$\log\left(New\ Participants_{c,t}\right)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Middle_c \times Post_t$	0.603	0.290	0.092	0.092	0.022	0.021
	(0.007)	(0.024)	(0.002)	(0.002)	(0.047)	(0.047)
	Wealth Cohorts		Wealth by Income by Age Cohorts		Wealth by Income by Age by State Cohorts	
Controls	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.868	0.875	0.390	0.390	0.324	0.324
Number of Observations	455	455	22,013	22,013	52,025	52,025

Note: P-values are in parentheses. This table estimates equation (D3), which assesses the robustness of the baseline results to a specification in which observational units are aggregates and, thus, not limited to eventual robo participants. Subscripts c and t index cohort and week. The regression equation is of the form

$$\log\left(New\ Participants_{c,t}\right) = \beta\left(Middle_c \times Post_t\right) + \alpha_c + \tau_t + \lambda X_{c,t} + u_{c,t},$$

where $Middle_c$ indicates if c belongs to the second or third U.S. wealth quintile (\$1k-\$42k), as opposed to the fourth or fifth quintile (>\$42k); $Post_t$ indicates if t is greater than the week of the reduction; and $New\ Participants_{c,t}$ is one plus the number of new robo participants from cohort c in week t. In columns (1)-(2), cohorts are defined by sorting the U.S. population into a maximum of 10 bins based on decile of liquid assets (10), where deciles are calculated using the SCF dataset. In columns (3)-(4), cohorts are defined by sorting the U.S. population into a maximum of 1,000 bins based on decile of liquid assets (10), age (10), and income (10), where deciles are calculated using the SCF dataset. In columns (5)-(6), cohorts are defined by sorting the U.S. population into a maximum of 6,250 bins based on state of residence (50) and quintile of liquid assets (5), age (5), and income (5), where quintiles are calculated using the SCF dataset. Controls are averages of the household-level controls from Table 2 across robo participants in cohort c and week t. Standard errors are two-way clustered by cohort and week. The remaining notes are the same as in Table 2.

Table A5: Robustness to Measurement Error from Increases in the Savings Rate

Outcome:	Δ*Savings Rate*$_i$		
	(1)	(2)	(3)
Middle$_i$	-0.163	-0.201	-0.198
	(0.000)	(0.000)	(0.000)
Household Controls	No	Yes	Yes
State FE	No	No	Yes
R-squared	0.054	0.123	0.138
Number of Observations	5,108	5,108	5,108

Note: P-values are in parentheses. This table estimates a variant of equation (2), which assesses whether measurement error in risky share biases the results in Table 6 upward because middle-class households increase their savings rate. The specification is the same as in Table 6 with a different outcome variable: Δ*Savings Rate*$_i$ is the ratio of annualized robo investment over the post-reduction period to the household's annual income. The remaining notes are the same as in Table 6.

Table A6: Consistency with Models of Portfolio Choice

Outcome:	Δ*Risky Share*$_i$ (1)	Δ*Total Return*$_i$ (2)
Middle$_i$	0.128	1.023
	(0.000)	(0.000)
Middle$_i$ × *High Risk Tolerance*$_i$	0.043	0.326
	(0.041)	(0.048)
High Risk Tolerance$_i$	-0.010	-0.073
	(0.367)	(0.383)
R-squared	0.067	0.076
Number of Observations	5,088	4,791

Note: P-values are in parentheses. This table estimates a variant of equation (2), which assesses whether the results in Table 6 are consistent with canonical models of portfolio choice. Explicitly, the regression equation is of the form

$$\Delta Y_i = \beta_0 Middle_i + \beta_1 \left(Middle_i \times High\ Risk\ Tolerance_i \right) + \delta High\ Risk\ Tolerance_i + \tau + u_i,$$

where i indexes household; and *High Risk Tolerance*$_i$ indicates whether i voluntarily chooses a higher risk tolerance score than that recommended by the advisor. The remaining notes are the same as in Table 6.

Table A7: Imputation of Participation in the Stock Market

Imputation Model:	Nonparametric Models		Regression Models	
	Boosted Trees (1)	Random Forest (2)	Logistic (3)	Lasso (4)
New Participants in the Stock Market as a Share of:				
New Middle-Class Robo Participants	0.61	0.57	0.99	0.99
New Upper-Class Robo Participants	0.07	0.01	0.29	0.29
Area under the ROC Curve (Validation Set)	0.99	0.95	0.86	0.86
Area under the ROC Curve (Test Set)	0.96	0.87	0.75	0.75
Accuracy (Test Set)	0.97	0.87	0.77	0.77

Note: This table shows the share of middle-class and upper-class households who previously did not participate in the stock market prior to becoming robo participants after the reduction. Stock market participation status is imputed, and each column corresponds to a separate prediction model. Columns (1)-(2) use nonparametric (i.e., tree-based) models and columns (3)-(4) use models based on logistic regression. Random Forest corresponds to a random forest classification algorithm applied to the SCF dataset, where the set of features are age, income, and liquid assets. Boosted Trees corresponds to a similar boosted trees algorithm. Logistic corresponds to a standard logistic regression. Lasso is a logistic regression with regularizations (i.e., "shrinkage" penalties). The bottom rows of the table report area under the ROC Curve in the validation and test sets as well as accuracy in the test set as an additional performance metric. Appendix C contains further methodological details. Participation in the stock market is defined in Table A3. Middle-class households are defined as belonging to the second or third U.S. quintile of liquid assets ($1k-$42k), and upper-class households are defined as belonging to the fourth or fifth quintiles (>$42k). Liquid assets are defined in Table 1.

Table A8: Imputation of Participation in Asset Management

Imputation Model:	Nonparametric Models		Regression Models	
	Boosted Trees (1)	Random Forest (2)	Logistic (3)	Lasso (4)
New Participants in Asset Management as a Share of:				
New Middle-Class Robo Participants	0.86	0.99	1.00	1.00
New Upper-Class Robo Participants	0.49	0.52	0.65	0.65
Area under the ROC Curve (Validation Set)	0.98	0.92	0.73	0.73
Area under the ROC Curve (Test Set)	0.95	0.82	0.60	0.60
Accuracy (Test Set)	0.96	0.84	0.70	0.70

Note: This table shows the share of middle-class and upper-class households who previously did not participate in professional asset management prior to becoming robo participants after the reduction. Participation in professional asset management is imputed, and each column corresponds to a separate prediction model. Columns (1)-(2) use nonparametric (i.e., tree-based) models and columns (3)-(4) use models based on logistic regression. Participation in professional asset management is defined in Table A3. The remaining notes are the same as in Table A7.

Table A9: Imputation of Homeownership

Imputation Model:	Nonparametric Models		Regression Models	
	Boosted Trees (1)	Random Forest (2)	Logistic (3)	Lasso (4)
Homeowners as a Share of:				
New Middle-Class Robo Participants	0.39	0.44	0.28	0.28
New Upper-Class Robo Participants	0.84	0.93	0.78	0.78
Area under the ROC Curve (Validation Set)	0.98	0.91	0.76	0.76
Area under the ROC Curve (Test Set)	0.95	0.83	0.67	0.67
Accuracy (Test Set)	0.96	0.84	0.71	0.71

Note: This table shows the share of new middle-class and upper-class robo participants who own owner-occupied residential real estate (i.e., homeowners). Homeownership is imputed, and each column corresponds to a separate prediction model. Columns (1)-(2) use nonparametric (i.e., tree-based) models and columns (3)-(4) use models based on logistic regression. The remaining notes are the same as in Table A7.

Table A10: Imputation of Wealth Class

Imputation Models:	Nonparametric Models	
	Boosted Trees (1)	Random Forest (2)
Middle-Class Robo Participants Classified as Middle-Class	0.58	0.61
Upper-Class Robo Participants Classified as Upper-Class	0.62	0.59
Accuracy (Validation Set)	0.90	0.89
Accuracy (Test Set)	0.85	0.84

Note: This table shows the results of wealth class reclassification of new robo participants based on nonparametric (i.e., tree-based) models. Random Forest corresponds to a random forest classification algorithm applied to the SCF dataset, where the set of features are age and income. Boosted Trees corresponds to a similar boosted trees algorithm. For each model and wealth class, we report the share of new robo participants whose wealth class based on self-reported liquid assets equals the wealth class based on imputed liquid assets. The remaining notes are the same as in Table A7.

Trust and Race: Evidence From the Market for Financial Advice

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PRELIMINARY WORKING PAPER, DO NOT CITE WITHOUT PERMISSION

Abstract

In this paper, we examine the relation of racial homophily between financial advisors and local households, and its effect on stock market participation. We find that in ZIP codes that are majority non-white, the presence of a local matched minority financial advisor increases stock market participation. We find this result to be concentrated in middle-income households with more modest effects among high-income households. Our results help explain the persistent racial group differences in stock market participation rates that remain even after controlling for income.

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1. Introduction

A puzzle in the household finance literature is why so many households in the U.S. do not participate in the stock market given the high returns and advantages of a well-diversified portfolio (Mankiw and Zeldes, 1991). One explanation put forth is that participation has both monetary and non-monetary fixed costs (Haliassos and Bertaut, 1995). Indeed, wealth and income levels are positively correlated with participation, suggesting that participation costs may be too high for low income households to justify investment. Yet, even among high income households, there exists significant variation in participation rates that can't be fully explained by fixed costs (Vissing-Jorgensen, 2003).

For example, participation rates among households in the Upper Midwest are substantially higher than those of the Deep South, even within the same income bracket (See Figure 1). Further, there is significant racial variation in participation rates. A study by the Social Security Administration found that even within the same income quartile, White households were twice as likely to invest in financial markets than Black and Latino households.[1] From a policy perspective, such a divide in participation rates can exacerbate gaps in wealth inequality.

We seek to contribute to this literature by studying the role that the racial composition of local financial advisors play in stock market participation. Because financial advisors play a key role in facilitating household access to financial markets, participation is likely driven by the degree to which households can trust their local advisors (Gennaioli, Shleifer, and Vishny, 2015). A 2018 survey by the Certified Financial Planning (CFP) board of hiring managers found that the majority believed that advisors have an advantage with clientele of their own racial and ethnic background. Absent repeated interactions with an individual, investors may form their expectations of trust based on observable signals of social group or background.

[1] A study by Ariel Investments found that 86% of White households with income of at least $50,000 owned stocks or mutual funds, while only 67% of Black households with similar income did.

For example, Stopler and Walter (2019) show that advisor-client homophily affects current clients' willingness to follow their advisors' financial advice. Male clients were more likely to follow the advice if their advisor was of the same gender and age, while female clients were more likely to follow the advice if their advisor had a similar marital and parental status.

In this paper, we ask what role, if any, does racial homophily between client and advisor play in stock market participation? Egan, Matvos, and Seru (2020) report less than 3% of financial advisors are black.[2] Given to the history of wealth distribution in the U.S. and the persisting racial wealth gap, it is not surprising that the financial planning profession currently has a predominantly white clientele base. While 14% of US households are Latino and 13% are black, only 8% and 6% of these households, respectively have incomes over $150k.[3]

Studying this issue presents several empirical challenges. First, it requires access to detailed data for a large sample of financial advisors and the ability to control for other potentially confounding characteristics likely to affect households' decision to participate in the stock market. Second, we need be able to categorize advisors and their potential clients by race. Third, we need to be able to measure investor stock market participation.

To this end, we begin by employing data from the FINRA Brokercheck, Meridian IQ, and Investment Adviser Public Disclosure databases. These three databases allows us to track over 1.3 million unique brokers across over 50,000 firms. The data give dates and branch locations on when individuals are employed with member firms, achieve professional advancement, and engage in professional misconduct. This allows us to not only control for observable characteristics, but to use fixed effects to control for unobservable heterogeneity across time and zip code.

[2]The 2018 survey by the Certified Financial Planning (CFP) board found only 3.5% of CFPs are Black or Latino.

[3]2019 Current Population Survey, US Census Office

Importantly, we can infer advisor race using Bayesian Improved First name Surname Geocoding (BIFSG) of Voicu (2018)[4]. Similarly, we can use detailed Census data (ACS Survey) to measure ZIP code level demographic and socioeconomic characteristics. Finally, we use detailed IRS data at the ZIP code level to examine localized stock market participation. The intersection of these data allows us to measure stock market participation at the ZIP code-year level and study how advisor race matters for trust in financial markets and stock market participation.

2. Preliminary Findings

We find that in ZIP codes that are predominantly non-white (See Figure 2), the presence of an advisor of similar race leads to an increase in stock market participation (See Table 1). For example, in a ZIP code that is predominantly Black, we find that even after controlling for socioeconomic data such as income and education, the presence of a black advisor leads to a 12% increase in stock market participation. To account for unobservable variation that may confound our results, we study how within-zip variation in minority representation affects participation rates. Within the same zip code, we find that the addition of at least one minority advisor leads to a 4% increase in stock market participation for clients of similar race. Our results suggest that, on average, racial homophily plays an important role in facilitating investor participation in equity markets.

Next, we turn to the interaction of race and income on stock market participation. As has been shown in the literature individuals with higher levels of income are more likely to participate in the stock market. In our own data, for example, we find that individuals making \$200K+ (\$50K-200K) are 11× (3×) more likely to participate in the stock market

[4]BIFSG can be viewed as a refinement of the more widely used BISG. While BIFSG has been shown to have modest improvement in classification over Bayesian Improved Surname Geocoding (BISG) in mortgage lending and voting datasets, the largest improvements occur for blacks, a group for which the BISG performance is weakest.

than investors making less than $50,000. Instead, we are interested in how different income levels affect the degree to which race is used a mechanism to form trust. For example, wealth may serve as a proxy for a client's education levels or experience in the financial markets. In this case, the role of racial homophily may be less important in forming trust.

We find that income appears to have a differential effect on how racial homophily and trust are formed (See Table 2). For low income earners, unconditional participation rates are quite low and racial homophily appears to play little role in participation, suggesting that fixed participation costs may be the driving force. For high income earners, however, while participation rates are extremely high, here too we find that racial homophily plays no role in participation. Instead, the effect of racial homophily is strongest among mid-income earners ($50K-200K). Relative to their unconditional rate of participation, minority zip codes are 25% more likely to participate in the market if there is at least one advisor in their area of similar race. For this group of households, the threshold for participation may be low enough to justify participation, yet subjective views of trust may impact their choice. To the extent that racial homophily helps these households to trust more, it may have policy implications on the role of racial diversity in the advisory industry.

The decision of an advisor and client to work together is a two-sided matching game. Firms and their advisor's have strong incentives to seek out wealthy clients, regardless of race, as their own compensation is directly tied to the size of their book of business. Historical wealth differences among groups and homophily preference among mid-income households, could lead to these subgroups underinvesting, missing out on the equity premium, and leading to persistence of group wealth inequity.

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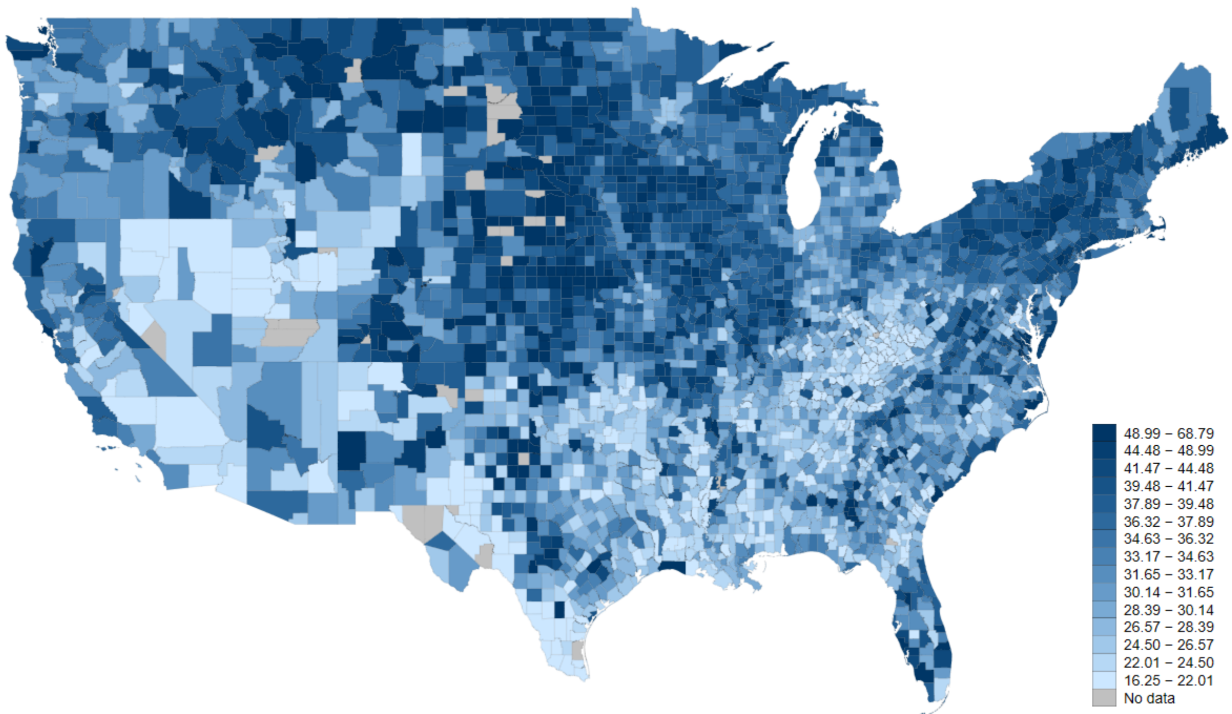

Fig. 1
Equity market participation
This figure documents the geospatial nature of equity market participation for households in the \$75k-\$100k income bracket. Darker shades of blue represent higher levels of equity participation. Grey represents missing data.

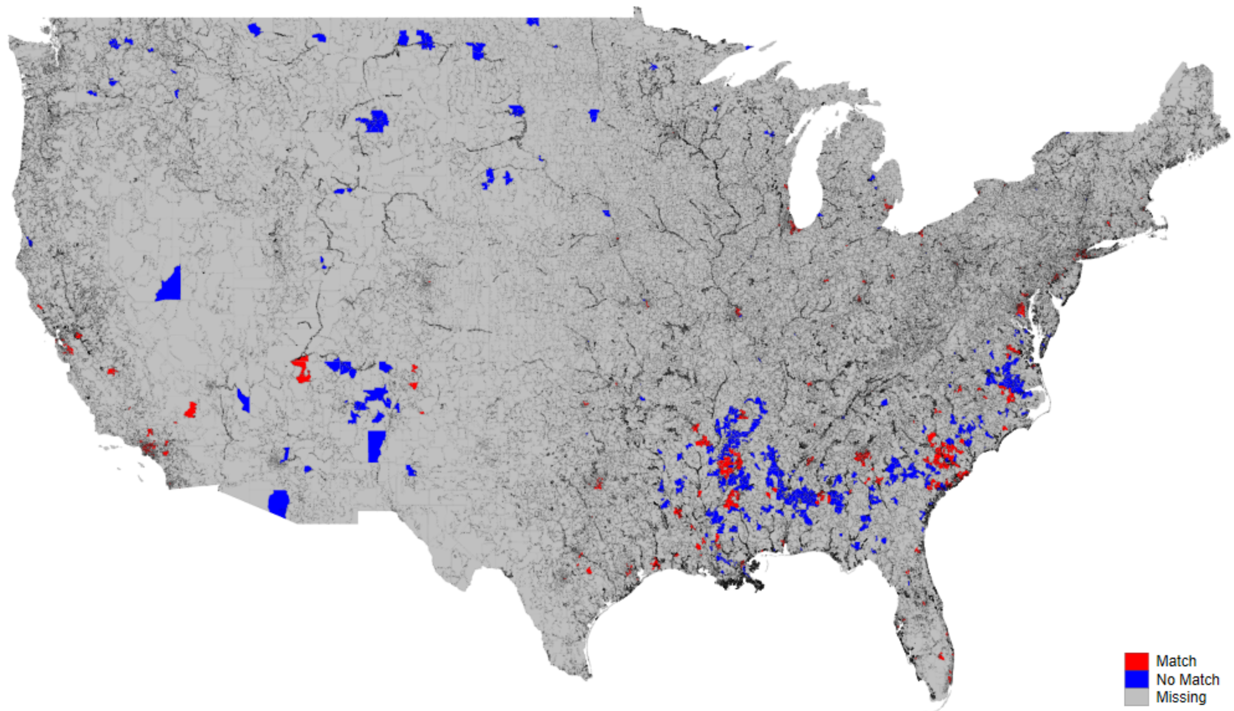

Fig. 2
Distribution of Minority Zip Code
This figure documents the universe of Minority-Majority zips in the US. A zip is Minority-Majority if more than 50% of its total population is represented by a single non-White race group. Red areas are zips with minority financial advisors that match the local majority race group. Blue areas are zips without matching advisors.

Table 1
Racial Homophily and Stock Market Participation

This table presents the effect of matching advisor and local population racial demographic on stock market participation. The unit of observation is a zip code-year. Participation is reported in percentage points. t-stats are reported in the parenthesis. Standard errors are clustered at the zip level.
*** p<0.01, ** p<0.05, * p<0.1

	1 Participation	2 Participation	3 Participation
Match	1.861*** (6.86)	0.782*** (2.99)	0.276** (2.57)
Year FE	Yes	Yes	Yes
Controls		Yes	
Zip FE			Yes

Table 2
Racial Homophily and Income Effects
This table presents the heterogeneous effect of matching advisor and local population racial demographic on stock market participation for households from different income brackets. The unit of observation is a zip code-year. Participation is reported in percentage points. t-stats are reported in the parenthesis. Standard errors are clustered at the zip level.
*** p<0.01, ** p<0.05, * p<0.1

	1	2	3
	Participation	Participation	Participation
50K-200K	9.287***	9.288***	9.167***
	(15.10)	(15.09)	(15.77)
200K+	39.28***	39.31***	32.69***
	(18.01)	(17.90)	(15.48)
Match	0.613***	0.706*	-1.551
	(3.87)	(2.12)	(-1.63)
Match × 50K-200K	2.295***	2.295***	2.400***
	(4.31)	(4.31)	(4.64)
Match × 200K+	-1.403	-1.413	2.765
	(-0.62)	(-0.63)	(1.26)
Year FE	Yes	Yes	Yes
Controls		Yes	
Zip FE			Yes

Where is the Intersection of Madison Avenue and Wall Street? Advertisement, Local Access to Investment Advice, and Stock Market Participation

July 31, 2021

Abstract

We examine the effects of advertisement by investment advisory firms on household stock market participation. Exploiting variation in exposure to financial advertising for households along designated market area (DMA) borders, we find evidence that increased advertising by investment advisory firms leads to higher stock market participation. Importantly, the effects are concentrated in counties where the advertising firm has a physical presence. Consistent with fixed cost frictions to participation, these effects are predominantly among higher income households. We also find larger effects in counties with higher income and racial diversity —areas that are are likely to have lower trust. Our results highlight the complementary nature of persuasive advertising and local access to finance for building trust in the market for investment advice.

Despite the potential benefits of investing in equity markets, household stock market participation rates are low in the U.S. (see e.g., Hung, Clancy, Dominitz, Talley, Berribi, and Suvankulov, 2008; Brown, Ivković, Smith, and Weisbenner, 2008). Households may lack the knowledge and capacity to evaluate investment opportunities (Lusardi and Mitchell, 2007; van Rooij, Lusardi, and Alessie, 2011) or may be too nervous or anxious to make risky investments on their own (Gennaioli, Shleifer, and Vishny, 2015). Instead, professional investment advice may help households overcome these shortcomings and participate in equity markets —if households know about and choose to acquire this advice.

Firms often use advertising to promote awareness and use of their products or services, and firms in the investment advisory industry are no exception. Collectively, financial firms spent $9 billion in advertising in 2019 —an amount that exceeded combined spending in the 2020 presidential election cycle (Kantar Media). Investment advisors typically advertise their services based not on past performance but instead on trust, experience, and dependability (Mullainathan, Schwartstein, and Shleifer, 2008). Thus, it is not surprising that investors cite "trust" as the most important factor when seeking professional advice (Hung, Clancy, Dominitz, Talley, Berribi, and Suvankulov, 2008). Using survey evidence, Burke and Hung (2015) find that trust is an important predictor of the use of professional investment advice. Consistent with the conjecture in Gennaioli, Shleifer, and Vishny (2015) that this trust in investment advisors derives from persuasive advertising, familiarity, and other personal connections, in this paper we examine how this spending on advertisement by investment advisory firms affects stock market participation.

Despite the large sums spent on advertising, understanding the effects of such expenditures is challenging due to the endogenous nature of advertising choices. For example, Jain and Wu (2000) find that mutual funds are more likely to advertise after periods of strong performance, and Mullainathan, Schwartstein, and Shleifer (2008) find mutual funds are more likely to include return metrics in advertisements during bull markets. To overcome such challenges, we take advantage of several unique features of the market for advertising, geographic data on the location of investment firms, and granular geographic data on household stock market participation. A key feature of our approach is that advertising is typically sold at the designated market area (DMA) level. These regional designations were first drawn based on broadcast areas during the birth of television in the 1950s and created arbitrary borders between areas that receive certain advertisements at the same point in time.

Take the example of Suwannee and Columbia counties in northern Florida. Suwannee County was carved out of Columbia County on December 21, 1858. These counties are quite similar in average income, educational attainment, demographics, population density, and climate.[1] Each county is located about a two hour's drive from both the cities of Jacksonville and Tallahassee. However, because of the DMA border running between them, households in neighboring Suwannee county receive one set of advertisements as a result of their placement in the Tallahassee DMA, while households in Columbia county receive a different set of advertisements in the Jacksonville DMA. Advertisement sales in each DMA may be influenced by many factors beyond demand from investment advisory firms including varying demand from local political campaigns, demand from other local industries, and other variation in local economic conditions in the DMA. In our study, we focus on small border counties like Suwanee and Columbia which make up only a tiny fraction of the total households in a DMA, such that these households are unlikely to influence a firm's choice to purchase advertising in a particular DMA. As such, these factors create arbitrary variation in the exposure to investment firm advertisements for households in the border counties.

We exploit this variation in advertising along these market boundaries by implementing a

[1]Suwannee County has an average income of \$23,000, college educational attainment of 16%, average age of 43 years, and a population density of 64 per square mile. Columbia County has an average income of \$26,000, college educational attainment of 15%, average age of 40 years, and a population density of 87 per square mile. Both voted heavily Republican in each of the last six elections.

border discontinuity strategy[2] to identify the effect of advertising on household stock market participation. Using aggregate county-level income tax data from the year 2004 to 2018, we find robust evidence that increased advertising leads to higher stock market participation. In our specifications, we include two sets of fixed effects. $Border \times DMA$ control for fixed characteristics such as demographic differences on each side of a DMA border, though we find little evidence of observable differences given the arbitrary DMA boundaries. $Border \times year$ fixed effects control for any time-varying factors that affect the entire border region on both sides of a DMA border. Across all households, the investment advisory firm advertising elasticities are significant, but somewhat smaller in magnitude than those found in other industries (see e.g., Shapiro, Hitsch, and Tuchman, 2021). However, when we disaggregate households by income tiers, we find that the effects are significantly larger among higher income households: for example, a one standard deviation increase in advertising dollars leads to a 2 percent increase in stock market participation for households with annual income above $200,000. Consistent with models in which fixed costs, such as those related to learning about investment opportunities, can help explain the low participation rates (e.g., Vissing-Jorgensen, 2003), we find little evidence of the effect of advertising among low earners.

We next consider the role that local access to finance has on the efficacy of the advertisement. After a household watches an advertisement and makes a decision about whether there is interest in an investment service, the potential client must take further action to obtain the service. Investment advice is inherently a local business. Geographic proximity between client and advisor can enhance the familiarity and other personal connections that Gennaioli, Shleifer, and Vishny (2015) argue are important for establishing trust. Not surprisingly, both major industry regulatory websites, FINRA Brokercheck's and the SEC's Investment Adviser Public Disclosure, allow potential clients to search for advisors within

[2]We follow a methodology similar to that used in recent papers that examine the effects of advertising on the demand for e-cigarettes (Tuchman, 2019), antidepressant drugs (Shapiro, 2018), and consumer packaged goods (Shapiro, Hitsch, and Tuchman, 2021).

a given city or ZIP code. Similarly, the CFP Board, an industry standard organization, defaults to geographic focused searches on its website.

Our data allow us to exploit variation in the geographic presence of investment advisory firms within the border county sample. Specifically, some counties have a branch office of an investment firm that engages in local advertising during a year, other counties contain branch offices of investment firms that choose not to advertise in that DMA during the year, and yet other counties do not have a branch office of an investment firm at all. This allows us to separately estimate the joint effect of having a local branch of a firm that advertises in a given year from the effect of simply having a local investment firm physically present in the county.[3]

Again, an example may help illustrate the approach. Hamilton County borders Suwanee County and likewise lies within the Tallahassee DMA. Baker County borders Columbia County and likewise lies within the Jacksonville DMA. Fidelity has branch offices in Suwanee and Baker counties, but not in Columbia and Hamilton. Thus, we are able to observe both counties with a local firm presence and those without. For those counties that have a local firm presence, whether the local firm advertises depends on Fidelity's decision to advertise in the Tallahassee and Jacksonville DMAs. Importantly, the Baker County Fidelity branch is only one of 40 Fidelity branches in the Jacksonville DMA, while the Suwannee County Fidelity branch is only one of 10 in the Tallahassee DMA. Thus it is unlikely that either of these remote branch locations are likely to the motivating factor for advertising in their respective DMAs.

We document that the effects of advertising are concentrated in those counties in which advertising firms have a local presence. The magnitude of the effect of advertising on participation in counties where a local firm advertises is nearly double in magnitude among

[3]Our approach assumes that potential clients who are exposed to advertising do not cross the DMA border and purchase in the adjoining DMA. Violations of this assumption will bias the estimates towards zero.

high income households. For comparison, this effect size is similar in magnitude to the effect of community effects documented in Brown, Ivković, Smith, and Weisbenner (2008). These results highlight the multifaceted nature of trust in the investment advisor industry as persuasive advertising is most effective in encouraging participation when complemented by local access to financial professionals.

If persuasive advertising helps to establish trust between local advisors and clients, then one might expect larger effects in areas with lower levels of trust. Using data from the General Social Survey, Alesina and La Ferrara (2002) document lower levels of trust among those living in a racially mixed community or in communities with a high degree of income disparity. Consistent with the findings of Guiso, Sapienza, and Zingales (2008), we indeed find lower participation in such areas; yet, we document that in these areas advertising is more effective in encouraging stock market participation relative to areas of high trust. These findings are consistent with advertising overcoming traditional barriers to participation through developing trust.

While the research design rules out most obvious confounding factors, one remaining concern is that that parallel-trends may not hold, invalidating the difference-in-differences design. We check observable characteristics including number of investment advisors on each side of the DMA borders and see no significant differences. We perform additional placebo tests. Using our main specification, we replace the dependent variable with average salary among households, helping to rule out the possibility that the association was spuriously caused by some time-varying local economic shocks. We then use our main specification and replace the independent variable with other non-investment financial advertising (advertising by and for credit unions, loans, and lending) to help rule out other spurious time-varying advertising shocks.

While the border sample aids the identification of the effect, the counties may not be representative and raise concerns about generalizability to the larger population. To address this, we run a naïve county-year panel regression using data from all counties in the US (i.e. across all 210 DMAs). While this approach sacrifices careful identification, we demonstrate that the method produces a similar estimate suggesting that the relationship between advertising and participation should generalize.

Our study contributes to the literature on the determinants of stock market participation. It is well documented that stock market participation is low (Brown, Ivković, Smith, and Weisbenner, 2008; Haliassos and Bertaut, 1995; Hong, Kubik, and Stein, 2004), and that a lack of trust (Burke and Hung, 2015; Guiso, Sapienza, and Zingales, 2008) and insufficient financial knowledge (Hilgert, Hogarth, and Beverly, 2003; Lusardi and Mitchell, 2007) are contributing factors to these low rates. It also relates to the growing literature about how the access to finance affects consumer financial well-being. Brown, Cookson, and Heimer (2019) find that local provision of finance matters for consumer financial credit outcomes. We present causal evidence that advertising investment advice is an effective means of addressing these shortfalls and spurring individual action to participate in markets. To our knowledge, this paper is the first to directly explore this question.

We also contribute to the broader literature on the efficacy of advertising in the financial services industry in general. Much of the literature on advertising in this space focuses on mutual funds despite the challenge that the endogenous advertising choice presents in establishing causality between advertising and flows. Jain and Wu (2000) examine a small sample of funds and find that after controlling for past performance, funds that advertise have higher flows than a group of funds matched on investment style and prior performance. Similarly, Gallaher, Kaniel, and Starks (2015) demonstrate that advertising weakens the sensitivity of the flow-performance relationship for poorly-performing funds while advertising increases the flow-performance relationship for top-performing funds. Barber, Odean, and Zheng (2005) find evidence that while mutual funds fees are associated with outflows, the negative effects of fees on flows is offset when the fees are spent on marketing. We supplement these studies by similarly documenting efficacy of advertising in the investment advisory space but employ an approach that overcomes the many issues of endogenous selection inherent to the current literature.

This paper is also related to literature about the persuasive view of advertising in financial products and services (e.g., see Hortaçsu and Syverson, 2004, and Elton, Gruber, and Busse, 2011, for the mutual fund industry; Gurun, Matvos, and Seru, 2016; Allen, Clark, and Houde, 2014, 2019, for mortgages; Green, Hollifield, and Schürhoff, 2007, for bonds; Duarte and Hastings, 2012, for privatized social security plans; Christoffersen and Musto, 2002, for money funds; and Brown and Goolsbee, 2002, for life insurance). The literature typically focuses on persuasion that creates "artificial" product differentiation. We differ in that we find evidence of the persuasive view of advertising that creates firm-specific ties that enable investors to take risk, consistent with the model of Gennaioli, Shleifer, and Vishny (2015). While costly, these expenditures help to build trust that enables households to participate in markets.

This paper proceeds as follows: in Section 1, we describe our identification strategy in detail. In Section 2, we summarize the advisor, advertising, and income data sets and define the construction of our main dependent variable. Section 3 presents our main results of the effects of advisor advertising on stock market participation, and includes placebo tests. In Section 4, we consider to what extent the interaction between advertising and the local presence of a financial advisor has on participation, and explore the varying effects of advertising on stock market participation due to county heterogeneity. Finally, Section 5 concludes.

1 Institutional Background and Research Strategy

Identifying a causal relationship between investment advisor advertising and stock market participation can be challenging. Advertising is not randomly assigned: financial advisory firms may target ads where residents are more likely to be stock market participants. Ordinary least squares estimates of the effects of advertising on action will lead to a positive bias if we fail to account for firms choosing to advertise where residents are more likely to trade. To overcome this endogeneity problem, we employ the methodology of Shapiro (2018) and Tuchman (2019) and take advantage of geographic discontinuities in local advertising markets. Specifically, we examine how demographically similar households on opposite sides of advertising market borders respond to financial advisor advertising.[4]

The Nielsen Company (Nielsen) assigns groups of counties in exclusive geographic areas to designated market areas (DMAs). The DMA to which a county is assigned determines what local programming a household within the DMA's borders will receive. FCC regulations and federal law in most cases prohibit broadcasters, including cable and satellite operators, from providing signal to a home in a DMA other than the signal to which homes in that DMA are meant to receive. Therefore, local television ads are transmitted to all households within a particular DMA, and ads purchased for a particular DMA only may not be shown in other DMAs.[5] Similarly, DMA-level advertising takes places at the magazine, newspaper, radio, and outdoor levels.

A useful demonstration is that of television commercials during the Super Bowl. Over 100 million viewers tune in to the NFL's annual championship game which commands the largest U.S. viewing audience each year. Naturally, ads aired nationally during the game garner much attention, and spots have cost over $5 million for 30 seconds. As they typically

[4]This section draws heavily from the descriptions of the identification strategy in Shapiro (2018) and Tuchman (2019).

[5]See Shapiro (2018) and Spenkuch and Toniatti (2018) for a thorough discussion of designated market areas.

do, networks also allot time during the broadcast to local ads.[6] In these slots, advertisers purchase slots to target ads to specific regional campaigns. For example, the Church of Scientology purchased time in 16 DMAs, including those where it has major centers. In the Lexington DMA, the local Winstar Stud Farm touted the prowess of its stallions in a concurrent commercial. Importantly, households in different regions watching identical programming at the same time received different advertisements.

Figure 1 presents a map of the 210 DMAs across the United States. DMAs are typically centered around metropolitan areas and include an average of 15 counties. Counties are assigned to only one DMA and are rarely reassigned. Nielsen originally drew boundaries to reflect demand for television programming while accounting for broadcast television airwave range. As such, boundaries do not reflect political jurisdictions: nearly half of DMAs cross state borders, with an average of 1.7 states represented per DMA. This in part alleviates the concern that the relationship between local advertising and stock market participation we study will be biased by unobserved variables pertaining to local laws and individuals choosing to live on one side of a border.

We obtain identification by comparing advertising and its effects on stock market participation for counties on opposite sides of a DMA boundary. The map of the states of Florida and Georgia presented in Figure 2 demonstrates this approach. The Tallahassee DMA consists of 10 counties in Georgia and 9 counties in Florida.[7] The Jacksonville DMA consists of 6 counties in Georgia and 9 counties in Florida. A total of 7 counties lie on the border of these two DMAs, with Clinch, Echols, Hamilton, and Suwanee counties on the western side of the border, and Ware, Baker, and Columbia counties on the east. Under the assumption that, for example, residents of Suwanee County and Columbia County are

[6] "Local Advertising Was Also On Display During Super Bowl XLIX". Kantar Media Report, 2015.

[7] Depending on the state, local administrative jurisdictions may be referred to as parishes, counties, boroughs, and/or independent cities. We use the terms "counties" to refer to all of these functionally similar regions.

similar on unobservables but exposed to different levels of local financial advisor advertising due to placement in different media markets, we can use their location on a DMA border as a setting for a natural experiment. A necessary condition of this framework is that there is limited selection by individuals more likely to be stock market participants to reside on certain sides of DMA borders. We test this possibility and discuss the results in Section 3.1.

This approach relies on variation in advertising both *across* DMAs and over time *within* a DMA. We graphically depict these distinct sources of variation for the Boston and New York City markets in Figure 3. Each point marks, for a given year, the units and average rate per unit of advertising (in dollars). Panel A shows the downward sloping demand curves in each of these markets: as on might expect, demand for units of advertising falls as the spot advertising rate increases. As apparent from Panel A, there is variation in this relationship within the Boston market and within the New York City markets. Likewise, there is significant variation across the Boston and New York due to distinct time-invariant characteristics inherent to these markets. Panel B of Figure 3 shows the demand curve in these markets with the inclusion of market fixed effects. Again, the demand for advertising in total units falls as the spot advertising rate increases, but here we control for those time-invariant market-specific characteristics. The variation in advertising is thus driven by the competition among advertisers for limited advertising spots.

Given these sources of variation, we incorporate two sets of fixed effects in our main specifications: *border-DMA* and *border-year* fixed effects. A "border" includes all adjacent counties on both sides of two neighboring DMAs' boundary. *Border-DMA* fixed effects permit time-varying advertising intensity *within* the border counties on one side of the border. For example, this allows systematically different levels of demand for advertising for Clinch, Echols, Hamilton, and Suwannee counties of the Tallahassee DMA relative to Ware, Baker, and Columbia counties of the Jacksonville DMA. This strategy relies on the assumption that stock market participation in counties across a DMA border would follow parallel trends in the absence of advertising exposure variation. *Border-year* fixed effects restrict this assumption of common trends in advertising to the local counties of a DMA border, in this case the seven counties Clinch, Echols, Hamilton, Suwannee, Ware, Baker, and Columbia on both sides of the Tallahassee-Jacksonville DMA border.

Firms likely target advertising to the populous metropolitan areas often at the center of DMAs rather than the relatively rural counties on DMA borders. This suggests that the different levels of advertising on DMA borders is less likely driven by characteristics of households in the border counties themselves. Continuing the example from Figure 2, both the Tallahassee and Jacksonville DMAs are named after the major metropolitan areas within their borders. The city of Tallahassee lies off the Tallahassee-Jacksonville DMA border in Leon County, which alone represents 39.7% of the DMA's 2019 population. Likewise, Jacksonville lies in Duval County, which represents 48.5% of the Jacksonville DMA's 2019 population. In contrast, the counties on the Tallahassee-Jacksonville DMA border represent a combined 8.8% and 6.9% of their respective DMA's population in 2019. Following the framework of Li, Hartmann, and Amano (2020), we limit our sample to these "small borders" where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA. On these borders, it is more plausible that local demand shocks in these relatively sparse counties are less likely to influence the advertising choices of financial advisors at the DMA level. Our final sample consists of 381 such borders (consisting of 1,155 unique counties), with each a setting for a separate experiment over our sample period.

2 Data

2.1 Registered Investment Advisors

The Investment Advisers Act of 1940 (IAA) defines an investment adviser as any person or company that is compensated for advising others on investing in securities. The IAA authorizes the Securities and Exchange Commission (SEC) to regulate and require registration by investment advisors. As part of their registration, registered investment advisors (RIAs) must file at least once annually a Form ADV with the SEC. Generally, only advisors with at least $100 million in assets under management and 15 or more U.S. clients must satisfy this registration and record-keeping requirement with the SEC.

We collect data on RIAs from their Form ADV, available on the SEC's *Investment Adviser Public Disclosure* website.[8] Because advisors may file more than one ADV per year as a result of material changes, we use the ADV filing active at the beginning of each calendar year from 2004 to 2018. We identify advertising firms based on their presence in the Kantar Media database, which we describe in the next subsection. No unique identifier links the Form ADV investment advisor data to the Kantar advertising data, so we manually match advisors to Kantar based on name. Of the 26,909 financial advisors that file a form ADV at any point over the period 2004-2018, approximately 7.6% or 2,039 RIAs are advertisers and present in the Kantar Media database.

Table 1 summarizes this sample. As one might expect, advertising RIA firms are significantly larger than non-advertising firms, with an average of $35.4 million more in assets under management (t-stat = 5.38). Advertising firms are similarly larger both in their number of accounts and number of employees. RIAs that advertise are also more likely to be retail focused: 54.8% of advertising firms mostly serve individuals and high net worth indi-

[8]Bulk downloads of historical ADVs are available at https://www.sec.gov/foia/docs/form-adv-archive-data.htm.

viduals, relative to the 48.5% of non-advertisers that primarily serve these groups. Finally, advertisers are significantly more likely to offer financial planning services.

2.2 Advertising

Advertising data come from Kantar Media (Kantar). The data include monthly advertising expenditures and advertising units for financial advertisers from 2004 to 2018 across television, print, radio, digital, and out-of-home (billboards, taxis, malls, cinema) channels. Spending and unit data is presented at the DMA and national levels.

Table 2 presents summary data on the Kantar dataset. The unit of observation is a border-county-year. *Total Ad Units* is the number of local television, print, radio, digital, and out-of-home advertisements in small border counties, on average 31,008.3 from 2004 to 2018. *Total Ad Dollars*, the total amount of RIA local advertising spending in a small border county in a year, averages $7.7 million, but is substantially skewed (the median is $1.45 million). The RIA advertising spending per household (*Ad $ per household*) is defined as an RIAs' national advertising expenditure scaled by the national population plus their local advertising expenditure scaled by the population of the DMA. In a small border county in a year, *Ad $ per household* averages $26.53, while the average number of RIAs in a small border county (*# of RIAs*) is 6.4.

2.3 Stock Market Participation

We use data from the IRS's Statistics of Income (SOI) and follow Brown, Ivković, Smith, and Weisbenner (2008) to develop our proxy for stock market participation. SOI provides annual data on tax returns in a zip code, including the number of filers, average reported salaries and wages, average adjusted gross income (AGI), number of returns filed, and number of returns reporting dividends. Following Brown, Ivković, Smith, and Weisbenner (2008), we proxy for stock market participation based on whether an individual reported dividend income on their federal tax return in a given year. That is, for county i in year t:

$$Participation_{i,t} = \frac{Number\ households\ reporting\ dividend\ income_{i,t}}{Tax\ returns\ filed_{i,t}} \tag{1}$$

Brown, Ivković, Smith, and Weisbenner (2008) note two weaknesses of this measure: (1) dividend income reported on tax returns includes distributions from any mutual fund, including those solely invested in fixed income and (2) it may not capture those who invest exclusively in non-dividend paying firms, such as growth-oriented stocks. To the extent that we wish to measure individuals' participation in financial markets overall, (1) does not present a serious issue, and (2) is not an issue so long as an investor holds any *one* dividend paying stock or mutual fund that makes a distribution. Brown, Ivković, Smith, and Weisbenner (2008) additionally show that the correlation between actual equity market participation as reported by the FED's Survey of Consumer Finances across four pooled cross-sections and their measure was 0.62. Lin (2020) finds that this measure of participation and the measure of participation from the University of Michigan's Health and Retirement Study used in Hong, Kubik, and Stein (2004) is 0.69.

Table 3 presents summary statistics on the SOI data by AGI in 2018. In Panel A, we present the full United States sample. There were 148.2 million tax returns filed in 2018. Our stock market participation measure is 24.8% overall, and monotonically increases from an average of 10.9% in the $1,000 - 25,000 AGI tier to 56.6% for households with AGI above $200,000. As we will describe in detail in the next section, we follow the framework of Li, Hartmann, and Amano (2020) and limit our sample to counties on "small DMA borders," or borders where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA. Panel B of Table 3 summarizes the households in these counties, with similar rates of participation across AGI tiers as in the full United States sample.

3 Advertising and Stock Market Participation

3.1 Baseline Tests

In our baseline tests, we regress our measure of stock market participation on advertising in the following fixed effects specification:

$$Participation_{i,t} = \beta Advertising_{d,t} + \delta_{b,d} + \delta_{b,t} + \epsilon_{i,t} \quad (2)$$

Subscripts are defined as: county i, year t, DMA d, and DMA-border b. *Participation* is the fraction of total household tax returns that report dividend income at the county-year level. We measure *Advertising* in three ways: (1) the natural logarithm of the units of RIA local advertising in a DMA-year, (2) the natural logarithm of dollars of RIA advertising expenditures in a DMA-year, or (3) *$ per household*, or RIAs' national advertising expenditure scaled by the national population plus their local advertising expenditure scaled by the population of the DMA following the approach in Shapiro (2018). $\delta_{b,d}$ represents the border-DMA fixed effects while $\delta_{b,t}$ represents the border-year fixed effects.

Table 4 presents the results of our baseline specification. Following the framework of Abadie, Athey, Imbens, and Wooldridge (2017), we cluster standard errors by DMA, the level of the assignment mechanism. All columns report coefficient estimates with the inclusion of the border-DMA and the border-year fixed effects. In columns (1) and (2), we find a positive and statistically significant relationship between stock market participation and local advertising both in financial advisor advertising units and financial advisor advertising expenditures. Given our specification and the inclusion of the border-DMA and border-year fixed effects, column (1) implies stock market participation in a county increases as a result of greater advertising intensity relative to local advertising on that county's side of the border ($\delta_{b,d}$) and relative to local advertising across all counties on both sides of the DMA border in that year ($\delta_{b,t}$).

In column (3) of Table 4, we take as our relevant measure of advertising the *scaled* dollars, or financial advisors' national advertising expenditure scaled by the national population plus their local advertising expenditure scaled by the population of the DMA. We include both a linear and squared term to highlight the diminishing marginal effects of advertising on participation. The scaled dollars measure of advertising is positive and significant while its squared term is negative and significant. Thus, the marginal effects of advertising on stock market participation is lower as the dollars of advertising per household gets increasingly large.

The coefficient estimates from column (1) imply that a one standard deviation increase from the average in local financial advisor units of advertising leads to an increase in stock market participation of 0.30% ($= 0.0016 \times \ln(49171.8 \div 31008.3) \div 0.25$) relative to the average rate of stock market participation. Likewise, for the dollars of advertising, a one standard deviation increase from the average in the dollars spent on DMA advertising leads to an increase in stock market participation of 0.39% ($= 0.0011 \times \ln(18900000 \div 7734262) \div 0.25$). This average advertising elasticity across all households is smaller in economic magnitude than the ones for consumer packaged goods (see e.g., Shapiro, Hitsch, and Tuchman, 2021).

We additionally test whether there are systematic differences in characteristics of county residents lying on either side of a DMA border. If, for example, individuals with higher income were more likely to cluster on the side of a DMA border with greater levels of advertising, it may bias our results if those individuals are more likely to be stock market participants. To test this, we compute the average number of financial advisors (scaled by the population), income, population, education attainment, debt-to-income ratios, social capital index, and age on both the sides of a DMA border. The number of advisors comes from FINRA BrokerCheck data. Income data is from IRS SOI. Population and educational attainment is from Census.gov. Debt-to-income ratios are from the Federal Reserve (federalreserve.gov), and the Social Capital Index is from the United States Congress Joint Economic Committee "The Geography of Social Capital in America" (jec.senate.gov). We consider the side of the border with greater (less) advertising to be the *Heavy* (*Light*) side of our small borders sample. We average across counties and aggregate to the border-DMA level.

Table A1 presents these results. On average, there are 10.06 financial advisors per 10,000 people on the side of the border with greater advertising and 10.55 financial advisors per 10,000 people on the side of the border with relatively lower levels of advertising. This difference is not statistically significant (t-stat = -0.50, p-value = 0.616). Similarly, the difference in average income, population, percent of residents with a college degree, debt-to-income ratios, social capital index, and age of county residents on the heavy and light sides of DMA borders cannot be shown to be statistically different from zero. These similarities across borders helps to alleviate the concern that individuals who are more likely to be stock market participants select onto the side of a DMA border with greater levels of advertising.

3.2 Adjusted Gross Income

Recalling Table 3, stock market participation varies substantially across income ranges. Overall, a quarter of households participate in trading, but only about 1 in 10 households with income less than \$25,000 invest while more than half of households with greater than \$200,000 in income invest. We next explore how advertising effects stock market participation among households with varying levels of income.

In order to determine the marginal effects of advertising on participation across households of disparate income, we interact our measure of advertising with income ranges, denoted with subscript k in the following specification:

$$Participation_{i,k,t} = \sum_k \beta_k(AGI\ Tier_k \times Advertising_{d,t}) + \delta_{b,d} + \delta_{b,t} + \delta_{k,t} + \epsilon_{i,t} \qquad (3)$$

As in our baseline specification presented in Equation 2, we include border-DMA $\delta_{b,d}$ and border-year $\delta_{b,t}$ fixed effects. Additionally, we incorporate AGI tier-year fixed effects $\delta_{k,t}$ to achieve identification of advertising on participation *within* an AGI tier and control for heterogeneity across households in different income groups.

Table 5 presents the results of Equation 3 and demonstrates that a positive and statistically significant relationship between advertising and participation is present for higher income levels only. Column (1) interacts the AGI tier with the natural logarithm of financial advisor units of advertising in the county's DMA, while column (2) interacts the AGI tier with the natural logarithm of the dollars of financial advisor advertising expenditures in the county's DMA. Among wealthier households, we find that the effects are significantly larger than our baseline effects. But we see no significant relationship between advertising and participation in either units or dollars of advertising for lower income households. In part, this contextualizes the economic magnitude of our estimates in Table 4: the relationship is driven by households that combined represent only approximately 20% of the total tax-filing households in the United States.

3.3 Retail-Focused RIAs

RIAs vary substantially in the services they provide. In our sample, about half of the RIAs primarily advise mutual funds, hedge funds, banks, or endowments while about half primarily offer planning and retirement services to individual investors. We hypothesize that advertising by RIAs with a retail focus will have effects on stock market participation. We test this in Table A2. We identify *Retail RIAs* as any RIA where at least 50% of its clients are either individuals or high-net worth individuals as reported on their Form ADV. From column (1), the coefficient on *Log(Units of Retail RIA Advertising)* is statistically significant at the 5% level. Thus, stock market participation increases as the units of advertising for retail-oriented RIAs increases. This relationship is not present in RIAs without a retail focus, as the coefficient on *Log(Units of Non-retail RIA Advertising* is not significant. Additionally, we reject that the difference between these two effects is zero.

Similarly, column (2) of Table A2 shows that the dollars of advertising by retail-oriented investors increases stock market participation while dollars spent on advertising by non-retail RIAs does not. The difference between these coefficients is different from zero. Taken together columns (1) and (2) of Table A2 support a role for trust in advertising and relationship between individuals and their investment adviser.

3.4 Alternative Specifications

In this section, we show the robustness of our baseline results with alternative advertising measures, sample selection, and border implementation. First, our identification strategy relies on the discontinuity of advertising across DMA borders. This identifying assumption could be violated if not all types of advertising are bought at the DMA level. To address this concern, we follow Shapiro (2018) and Tuchman (2019) and repeat our main analysis using television advertising spending only. This result is presented in Table A3, column (1). We find results similar to our main analysis using all adverting types.

Second, we determine whether our results hold in a naive panel setting where we include only county and year fixed effects. In this setting, we do not restrict the sample to border counties, nor control for border-DMA or border-year fixed effects. This specification may lack the clean identification of the border strategy, but it offers broader applicability by including all counties. The results presented in column (2) of Table A3 are similar to our main specification.

Finally, we explore an alternative strategy where we pair counties on a DMA border. As opposed to our main tests where we aggregate all border counties on one side of a border, this alternative implementation allows us to include more small counties in the analysis. Rather than limit our analysis to those counties on a border that combined have a population share less than 10% of their DMA, we restrict our sample to individual county pairs that are each less than 3% of their respective DMA population. We additionally include county-pair and pair-year fixed effects. In column (4) of Table A3, we show that this estimate is similar to what we find in Table 4.

3.5 Placebo Tests

Our identification strategy relies on the assumption that stock market participation in counties across a DMA border would follow a parallel trend in the absence of differences in advertising exposure. To mitigate the concern that this parallel trend assumption is violated, we conduct two sets of placebo tests.

First, we replace the dependent variable $Participation_{i,t}$ in our baseline specification presented in Equation 2 with the average salary in a county-year. If there are no differences in economic conditions across DMA borders, we should observe no advertising effects on average salary. Columns (1) and (2) of Table 6 present these results. Neither the units nor dollars of RIA advertising in a county-year have a statistically significant effect on the average salary of residents of a county.

Second, we want to be sure that our main effect is not driven by differences in general advertising across DMA borders. To do so, we replace the main independent variable, RIA advertising $Advertising_{d,t}$, in our baseline specification presented in Equation 2 with measures of other forms of financial firm advertising in a DMA-year. If our main effect is driven by different advertising trends across borders, we should see effects for these types of advertising on stock market participation. Table 6 presents these results. Column (3), (4), and (5) respectively show that the units of credit union advertising, loan advertising, and lending advertising by other financial firms have no statistically significant effect on stock market participation.

4 Advertising and Access to Local Investment Advice

We next consider the role that local access to finance has on the efficacy of the advertisement. After a household watches an advertisement and makes a decision about whether there is interest in an investment service, the potential client must take further action to obtain the service. Investment advice is inherently a local business. Geographic proximity between client and advisor can enhance the familiarity and other personal connections that Gennaioli, Shleifer, and Vishny (2015) argue are important for establishing trust.

In this section, we test whether the *local* presence of a RIA advertiser encourages stock market participation by *local* households. Additionally, we determine to what extent county heterogeneity results in disparate effects in the response by locals to the advertisement of financial advice.

4.1 Local Investment Advisors

We obtain detailed advisor location data from FINRA and the SEC. We then identify the local branches of firms that choose to advertise in a particular DMA, and also those that do not. To examine the extent to which the local access to investment advice has on stock market participation, we regress our proxy for stock market participation in county i in year t on an indicator for the presence of any local RIA and an indicator for the presence of any local advertising RIA:

$$Participation_{i,t} = \beta_1 AnyLocalRIA_{i,t} + \beta_2 AnyLocalAdvertisingRIA_{i,t} + \delta_{b,d} + \delta_{b,t} + \epsilon_{i,t} \quad (4)$$

As in our baseline specification presented in Equation 2, we include border-DMA and border-year fixed effects. These results are presented in Panel A of column (1) in Table 7. The coefficient on *Any Local RIA* is not statistically significant: the physical presence of one or more RIA branches in a county alone does not appear to encourage residents of that county to participate in the stock market. Yet, the coefficient on *Any Local Advertising RIA* is positive and statistically significant, indicating that the presence of any local financial advisory firm that has advertised in that county's DMA in that year does indeed have an incremental and positive effect on stock market participation in that county.

In column (2) of Panel A, Table 7, we substitute the binary variable for any local advertising RIA's presence in column (1) with continuous counts of the number of advertising units of local and non-local RIA advertising in a county. There is a positive and statistically significant coefficient on *Log(Units of Local RIA Advertising)* but no loading on *Log(Units of Non-local RIA Advertising)*. We further confirm that the difference between the coefficients on the *Log(Units)* if local and non-local RIA advertising is different than zero. Similarly, when we examine the dollars of advertising spent by local and non-local RIAs in column (3), we find increased spending by RIA's with a local presence has an effect on participation while spending by non-local RIAs does not. Again, we find the difference between these two coefficient estimates is statistically significant. The collective results presented in Table 7 are consistent with trust building in the advertising of financial advice.

Given the the relationship between advertising and stock market participation is concentrated in high income households (Table 5), we next consider the interaction between local units and dollar spending of advertising with AGI tiers in Panel B of Table 7. In column

(1), we interact AGI tiers with local RIA advertising units and show positive and significant effects for households with annual income in excess of $75,000. There is no statistically significant relationship between local advertising and participation among lower household income tiers. In column (2), we show this relationship similarly holds for dollar spending on local advertising.

In sum, we find compelling evidence that the effects of advertising are concentrated in those counties in which advertising firms have a local presence. Moreover, we find muted effects of advertising in areas without a local presence. These results highlight the multifaceted nature of trust in the investment advisor industry as persuasive advertising is more effective encouraging participation when complemented by local access to financial professionals.

4.2 Community Trust and Participation

Next, we consider heterogeneity in trust across communities. Guiso, Sapienza, and Zingales (2008) present evidence that areas with higher levels of trust are more likely to participate in the stock market. Alesina and La Ferrara (2002) find that high income and racial disparities are among the strongest determinants of low trust. We hypothesize that in areas with low trust, advertising will have a greater effect in encouraging stock market participation insofar as advertising investment advice plays a role in establishing trust between potential clients and financial advisors.

To test this, we use Census data to compute income and racial disparity at the county level by the normalized Herfindahl index.[9] We classify a county as having *High Income Disparity* if the county's normalized Herfindahl index for AGI tiers is above the median for all counties in a given year. We classify a county as *High Racial Disparity* if the county's

[9]We compute the disparity indices as $H = \sum_{i=1}^{N} s_i^2$, and then normalize as $H^* = \frac{H-1/N}{1-1/N}$ for $N > 1$ and $H^* = 1$ for $N = 1$. For income disparity, s is the ratio of tax filers in an AGI tier to the total number of tax filers in that county-year, and N is the number of AGI tiers in that county-year. For racial disparity, s is the ratio of a race group to the total population in the county year, and N is the number of race groups in that county year.

normalized Herfindahl index for race groups in a given year is above the median for all counties in that year. Crucially, we control for the ratio of each race group in each county, to pick up the homogeneity in race, not the variation due to composition for *specific* races. We take as our dependent variable stock market participation for households with AGI in excess of $100,000 given the results in Panel B of Table 7 demonstrating the effects of advertising on participation are concentrated in households with high income.

Table 8 presents these results. As expected areas with low trust as proxied by *High Income Disparity* or *High Racial Disparity* have lower levels of participation consistent prior studies such as Guiso, Sapienza, and Zingales (2008). Households from communities with low trust are less likely to participate in markets. To examine our assertion about the interaction between low trust and advertising, we include interactions between our low trust proxies and local RIA and local advertising RIA indicators. In column (1), we show the interaction between *High Income Disparity* and the presence of a local advertising RIA is positive and statistically significant. In column (2) we show a similar relationship between stock market participation and the interaction of *High Racial Disparity* and local advertising by RIAs. While households in counties with high racial disparity are less likely to participate in the stock market, in these are of low trust, advertising is more likely to encourage participation.

5 Conclusion

In this paper, we demonstrate that advertising by financial advisers increases stock market participation. This relationship is stronger for high-income households and in counties that have a local advertising advisor present. Strength of the community matters for stock market participation, and we show that advertising may help to establish trust in areas with weaker community ties. We achieve identification in the relationship between advertising and participation by comparing differences in participation rates across borders of otherwise similar counties in different designated market areas. Our incorporation of a rich set of fixed effects at the border-DMA and border-year level exploit variation in advertising both *across* and *within* regions.

Our findings speak to the ability of persuasive advertisement to help build trust that allows households to participate in equity markets. We also highlight the importance of local access to finance. Moreover, we document the complementary nature of local access and trust building through persuasive advertising. Together these findings suggest that under-served neighborhoods that lack access to investment advisors may not be able to reap the benefits of promotional campaigns that help encourage broader participation in the markets.

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Figure 1: **Nielsen Designated Market Areas**

Figure 2: **Tallahassee-Jacksonville DMA Border**

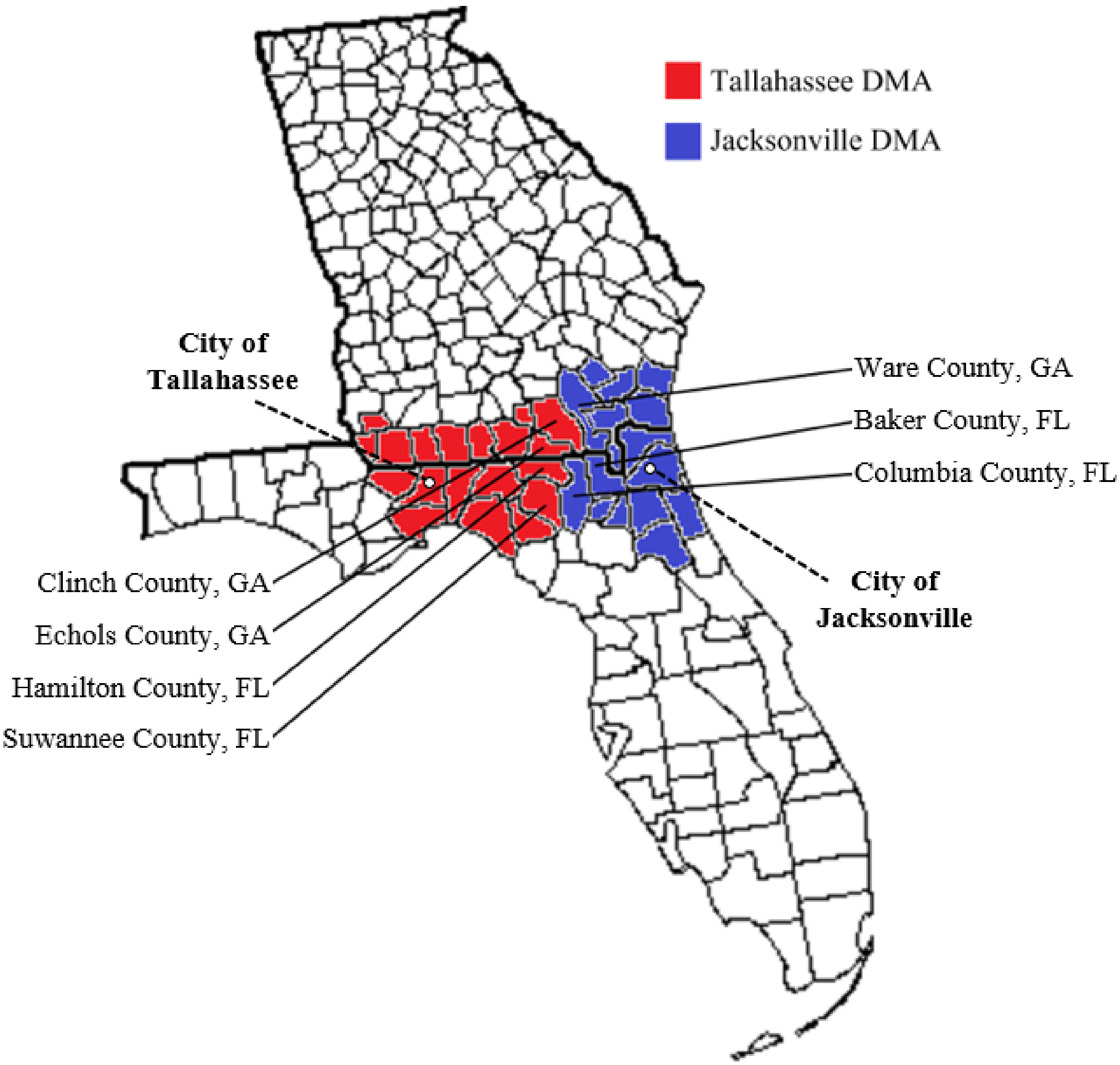

Figure 3: **Price of Spot TV Advertising vs. Financial Ad Units Purchased**

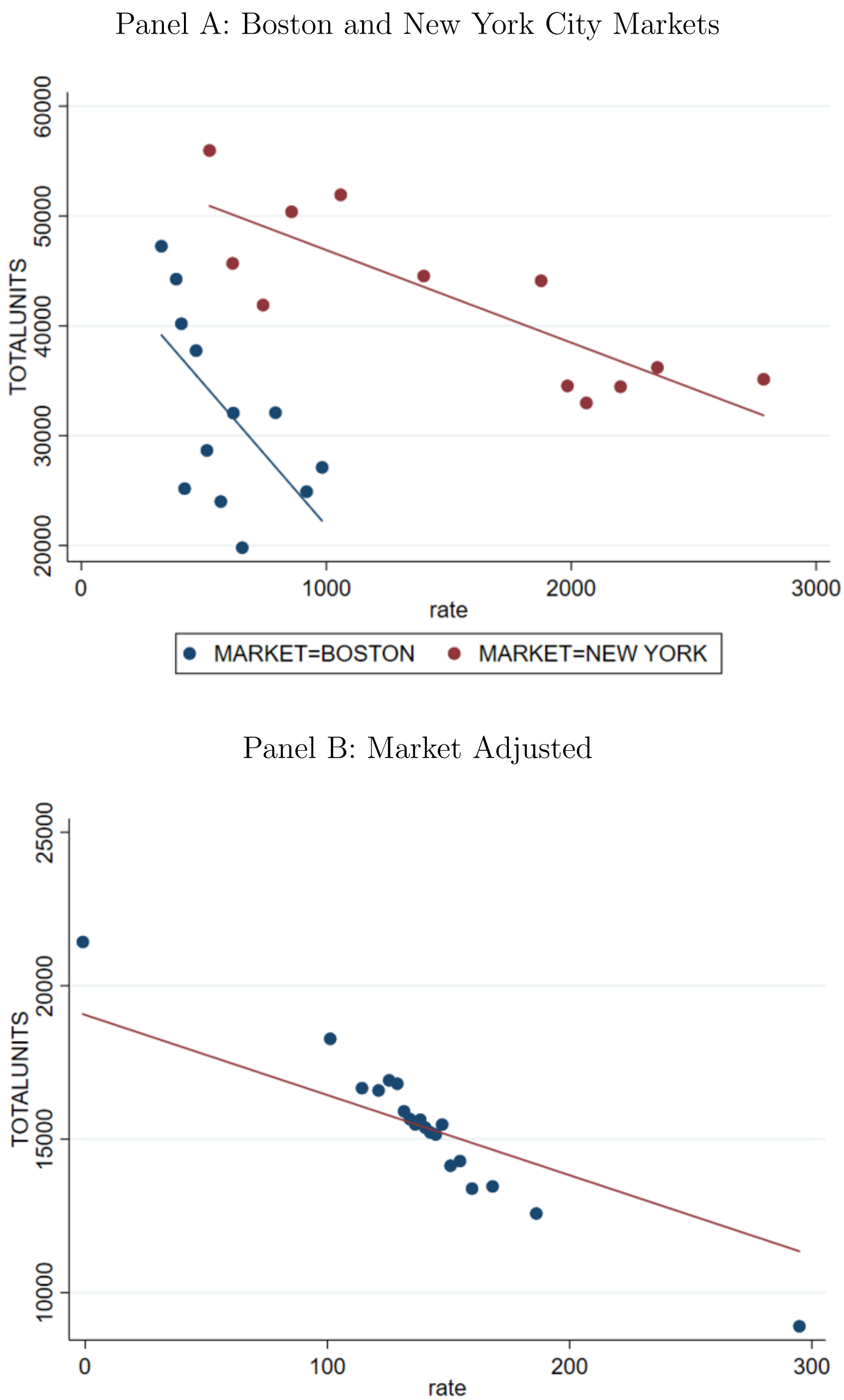

Table 1: **RIA Sample**

This table summarizes advertising and non-advertising RIAs from 2004 to 2018. The unit of observations is an RIA-year. RIA characteristics come from the advisor's Form ADV filings. An *Advertiser* is an RIA that matches to the Kantar Media database while a *Non-advertiser* is an RIA with no matching record to the Kantar Media advertising database. *AUM* is the RIA's assets under management in millions of US dollars. *Number of Accounts* is the RIA's total number of discretionary and non-discretionary accounts. *Employees* is the RIA's total number of full and part-time non-clerical employees. *Retail* is an indicator equal to 1 if 50% or more of the RIA's clients are individuals or high net worth individuals. *Planning* is an indicator equal to 1 if the RIA offers financial planning services. Standard errors (reported in parentheses) are clustered at the individual RIA level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Advertiser	Non-advertiser	Difference	t-stat
AUM (million of USD)	38,363	3,010	35,353	5.38***
Number of Accounts	1,748	392	1,356	8.38***
Employees	161	31	130	12.55***
Retail	54.8%	48.5%	6.25%	3.63***
Offer Planning Services	46.1%	36.7%	9.5%	5.19***

Table 2: **Kantar Financial Advertising Sample**

This table summarizes the advertising expenditure and financial advisor characteristics for the small border counties sample from 2004 to 2018. Small borders are defined as borders where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA. *Total Ad Units* is the RIAs' local advertising units in the current year. *Total Ad Dollars* is the RIAs' local advertising expenditure in the current year. *Ad $ per household* is defined as the RIAs' national advertising expenditure scaled by the national population plus their local advertising expenditure scaled by the population of the DMA. *# of RIAs* is the number of RIAs with a physical presence in the county-year.

	Mean	Std. Dev	25^{th}	50^{th}	75^{th}
Total Ad Units	31,008.3	49,171.8	2,371	11,358	40,771
Total Ad Dollars	$ 7,734,262	18,900,000	148,797	1,445,481	7,414,517
Ad $ per household	$ 26.53	5.96	23.08	25.58	28.92
# of RIAs	6.4	11.3	1	3	8

Table 3: **IRS Summary Statistics**

This table reports the summary statistics on the number of tax return filers in 2018 and stock market participation rates by adjusted gross income. The stock market participation rate is defined as the fraction of household tax returns that report dividend income. Panel A reports the summary statistics in the IRS's Statistics of Income sample. Panel B reports the summary statistics in our small border counties sample from 2004 to 2018. Small borders are defined as borders where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA.

Panel A: Full United States Sample

Income	Households (millions, 2018)	Participation
$1-25k	48.9	10.9%
25 - 50k	35.7	15.7%
50 - 75k	20.9	23.1%
75 - 100k	13.6	27.8%
100 - 200k	20.8	35.9%
200k+	8.2	56.6%
U.S.	148.2	24.8%

Panel B: Small Borders Sample

Income	Households (millions, 2018)	Participation
$1-25k	5.0	9.3%
25 - 50k	3.5	14.2%
50 - 75k	2.0	21.8%
75 - 100k	1.3	26.8%
100 - 200k	1.8	36.6%
200k+	0.5	52.9%
U.S.	14.2	25.0%

Table 4: **Baseline**

This table reports estimates from regressions of stock market participation rates on RIAs' local advertising spending. We restrict our sample to the small border counties from 2004 to 2018. Small borders are defined as borders where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA. The unit of observation is the county-year. We create a county-year level proxy of stock market participation rate based on the measure from Brown et al. (2008). The county-year level stock market participation rate is defined as the fraction of household tax returns that report dividend income. *Log (Units of Advertising)* is the logarithm of RIAs' local advertising units in the current year. *Log ($ of Advertising)* is the logarithm of RIAs' local advertising expenditure in the current year. *$ per household* is defined as the RIAs' national advertising expenditure scaled by the national population plus their local advertising expenditure scaled by the population of the DMA. All specifications include Border × DMA and Border × Year fixed effects. Standard errors (reported in parentheses) are clustered at the DMA level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Log(Units of Advertising)	0.0016*		
	(0.0008)		
Log($ of Advertising)		0.0011**	
		(0.0005)	
$ per household			0.0017**
			(0.0007)
$ per household squared			-0.00003***
			(0.00001)
Border × DMA FE	Yes	Yes	Yes
Border × Year FE	Yes	Yes	Yes
R^2	0.679	0.679	0.679
Observations	19,086	19,099	19,099

Table 5: **Effects by Household Income Level**

This table reports estimates from regressions of stock market participation rates on RIAs' local advertising spending, interacted with different AGI tier. We restrict our sample to small border counties from 2004 to 2018. Small borders are defined as borders where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA. The unit of observation is the county-AGI tier-year. The county-year level stock market participation rate is defined as the fraction of household tax returns that report dividend income. *Log(Units of Advertising)* is the logarithm of RIAs' local advertising units in the current year. *Log($ of Advertising)* is the logarithm of RIAs' local advertising expenditure in the current year. We include the following household AGI tiers: 1-75k, 75k-100k, 100k-200k, and >200k. All specifications include Border × DMA, Border × Year, and AGI Tier × Year fixed effects. Standard errors (reported in parentheses) are clustered at the DMA and year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
200k+ × Log(Units of Advertising)	0.0123***	
	(0.0038)	
100k-200k × Log(Units of Advertising)	0.0042**	
	(0.0018)	
75k-100k × Log(Units of Advertising)	-0.0004	
	(0.0015)	
Under 75k × Log(Units of Advertising)	-0.0017	
	(0.0014)	
200k+ × Log($ of Advertising)		0.0105***
		(0.0029)
100k-200k × Log($ of Advertising)		0.0026*
		(0.0014)
75k-100k × Log($ of Advertising)		-0.0009
		(0.0010)
Under 75k × Log($ of Advertising)		-0.0017
		(0.0013)
Border × DMA FE	Yes	Yes
Border × Year FE	Yes	Yes
AGI Tier × Year FE	Yes	Yes
R^2	0.695	0.695
Observations	107,830	107,939

Table 6: **Placebo Tests**

This table reports placebo test results. We restrict our sample to the small border counties from 2004 to 2018. Small borders are defined as borders where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA. The unit of observation is the county-year. In columns (1) and (2), the dependent variable is the average household income level. *Log(Units of RIA Advertising)* is the logarithm of RIAs' local advertising units in the current year. *Log($ of RIA Advertising)* is the logarithm of RIAs' local advertising expenditure in the current year. In column (3) – (5), the dependent variable is the county-year level stock market participation rate. *Log(Units of Credit Union Advertising)* is the logarithm of credit union firms' local advertising units in the current year. *Log(Units of Loan Advertising)* is the logarithm of loan institutions' local advertising units in the current year. *Log(Units of Lending Advertising)* is the logarithm of lending firms' local advertising units in the current year. All specifications include Border × DMA and Border × Year fixed effects. Standard errors (reported in parentheses) are clustered at the DMA level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Avg. Salary		Participation		
	(1)	(2)	(3)	(4)	(5)
Log(Units of RIA Advertising)	-0.0522				
	(0.0450)				
Log($ of RIA Advertising)		-0.0392			
		(0.0573)			
Log(Units of Credit Union Advertising)			0.0002		
			(0.0004)		
Log(Units of Loan Advertising)				0.0004	
				(0.0005)	
Log(Units of Lending Advertising)					-0.0003
					(0.0003)
Border × DMA FE	Yes	Yes	Yes	Yes	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.754	0.754	0.688	0.673	0.683
Observations	19,086	19,099	17,933	17,267	10,219

Table 7: **Local Presence and Advertising**

This table reports estimates from regressions of stock market participation rates on the presence of local RIAs and local advertising spending by RIAs. Panel A reports the average effects across all households and Panel B reports the effects by income levels. We restrict our sample to the small border counties from 2004 to 2018. Small borders are defined as borders where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA. The county-year level stock market participation rate is defined as the fraction of household tax returns that report dividend income. *Any Local RIA* is an indicator variable equal to one if any RIA has physical presence in the county-year. *Any Local Advertising RIA* is an indicator variable equal to one if any advertising RIA has physical presence in the county-year. *Log(Units of Local RIA Advertising)* is the logarithm of the units of local advertising purchased by an RIA with a local presence in the county-year. *Log(Units of Non-local RIA Advertising)* is the logarithm of the units of local advertising purchased by an RIA without a local presence in the county-year. *Log ($ of Local RIA Advertising)* is the logarithm of the dollar amount of local advertising purchased by an RIA with a local presence in the county-year. *Log ($ of Non-local RIA Advertising)* is the logarithm of the dollar amount of local advertising purchased by an RIA without a local presence in the county-year. *Test of difference: Local Units vs. Non-Local Units* reports the test of the difference in the coefficients on *Log(Units of Local RIA Advertising)* and *Log(Units of Non-local RIA Advertising)* in column (2). *Test of difference: Local $ vs. Non-Local $* reports the test of the difference in the coefficients on *Log ($ of Local RIA Advertising)* and *Log ($ of Non-local RIA Advertising)* in column (3). All specifications include border × DMA and border × year fixed effects. Standard errors (reported in parentheses) are clustered at the DMA level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Average Effects

	(1)	(2)	(3)
Any Local RIA	-0.0012	-0.0000	-0.0016
	(0.0052)	(0.0054)	(0.0054)
Any Local Advertising RIA	0.0176***		
	(0.0044)		
Log(Units of Local RIA Advertising)		0.0032***	
		(0.0008)	
Log(Units of Non-local RIA Advertising)		0.0007	
		(0.0010)	
Log($ of Local RIA Advertising)			0.0020***
			(0.0005)
Log($ of Non-local RIA Advertising)			0.0003
			(0.0008)
Border×DMA FE	Yes	Yes	Yes
Border×Year FE	Yes	Yes	Yes
R^2	0.689	0.687	0.689
Observations	19,764	19,086	19,099
Test of difference: Local Units vs. Non-Local Units		0.0025*	
Test of difference: Local $ vs. Non-Local $			0.0017*

Panel B: Effects by Income Levels

	(1)	(2)
Any Local RIA	0.0169*	0.0142*
	(0.0081)	(0.0078)
200k+× Log(Units of Local RIA Advertising)	0.0237***	
	(0.0037)	
100k-200k× Log(Units of Local RIA Advertising)	0.0059***	
	(0.0013)	
75k-100k× Log(Units of Local RIA Advertising)	0.0058***	
	(0.0015)	
Under 75k× Log(Units of Local RIA Advertising)	0.0007	
	(0.0008)	
200k+× Log(Units of Non-local RIA Advertising)	-0.0040	
	(0.0031)	
100k-200k× Log(Units of Non-local RIA Advertising)	0.0022	
	(0.0018)	
75k-100k× Log(Units of Non-local RIA Advertising)	-0.0022	
	(0.0014)	
Under 75k× Log(Units of Non-local RIA Advertising)	-0.0001	
	(0.0010)	
200k+× Log($ of Local RIA Advertising)		0.0162***
		(0.0026)
100k-200k× Log($ of Local RIA Advertising)		0.0043***
		(0.0008)
75k-100k× Log($ of Local RIA Advertising)		0.0036***
		(0.0009)
Under 75k× Log($ of Local RIA Advertising)		0.0005
		(0.0005)
200k+× Log($ of Non-local RIA Advertising)		-0.0028
		(0.0022)
100k-200k× Log($ of Non-local RIA Advertising)		0.0010
		(0.0012)
75k-100k× Log($ of Non-local RIA Advertising)		-0.0016
		(0.0009)
Under 75k× Log($ of Non-local RIA Advertising)		0.0005
		(0.0008)
Border×DMA FE	Yes	Yes
Border×Year FE	Yes	Yes
AGI Tier×Year FE	Yes	Yes
R^2	0.710	0.713
Observations	107,830	107,939

Table 8: **County-level Heterogeneous Effects: Stock Market Participation Rates for 100k+ Households**

This table reports estimates from regressions of stock market participation rates for households with annual income in excess of $100,000 on the presence of local RIAs and local advertising RIAs, interacted with county-level income and racial disparity measures. We restrict our sample to the small border counties from 2004 to 2018. Small borders are defined as borders where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA. The county-year level stock market participation rate is defined as the fraction of household tax returns that report dividend income. *Any Local RIA* is an indicator variable equal to one if any RIA has physical presence in the county-year. *Any Local Advertising RIA* is an indicator variable equal to one if any advertising RIA has physical presence in the county-year. *High Income Disparity* is an indicator variable equal to one if the county-year level normalized Herfindahl index based on household total income is above the median for all counties in the given year. *High Racial Disparity* is an indicator variable equal to one if the county-year level normalized Herfindahl index based on ratios of all race groups is above the median for all counties in the given year. All specifications include border × DMA and border × year fixed effects. Standard errors (reported in parentheses) are clustered at the DMA level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Any Local RIA	0.0112	0.0408**
	(0.0136)	(0.0184)
Any Local Advertising RIA	0.0206**	0.0379***
	(0.0081)	(0.0117)
High Income Disparity× Any Local Advertising RIA	0.0353***	
	(0.0113)	
High Racial Disparity× Any Local Advertising RIA		0.0257*
		(0.0140)
High Income Disparity× Any Local RIA	0.0303*	
	(0.0172)	
High Racial Disparity× Any Local RIA		0.0139
		(0.0260)
High Income Disparity	-0.0927***	
	(0.0169)	
High Racial Disparity		-0.0427*
		(0.0241)
Racial Group Control	–	Yes
Border×DMA FE	Yes	Yes
Border×Year FE	Yes	Yes
R^2	0.635	0.641
Observations	16,518	16,528

Appendices

Table A1: **Test for Selection Across Borders**

This table reports the average number of financial advisors (scaled by the population), income, population, education attainment, debt-to-income ratios, social capital index, and age on both the sides of a DMA border. We calculate average values across counties and aggregate them to the border-DMA level. We consider the side of the border with greater (less) advertising to be the Heavy (Light) side of a DMA border. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Heavy	**Light**	**t-stat**	**p-value**
Advisors per 10,000	10.06	10.55	-0.50	0.616
	(0.60)	(0.76)		
Income	31,609.77	30,826.50	1.22	0.223
	(436.47)	(470.04)		
Population	52,216	66,714	-1.20	0.231
	(4,038)	(11,390)		
% College Degree	13.54	13.61	-0.15	0.883
	(0.33)	(0.35)		
Debt to Income	1.64	1.66	-0.30	0.763
	(0.06)	(0.07)		
Social Capital Index	0.027	-0.008	0.03	0.746
	(0.08)	(0.08)		
Age	40.02	40.12	-0.35	0.729
	(0.20)	(0.20)		

Table A2: **Retail RIA Advertising**

This table reports estimates from regressions of stock market participation rates on local advertising spending by retail RIAs. We restrict our sample to the small border counties from 2004 to 2018. Small borders are defined as borders where the combined population of all counties on each side of the DMA border is less than 10% of the total population in its respective DMA. The county-year level stock market participation rate is defined as the fraction of household tax returns that report dividend income. *Log(Units of Retail RIA Advertising)* is the logarithm of the units of local advertising purchased by an RIA with more than 50% individual clients or more than 50% high net worth clients in the county-year. *Log(Units of Non-retail RIA Advertising)* is the logarithm of the units of local advertising purchased by an RIA with less than or equal to 50% individual clients and less than or equal to 50% high net worth clients in the county-year. *Log ($ of Retail RIA Advertising)* is the logarithm of the dollar amount of local advertising purchased by an RIA with more than 50% individual clients or more than 50% high net worth clients in the county-year. *Log ($ of Non-retail RIA Advertising)* is the logarithm of the dollar amount of local advertising purchased by an RIA with less than or equal to 50% individual clients and less than or equal to 50% high net worth clients in the county-year. *Test of difference: Local Units vs. Non-Local Units* reports the test of the difference in the coefficients on *Log(Units of Retail RIA Advertising)* and *Log(Units of Non-retail RIA Advertising)* in column (1). *Test of difference: Retail $ vs. Non-retail $* reports the the test of the difference in the coefficients on *Log ($ of Retail RIA Advertising)* and *Log ($ of Non-retail RIA Advertising)* in column (2). All specifications include border × DMA and border × year fixed effects. Standard errors (reported in parentheses) are clustered at the DMA level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Log(Units of Retail RIA Advertising)	0.0020**	
	(0.0009)	
Log(Units of Non-retail RIA Advertising)	0.0002	
	(0.0005)	
Log($ of Retail RIA Advertising)		0.0016**
		(0.0007)
Log($ of Non-retail RIA Advertising)		-0.0003
		(0.0003)
Border×DMA FE	Yes	Yes
Border×Year FE	Yes	Yes
R^2	0.676	0.676
Observations	18,665	18,652
Test of difference: Retail Units vs. Non-retail Units	0.0018**	
Test of difference: Retail $ vs. Non-retail $		0.0019**

Table A3: **Alternative Specifications**

This table reports estimates from regressions of stock market participation rates on financial advisers' advertising spending with alternative specifications. In column (1), we report estimates in the small border counties sample using TV advertising spending. The independent variable in column (1) is the logarithm of financial advisers' local TV advertising units in the current year. We include border × DMA and border × year fixed effects in column (1). In column (2), we report estimates in all counties sample. The independent variable in column (2) is the logarithm of financial advisers' local advertising units in the current year. We include county and year fixed effects in column (2). Column (3) reports estimates in a sample of county pairs that are each less than 3% of their DMA population. The independent variable in column (3) is the logarithm of financial advisers' local advertising units in the current year. We include county × pair and pair × year fixed effects in column (3). Standard errors (reported in parentheses) in all specifications are clustered at the DMA level. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	TV Only (1)	Panel (2)	County Pair Approach (3)
Log(Units of Advertising)	0.0009**	0.0016***	0.0017**
	(0.0004)	(0.0004)	(0.0008)
Border×DMA FE	Yes		
Border×Year FE	Yes		
County FE		Yes	
Year FE		Yes	
County×Pair FE			Yes
Pair×Year FE			Yes
R^2	0.682	0.883	0.925
Observations	19,764	41,194	24,508

Addressing Market Access (Part 2 - Industry)
Friday, October 22
1:30 p.m. – 2:20 p.m.

Industry firms explore innovative approaches to increasing market access for underserved communities, including scouting programs, the use of non-traditional platforms and the democratization of wealth building opportunities.

Moderator: Mark Lush
Manager and Behavioral Scientist at the Behavioral and Economic Analysis and Decision-Making (BEAD) Program
NORC at the University of Chicago

Panelists: Adam Minehardt
Director, Federal Government Affairs
Citigroup

David Richardson
Managing Director of Research
TIAA Institute

Kai Walker
Head of Inclusion Transformation, Retirement & Personal Wealth Solutions
Bank of America

Addressing Market Access (Part 2 - Industry) Panelist Bios:

Moderator:

Mark Lush is Manager and Behavioral Scientist at the Behavioral and Economic Analysis and Decision-Making (BEAD) team at NORC at the University of Chicago. Mr. Lush received his B.A. in Anthropology from Oberlin College and M.A. in Social Sciences from the University of Chicago where he focused on financial decision-making and conducted original research investigating how users respond to required versus suggested credit card repayment amounts. Mr. Lush specializes in applying traditional as well as behavioral economic methods to delivery actionable insights and design for behavior change. He has managed and administered focus groups, in-depth interviews, and behavioral design studies on topics related to financial decision-making, disclosure, and risk tolerance. He has spent over 15 years in the financial advice and insurance industries in both Australia and the U.S. Mark's research has been presented at the American Council on Consumer Interests, American Association of Public Opinion Research, Association for Financial Counseling & Planning Education, and Economic Science Association. He chairs the career and networking committee of the University of Chicago's Social Science Alumni board and is former co-organizer of the Chicago chapter of Action-Design Network, a non-profit whose purpose is to promote the use of behavioral economics and psychology in policy and product design.

Panelists:

Adam Minehardt joined Citi in December 2019 as Director of Federal Government Affairs in the Washington, D.C. Global Government Affairs Office. Mr. Minehardt represents Citigroup before Congress and the Biden administration on issues pertaining to capital markets, COVID-related stimulus efforts, housing, diversity and inclusion, and small business. Prior to joining Citi, Mr. Minehardt worked on Capitol Hill for more than 16 years and served as Chief of Staff for Rep. Nydia Velazquez (D-NY; Senior Member of the House Committee on Financial Services and Chairwoman of the Committee on Small Business) and as Staff Director for the Committee on Small Business. As Chief of Staff, Mr. Minehardt managed all areas of Rep. Velazquez's personal office, including legislative strategy and development, Financial Services Committee activity, and key relationships with congressional leadership and the administration. As Staff Director, Mr. Minehardt directed all aspects of the Committee's operations, including congressional hearings and legislative activity. Mr. Minehardt was selected as a Stennis Congressional Senior Staff Fellow in 2019. Prior to becoming Chief of Staff and Staff Director, Mr. Minehardt served as Deputy Staff Director and was Rep. Velazquez's banking policy advisor for all matters before the House Committee on Financial Services. Before coming to the Hill, Mr. Minehardt was on the staff of the Federal Reserve Board of Governors in Washington, D.C. where he developed and oversaw policies related to the Fed's intraday extension of credit and associated payment systems issues. Prior to the Fed, Mr. Minehardt worked at PriceWaterhouseCoopers LLP where he developed financial models for the Federal Housing Administration's loan portfolios. He holds a B.A. in political science from Rutgers College and an M.P.P. from the College of William and Mary and resides in Washington, DC.

David P. Richardson is Managing Director of Research and Head of the TIAA Institute. Prior to joining the Institute, he was serving as Senior Economist for Public Finance at the White House Council of Economic Advisers and held the New York Life Chair in Risk Management and Insurance at Georgia State University. Previously, Dr. Richardson worked as a Financial Economist in the Office of Tax Policy at the U.S. Treasury, and was an Assistant Professor in the Department of Economics at Davidson College. Dr. Richardson's research interests focus on how dimensions of public pensions, employer retirement benefit plans, and behavioral biases impact household financial security. He is an Employee Benefit Research Institute trustee, and a member of the National Academy of Social Insurance, the Pension Research Council Advisory Board, the Research Committee of the International Centre for Pension

Management, the American Economic Association, the American Risk and Insurance Association, and the National Tax Association.

Kai R. Walker is Head of Inclusion Transformation and Bank of America and ensures that the delivery of Retirement and Personal Wealth Solutions' products and services are effective in meeting the needs of diverse clients and communities. In this role, he collaborates with colleagues and partners to enhance employee well-being, foster financial inclusion and address the unique challenges confronting diverse populations. Mr. Walker began his career as an executive in Global Wealth & Investment Management and most recently served as Enterprise Relationships Director. In this role, he was responsible for delivering innovative thought leadership, actionable ideas and relevant solutions to clients as an effective means in attracting, retaining, and motivating employees in an increasingly competitive business environment. He also served as the National Director of Institutional Client Relationships where he was responsible for coordinating the service and acquisition functions of the institutional and national client segment with over $200 billion in assets and four million accounts under management. Mr. Walker is a leading industry professional with over 25 years of experience in retirement and financial services. Prior to joining Bank of America, he held a variety of positions with market leading financial services firms where he focused on helping corporate executives meet their fiduciary obligations and empowered their employees to achieve financial wellness. Mr. Walker holds a B.S. in mathematics from Gordon College and maintains certification in economics from the University of Wisconsin. He maintains the FINRA Series 7, 66 and 24 registrations and is an acting member of the American Economic Association, the Society of Human Resources and the Florida Council on Aging. Mr. Walker is also member of the firm's Black Executive Leadership Council, co-executive sponsor for the Jacksonville Inter-Generational Employee Network and a member of the Retirement and Personal Wealth Solutions Operating Committee.

Addressing Market Access (Part 2 - Industry)

Panelists

- **Moderator**
  - Mark Lush, Manager and Behavioral Scientist at the Behavioral and Economic Analysis and Decision-Making (BEAD) Program, NORC at the University of Chicago
- **Panelists**
  - Adam Minehardt, Director, Federal Government Affairs, Citigroup
  - David Richardson, Managing Director of Research, TIAA Institute
  - Kai Walker, Head of Inclusion Transformation, Retirement & Personal Wealth Solutions, Bank of America

Closing Remarks
Friday, October 22
2:20 p.m. – 2:30 p.m.

Speaker: Angela Fontes
Vice President in the Economics, Justice, and Society Department, Director of the Behavioral and Economic Analysis and Decision-Making (BEAD) Program
NORC at the University of Chicago

Closing Remarks Speaker Bio:

Speaker:

Angela Fontes, Ph.D., is vice president in the Economics, Justice, and Society department and director of the Behavioral and Economic Analysis and Decision-making (BEAD) program at NORC at the University of Chicago. At NORC, Dr. Fontes oversees research focused on household finance and investor decision-making, with a specific focus on the financial well-being of African American and Hispanic/Latino families. Using both traditional economic methods, as well as methods from behavioral science and marketing, Dr. Fontes delivers actionable insights for a diverse set of stakeholders. A nationally recognized expert in household finance, Dr. Fontes is regularly quoted in national and trade press and is a frequent speaker on topics related to financial wellbeing. She is the Principal Investigator on several projects, including work with the Securities and Exchange Commission to conduct investor protection research, and NORC's ongoing collaboration with the FINRA Investor Education Foundation. Her research can be found in journals such as the *Hispanic Journal of Behavioral Sciences*, the *Journal of the American Medical Association*, the *Journal of Family and Economic Issues*, the *Journal of Women, Politics, and Policy*, and *Financial Counseling and Planning*. Prior to NORC, Dr. Fontes worked in business and market research consulting with Chamberlain Research Consultants and Leo Burnett. She is adjunct faculty at Northwestern University where she was recently awarded a Distinguished Graduate Teaching Award. At Northwestern, Dr. Fontes teaches graduate courses in behavioral economics and public policy, policy analysis, predictive analytics, and research writing. Dr. Fontes is incoming President of the American Council on Consumer Interests, and on the Board of Directors at the Northwest Side Housing Center. Dr. Fontes holds a Ph.D. in Consumer Behavior and Family Economics with a minor in Sociology from the University of Wisconsin-Madison and is a certified Project Management Professional (PMP®).

Closing Remarks

Speaker

- Speaker
  - Angela Fontes, Vice President in the Economics, Justice, and Society Department, Director of the Behavioral and Economic Analysis and Decision-Making (BEAD) Program, NORC at the University of Chicago