Impact of Robo-advisors on the Labor Market for Financial Advisors

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Abstract

Using hand-collected data on robo-advisors, I study the impact of robo-advisors on the corresponding high-skilled (financial advisors) labor market. I find that robo-advisors and financial advisors are complements. This complementarity can be explained by the expansion in market for financial services through (1) an increase in financial advisors at firms that directly compete with robo-advisors in terms of services provided (relative to the rest of the firms) and (2) an increase in investor-level demand for financial advisors. I also find that the observed increase in the number of financial advisors is due to a reduction in separations and an increase in hirings. This is associated with an increase in the average experience of a financial advisor with no effect on the misconduct behavior of a financial advisor at the firm.

JEL classification: G20, J40, J44, O30, O33.

Keywords: Non-routine-based technology, robo-advisors, financial technology, high-skilled labor, labor substitution, labor complementing, financial advisors.

1 Introduction

In the past decade, technology has evolved to perform tasks of a high-skilled laborer. This change has allowed the service-sector firms to increasingly adopt such technologies. A Robo-advisor[1] is one particular technology that performs tasks similar to those of financial advisors (high-skilled laborer), and robo-advisors have seen widespread implementation within the financial advisory industry since the 2008 financial crisis. In this paper, I study the impact of robo-advisors on the labor market for financial advisors.

The financial advisory industry provides a good setting to study the effect of technology adoptions on high-skilled labor due to the availability of detailed advisor-level data. I supplement the publicly available data on the financial advisory firms and financial advisors with hand-collected data on robo-advisors. I create a comprehensive database at the advisor-firm-level that can also identify robo-advisory firms. The final data allows me to track financial advisors and brokers at every branch of all firms over time.

A naïve regression with number of financial advisors (at the firm level) as dependent variable and number of firms offering robo-advisory services as independent variable suffers from omitted variable bias and is not sufficient for causal interpretation. For example, a firm's decision to change the number of financial advisors and the number of firms entering the market as robo-advisors could be due to an unobserved state variable. To overcome this omitted variable bias, I take an instrumental variable (IV) approach.

For the construction of the IV, I use (1) the minimum financial requirements for a financial advisory firm establishment in a state[2] and (2) a plausibly exogenous shock due to payroll tax credits provided by the PATH Act 2016.[3] The minimum financial requirements for a firm are different across states, and the stringency of these requirements is correlated with a firm's establishment in that state. The PATH Act 2016 is observed to have a differential effect on the entry number of robo-advisor firms across states with lax financial requirements relative to the states with strict financial requirements.

Thus, a difference-in-differences (DID) setting provides an instrument for the number of robo-advisors in a state. Specifically, I use the interaction between an indicator variable that assigns a value of 1 to states with lenient financial requirements and an

[1]Robo-advisors perform portfolio management and tax-loss harvesting. However, they do not offer complex financial planning services. Robo-advisors are also relatively inexpensive. A robo-advisor charges 0.25% expense fee per annum, whereas a financial advisor charges about 1.25%, on average.

[2]NASAA Model Rule 202(d)-1, amended in 2011, requires a firm to have a certain minimum net worth depending on its client profile though a combination of capital and/or bond.

[3]The PATH Act 2016 is particularly beneficial for tech-oriented start-ups as the provisions in the act allow start-up companies to take a payroll tax credit, even without incurring actual tax liability.

indicator variable that assigns a value of 1 for time period after (the passage of PATH Act) 2016 as an IV. I also exploit the presence of same firm across various states, and estimate the differential impact of number of robo-advisors on the same firm located at different branch states.

With the IV as constructed, I consider the period between 2012 and 2019 for my study. I examine the effect of number of robo-advisors on the number of financial advisors in the state. I find that a one-unit increase in number of robo-advisors at the state leads to an increase in the number of financial advisors by about 800, on an average, at that state. This positive significant effect of robo-advisors on number of financial advisors is robust to the addition of various time-varying state characteristics.

The observed positive effect of number of robo-advisors on the number of financial advisors at the state level obscures the heterogeneous effects at the firm level that may better explain the observed result. Therefore, I conduct the rest of the analyses at the firm level. I find that a one-unit increase in robo-advisors at the state increases the number of financial advisors by about 1.13, on an average, at a firm in that state. This positive significant result is robust to various firm-state-year and state-level controls, and fixed effects (firm, state, year and firm-by-year).

The estimated effect of robo-advisors on the number of financial advisors at a firm corresponds to an increase in the number of financial advisors by about 640 at the state-level. Thus, this estimate is consistent with the estimate obtained with state-level analysis. The estimated increase in number of financial advisors at the state-level corresponds to about 5% of the total number of financial advisors in a state. Thus, robo-advisors have an economically significant effect on the number of financial advisors.

Before I proceed to perform further analyses to understand the observed effect, I establish the validity of the IV. First, I find that there is significant correlation between the number of robo-advisors at state-level and the IV. I also find that the IV is not weak (based on F-statistic). Next, I test whether the IV satisfies exclusion restriction criterion by establishing that (1) the IV does not exhibit any significant pre-trends and (2) the IV is not relevant when the exogenous shock is artificially shifted to 2013.

Next, to provide external validity for the results observed here, I construct a different IV. I take a similar approach as above and interact a variable that explains cross-sectional variation with another variable that explains time variation in the number of robo-advisors in a state. The IV is a product of the number of financial advisory firms providing services through the internet during 2003 in a state and the yearly growth rate in the number of Financial Technology (FinTech) deals between 2006 and 2019 in the United Kingdom (UK).

This IV relies on the mechanics of constructing a Bartik-like instrument. Thus, this IV is a proxy for change in the number of robo-advisors in a state rather than being a proxy for the number of robo-advisors. Consequently, I study the impact of change in number of robo-advisors on the change in number of financial advisors during 2006-2019. I find that the estimates obtained with this IV are consistent with those obtained using the main IV, both in terms of magnitude and direction. The Bartik-like IV is used only to establish robustness of the relationship between robo-advisors and financial advisors.

For the rest of the study, I use the main IV and consider the variables in levels again. Here, I examine the differential response to the increase in robo-advisors across various firms within the financial advisory industry. Here, I examine (1) small vs. large firms and (2) firms that adopt robo-advisory technology. I find that the response of small firms [4] is not statistically different from that of large firms, and firms that adopt robo-advisory technology increase financial advisors by about 22 relative to firms that do not adopt robo-advisory services, in response to a unit increase in number of robo-advisors.

The much stronger response by firms that adopt robo-advisory technology could be due to the composition of these firms. Firms that adopt robo-advisory technology are either incumbent firms with financial advisors above the 90^{th} percentile or start-ups that have high growth potential. Such composition could be the reason for the observed stronger response among these firms. Also, an observed increase in demand for financial advisors (which is presented later) due to robo-advisors can explain this result.

Overall, firms increase their financial advisors as their exposure to robo-advisory firms increases. This implies that robo-advisors and financial advisors are complements. Two factors are complements only if one observes an increase in the output along with an increase in both the input factors.[5] As complementarity between two input factors increases the level of output, it implies that there is an expansion in the market for the output produced (services provided) from such factors.

Thus, to test whether the robo-advisors and financial advisors are indeed complements, I study to examine whether there is an expansion in market size. I study two different, but complementary, effects to test if there is an expansion in market size. First,

[4] I use SEC's definition to define a small firm as a firm with less than $25 million in regulatory assets under management.

[5] Two factors are substitutes only if one observes that with an increase in one factor of production there is a corresponding decrease in another factor of production for the same level of output.

I study the response of firms that provide services similar to those provided by robo-advisory firms. And second, I study the effect on demand for financial advisors due to robo-advisors.

The logic behind the two tests is as follows. If there is an expansion in the market for financial advisory services due to robo-advisors, then there is an increase in demand for financial advisors through the increase in robo-advisors. In this scenario, there will also be an increase in demand for services that are similar to those provided by robo-advisory firms. This is because these two types of firms will be catering to a similar clientele due to the growing demand for these services at the market level.

To study the response of firms that provide services similar to those offered by robo-advisors, I study the effect of robo-advisors on firms that (1) predominantly cater to individual clientele, (2) provide wrap fee programs,[6] and (3) provide pension services.[7] I find that these firms increase financial advisors more (relative to the firms whose services are dissimilar from robo-advisory firms) in response to an increase in robo-advisors in the branch state.

To study the effect of robo-advisors on the usage of financial advisors at the state level, I use the survey data on investor usage of financial advisors at the state-level from FINRA. I find that the probability of using a financial advisor increases with an increase in the number of robo-advisors at the state-level. I also find that the probability of using a financial advisor increases if the investor is utilizing robo-advisory services.

The response of the firms providing robo-advisory type services, along with the response of demand for financial advisors indicate that there is generally an expansion in the market for financial services due to robo-advisors. These results indicate that this expansion in the market for financial services drives the complementarity between robo-advisors and financial advisors.

Having established the mechanism through which robo-advisors and financial advisors complement each other, I next turn to understand their effect on the dynamic components of financial advisors labor market. Here, I study the effect of robo-advisors on the number financial advisors leaving a firm (separations) and on the number of new financial advisors entering a firm (hirings).

[6]This a fixed fee for a bundle of services. This fee is usually a percentage of assets in an investors' account. In construct, a wrap fee program is very similar to the services provided by robo-advisors.

[7]A recent study Fisch, Labouré, and Turner (2018) discusses the growing demand for robo-advisors to provide pension services.

I find that the increase in the number of financial advisors due to robo-advisors can be explained by both a decrease in separations and an increase in hirings. This combined effect on separations and hiring will imply a change in the composition of financial advisors. Therefore, I study the effect of robo-advisors on the average experience level of a financial advisor at the firm and consequently their effect on the misconduct behavior of a financial advisor at the firm.

I find that there is an increase in the average experience level of a financial advisor at the firm-state level due to the increase in the number of robo-advisors. This increase in average experience level does not correspond to any effect on the misconduct behavior at the firm-state level. To a limited extent, these results indicate that robo-advisors may be benefiting the investors too. As I do not study the effect on the fee structure and performance at the firm level, I cannot make a stronger claim on the benefits accruing to investors due to robo-advisors.

Overall, my results suggest that there is a positive effect of robo-advisors on financial advisors labor market. In the face of recent evidence on the negative effects of technology adoption on high-skilled labor (Webb (2019), Grennan and Michaely (2020) and Jiang, Tang, Xiao, and Yao (2021)), my study emphasizes the importance of industry-specific characteristics in determining the relationship between technology and high-skilled labor.

Robo-advisors in financial advisory markets are not adopted to provide the same services,[8] but to provide additional services without affecting the already existing services (as evidenced by the consistent growth in wrap fee programs, financial product sales, etc. at firms that are not providing robo-advisory services). This possibility of expanding services could be an artifact of financial advisory services, and may have played a key role in the observed effect of robo-advisors on financial advisors.

1.1 Literature

The main results of the literature that studies the impact of routine-based technology[9] adoption on labor can be summarized as follows: (1) the technology adopted has been skill-biased (Acemoglu (1998) and Acemoglu (2002)), and (2) the technology adopted has been a substitute for routine labor and complement for non-routine labor (Autor, Levy, and Murnane (2003), Acemoglu and Autor (2010), Chen (2016) and Cortes et al. (2017)).

[8]For example, Grennan and Michaely (2020) look at AI generating reports on securities. Here, AI is generating the same reports that otherwise would have been generated by a human security analyst.

[9]Routine-based technology performs repetitive tasks with a minimal requirement for problem-specific analysis.

Studies that look at the impact of routine based technology adoption on jobs in the banking sector (Autor et al. (2000), Fung (2006) and Bessen (2016)) show a positive effect of technology adoption on employment. These studies emphasize the heterogeneous effects of routine-based technology on the labor market based on industry and labor type.

Recent research on non-routine-based technology[10] finds a positive relationship between technology adoption and labor (Acemoglu and Restrepo (2017), Acemoglu and Restrepo (2018) and Acemoglu et al. (2020)). However, Webb (2019) predicts that the recent technology adoptions may lead to the displacement of high-skilled labor. This paper contributes to this debate on the effect of non-routine-based technology on high-skilled labor by specifically examining the effects of robo-advisors on labor market for financial advisors.

Also, this paper complements the recent studies by Grennan and Michaely (2020) and Jiang et al. (2021). Grennan and Michaely (2020) study the the impact of AI on the labor supply of security analysts and find that AI acts as a substitute for security analysts. While my paper also looks at the impact of technology on high-skilled labor, I find a positive effect of robo-advisors on financial advisors. I attribute the difference between these industries in the impact of technology to the nature of the industries and their abilities to expand services.

Jiang et al. (2021) study the impact of FinTech on employment and find that the jobs that are more exposed to FinTech see a reduction in the supply of such jobs. I look at a specific FinTech industry (robo-advisors) and find that an increase in exposure to robo-advisors increase the number of financial advisors. Thus, this paper emphasizes the importance of industry-specific characteristics that can determine the relationship between technology and labor.

In a related paper, Acemoglu et al. (2020) study AI adoption in a task-based framework[11] and conclude, "*focus on AI adoption that is driven by the task structure of establishments may leave out other types of AI impacts that are less related to task structures, such as the use of AI to launch new products and services.*" Many recent studies (Acemoglu et al. (2020), Brynjolfsson et al. (2018) and Grennan and Michaely (2020)) that examine the impact of technology on labor do not study the effects of technology that is used to launch a new product and/or service.

[10]Non-routine-based technology performs non-repetitive tasks with high adaptability to provide problem-specific solutions.

[11]In a task-based framework, a job is characterized as a combination of discrete tasks. The impact of AI adoption on labor is understood based on the number of tasks of a particular job that AI can perform.

Also, the survey results of Bessen et al. (2018) show that the third-most frequent use of recent technology developments is to create new products and services. Robo-advisors are new services that have been launched due to the recent technology developments. Therefore, this paper contributes to the understanding of the impact on high-skilled labor when technology is introduced as a new service.

The rapid evolution of robo-advisors has given rise to the nascent studies on the various effects of robo-advisors. The studies on robo-advisors have mostly concentrated on understanding (1) the characteristics of investors who use robo-advisors (Todd and Seay (2020), Kim et al. (2019), Fan and Chatterjee (2020) and Rossi and Utkus (2020a)) and, (2) the effects on (robo-advisory-adopting) investors' investment choices and biases (D'Acunto et al. (2019), Rossi and Utkus (2020b), D'Acunto and Rossi (2020), Back, Morana, and Spann (2021), Bianchi and Brière (2021), D'Acunto and Rossi (2022)).

The impact of robo-advisors on economy, broadly, is still an understudied topic. This is probably due to the unavailability of comprehensive data on robo-advisors. I leverage hand-collected data on robo-advisors and study the effects of robo-advisors on financial advisor labor market. Thus, this paper contributes to the understanding of the impact of robo-advisors on one important aspect of economy.

Few recent studies have attempted to understand the impact of robo-advisors on human financial advisors. However, these studies provide very limited evidence on the effect of robo-advisors on the financial advisor labor market due to their inherent limitations. Brenner and Meyll (2020) argue that robo-advisors are substitutes for human financial advice using a single cross-section of investor survey data. Rossi and Utkus (2020a) use survey findings to highlight that investors who opt for robo-advisors show an inclination to use human financial advisors, too.

Bianchi and Brière (2021) use prior literature on the impact of robots on human decision-making and argue that robo-advisors could be complementing human advisors. This paper contributes to this strand of literature by providing direct empirical evidence to understand whether the availability of robo-advisors increases or decreases the market's overall reliance on human advisors.

Recent literature in finance has studied the market for financial advisors in the context of their misconduct behavior. Egan et al. (2019) study misconduct in the financial advisory industry and examine whether the labor market can regulate this behavior of financial advisors. That is are financial advisors fired and/or do they find it difficult to enter a new firm if they have misconduct disclosure on their resume? They do not find strong evidence that the labor market regulates such behavior.

Parsons et al. (2018) find that regions with high unethical behavior among professionals such as doctors and politicians have high misconduct among financial advisors. Dimmock et al. (2018) study mergers between financial advisory firms and find that co-workers have a positive effect on the misconduct behavior. My paper contributes to this strand of literature by studying the effect of robo-advisors on the misconduct behavior of financial advisors.

The paper is organized as follows: Section 2 describes the data, construction of the IV, and methodology. Section 3 presents results and corresponding discussion. Section 4 concludes.

2 Data and Methodology

2.1 Data

In this section, I describe the various data sources I employ in this study. I restrict my sample between 2006 and 2019. The starting period for this study is chosen based on when the first robo-advisory firms appear in my sample. And ending period is chosen as 2019 because of the various economy-wide Covid effects that came into effect from around mid-2020. A more detailed description on the variables used in this study is provided in the Methodology subsection.

2.1.1 Data on Robo-advisors

I hand collect the complete list of robo-advisors (with names and launch dates) for the study. I rely on the articles from several news and blog sources for financial advisory industry (thinkadvisor, financial planning, KITCES.com, etc.) to identify the names of robo-advisor service providers. As there is no reliable consistency in the way the news on robo-advisors is reported, I read through each article to obtain this list.[12]

For most of these firms, launch date of the robo-advisory services is also obtained from the news and blog articles. For a few cases I could not obtain a reliable launch date from these articles[13]. I use the information from social network platforms (facebook, twitter and LinkedIn) to gather the missing launch dates. I have identified 174 firms as the

[12]Sometimes the news is just a couple of lines, hidden within another main news.

[13]In some cases, the articles just mention that a robo-advisor was launched in the past month/this month. Or, sometimes they refer to a launch of robo-advisor sometime in the future.

providers of robo-advisory services for a period between 2006 and 2019. Table 1 provides the details on these firms.

[Table 1 about here.]

For the purpose of this study, I utilize the data on firms that started as robo-advisory firms and incumbent firms that offer robo-advisory services. Figure 1 shows the distribution of firms offering robo-advisory services across various US states during 2006 and 2019. As can be seen from the figure, there is an increase in the number of firms offering robo-advisory services in 2019 from 2006. The other point to notice is that robo-advisory services are present across most US states even during 2006.

[Figure 1 about here.]

2.1.2 Data on Financial Advisory Firms

The Investment Advisers Act of 1940 requires all investment advisors to register with the SEC as Registered Investment Advisors (RIAs). The Act also allows for some specific exemptions[14] when the firm is exempted from registering with SEC. Such firms are still required to register with the states. Registration with the SEC is at two levels: (1) at the advisory firm level, and (2) at the individual advisor level.

Firms that register with SEC must file a Form ADV (Uniform Application for Investment Adviser Registration) at least once every year. Specifically, a firm has to file Form ADV every time there is a material change to their organization (for example, change in legal name, change of organization type, etc.) which leads to multiple filings by a firm in any year. If there are no material changes during the year, every firm still has to file Form ADV once every year to report various firm level details. Therefore, the firm level variables are available for all the firms within financial advisory industry for every year, since the inception of every firm.

Form ADV has two parts: (1) Part I, which contains general information about the firm, like headquarter location, state(s) where the firm is registered, number of financial advisors and brokers employed[15], number of accounts managed, clientéle categories, assets under management (AuM), misconduct details, etc., and (2) Part II, which contains details on management and compensation structure, disclosures on conflicts of interest, etc. For the purpose of this study I employ data from Form ADV Part I, obtained from

[14]Exemptions: (1) when the firm is small and is regulated by one or more states or (2) when the firm qualifies for an exception from the Act's registration requirement (Rule 203(a) of the Investment Advisers Act of 1940).

[15]Before 2012, these employment numbers are only available as a range variable. In the following paragraphs I explain how I backfill this missing employment data.

the SEC website[16]. Figure 2 shows the distribution of firms across US states for the years 2006 and 2019. Panel A in table 2 contains some of the details on the firms in my data sample.

2.1.3 Data on Individual Financial Advisors

All registered individual financial advisors have to file the U4 form with FINRA, when their employer files a Form ADV. The U4 form includes current employment, employment history, states of registration and misconduct details. The advantage this data offers me is that I can obtain branch locations of each firm across various states.

This individual advisor data is obtained from BrokerCheck, maintained by FINRA.[17] The data from BrokerCheck does not give complete details if the individual is solely a financial advisor. Therefore, I complement the data from BrokerCheck with data obtained from Investment Adviser Public Disclosure (IAPD).[18] The final dataset contains the universe of individuals who are practicing as either brokers or financial advisors, or both.

2.1.4 Combining Data on Financial Advisory Firms with Individual Advisor Data

SEC has revised Form ADV twice during my sample period, once in 2011 and then in 2017. The revisions are aimed at improving the quality of data that a firm reports. For example, some of the variables (like financial advisors and brokers employed, clients who are outside USA) were collected as range values before 2012. After the revision of 2011, firms are required to report these variables as an exact number. As a result, the data on number of financial advisors is only available from 2012 onward at the firm level.

To back-fill this missing number of financial advisors prior to 2012, I use data on individual registered investment advisors. Individual advisors filings include data on their current and previous employment, and branch state location for each employment duration. I aggregate this data at the firm-state level to get the number of financial advisors in each firm at each state. Finally, I check if the aggregate firm-level financial advisors number obtain from individual advisor filings matches the range values reported by the firm (matches around 95% of the time).

I take advantage of the fact that many of the firms file multiple times in a given fiscal year. I use the nearest filing data to back-fill any missing data for each year. The final

[16] Data is available for download from SEC, `https://www.sec.gov/foia/docs/form-adv-archive-data.htm`.

[17] Data is scraped from `https://brokercheck.finra.org/`.

[18] Data is available for download from IAPD, `https://adviserinfo.sec.gov/compilation`.

dataset used for this study is at firm-branch state-year level. Panel B of Table 2 shows summary statistics for few of the variables in my data sample.

[Figure 2 about here.]

[Table 2 about here.]

2.1.5 Survey Data on Demand for Financial Advisors

FINRA conducts National Financial Capability Study (NFCS) every three years once (starting 2012 till 2021).[19] The survey elicits information on various financial decisions made by an investor. One of the question the survey asks the investor is whether they use a financial advisor to make any financial decision. I use the response to this question to estimate the demand for financial advisors.

The recent surveys have also asked if the investor uses robo-advisory services. I also use the response to this question in the analysis. The survey collects demographic information about each investor. The data also provides information on the state of residence for each investor. Therefore, I can estimate the demand for financial advisors at the state level over years.

2.1.6 Macro Data

Data on macroeconomic variables (like employment in financial service sector, unemployment rate, share of female employees, etc.,) at the state level has been obtained from Bureau of Economic Analysis, Bureau of Labor Statistics and Census Bureau. Growth in FinTech deals in UK is calculated using the number of FinTech deals in UK between 2006 and 2020. The data on number of FinTech deals is obtained from PitchBook.

2.2 Methodology

I employ an instrumental variable (IV) approach to study the effect of number of robo-advisors on the financial advisors labor market. I use two levels of variation to obtain the instrument. The first level of variation (cross-sectional variation) comes from the state level differences in the financial requirements imposed on a financial advisory firm. The second level of variation comes from a plausibly exogenous shock that generates a differential effect to the entry of robo-advisors across different states.

[19] https://finrafoundation.org/knowledge-we-gain-share/nfcs/about-nfcs.

2.2.1 State Regulations

NASAA provides recommendations on minimum financial requirements a financial advisory firm has to adhere to, before it provides services to the investors in that state. These recommendations are provided in Model Rule 202(d)-1 and was last amended in 2011. These recommendations are in terms of minimum net worth and/or bond requirements a firm should maintain. Various State regulatory authorities have adopted these recommendations to varying degrees.

Figure 3 shows the variation in adoption of NASAA recommendations across states. Some states have adopted these recommendations as is, and some have adopted a more stricter versions of these recommendations. But, some states have also adopted much laxer versions of these recommendations. For the purpose of this study, I define a state to be stringent (lenient) if its' financial requirements are on par or stricter (laxer) than NASAA recommendations. According to this definition, there are 29 stringent states and 23 lenient states.

[Figure 3 about here.]

States that adopted stricter versions are on an average those with relatively less number of financial advisory firms. In other words, stringency in the adoption of these regulations is translating into the stringency of barriers to entry for financial advisory firms. This is because every financial advisory firm should register in a state if it has to provide services to an investor in that state. And every firm operating in a state should adhere to the state level financial requirements imposed by the state regulatory authorities.

Since robo-advisors provide financial advisory services, it should adhere to all the rules that apply to a financial advisory firm. Thus, the varying degrees of adoption of NASAA recommendations by states generates varying levels of barriers to entry for robo-advisors too. Also, there has been no changes in NASAA recommendations after 2011, which implies the barriers to entry has not changed over time across states. Evidently, I find a correlation between the stringency in adoption of NASAA recommendations by a state and number of robo-advisors at that state.

NASAA recommendations for financial advisory firms not only provides a cross-sectional variation in the number of robo-advisory firms but also could be correlated with the number of financial advisors in these states. To provide a plausibly exogenous variation in the robo-advisory firms' entry across these states I rely on the latest iteration of R&D tax credits during 2016.

2.2.2 PATH Act 2016

Congress passed PATH Act on December 18, 2015, and this version incentivized firms that rely on human capital to claim payroll tax credits even when they have no tax liability. This version of R&D tax credits benefits firms firms that rely on human capital for innovation. That is, technology producing firms that rely on human capital for innovation benefit from this PATH Act. Firms developing Robo-advisory technology fall under the category of technology producing human capital intensive firms. And passage of PATH Act benefits firms developing robo-advisory technology.

Thus, there is an increase in the number of robo-advisory firms after 2016. Because of the inherent barriers to entry for robo-advisory firms across states (due to the varying levels of financial requirements) this increase in the number of robo-advisors is not uniform across states. The states with lenient conditions saw more robo-advisory firms entering the market than the states with stricter conditions. Figure 4 shows that the states with lenient recommendations see a higher increase in robo-advisory firms' entry after 2016.

[Figure 4 about here.]

2.2.3 Instrumental Variable

I exploit the differential effect on the entry of number of robo-advisors across stringent and lenient states after the passage of PATH Act to construct an instrument for number of robo-advisors at a state. Specifically, I use the interaction between an indicator variable that represents lenient states and an indicator variable that represents the time period after the passage of PATH Act as an instrument for the number of robo-advisors in a state.

The constructed instrument captures the difference in differential entry of robo-advisors across states after the passage of PATH Act. The logic being that there is a differential entry of robo-advisors between stricter and laxer states even before the passage of PATH Act. However, the differential entry is more pronounced between these states after the passage of PATH Act. Thus, the instrument allows me to compare number of financial advisors at firms (in a state) with higher exposure to robo-advisors to those firms (in a state) with lower exposure to robo-advisors.

One concern using PATH Act to obtain an instrument for the number of robo-advisors is if passage of PATH Act has an effect on financial advisory industry itself. It could be that the PATH Act encouraged more number of financial advisory firms to start and, in turn increased the total number of financial advisors. To alleviate such concern I examine the average number of financial advisory firms across states over time. Figure 5 shows that there is no discernible effect on the number of financial advisory firms after 2016 across states.[20]

[Figure 5 about here.]

Another concern could be that the financial advisory firms just increase the number of financial advisors after passage of PATH Act and claim the benefits. However, a firm can only benefit from PATH Act if it is less than or equal to five years since the firm has been founded. And, it also places limits on the amount of payroll tax credits a firm can claim. These conditions precludes PATH Act from directly affecting the number of financial advisors at the state level.

Yet another concern could be the influence of robo-advisory firms in the passage of PATH Act or effect on robo-advisory firms due to the anticipated passage of PATH Act. First, the robo-advisory industry is very small to have an influence on the passage of PATH Act. Second, R&D tax credits are renewed every years once near their expiration period with relevant modifications. The exact amendments will itself not be certain till the congress signs the act. Thus the effect on robo-advisory firms due to the anticipated passage of PATH Act is minimal. This is also confirmed with the observed increase in number of robo-advisors only after 2016 in Figure 4.

2.2.4 Alternate IV

I construct another IV to validate the results obtained with the previous IV. This IV is also obtained by interacting two variables, one correlated with cross-sectional variation in number of robo-advisors, and another correlated with time variation in number of robo-advisors. The IV relies on the mechanics of constructing a Bartik instrument. And the details of construction are provided in Appendix B.

I use the number of financial advisory firms providing services through internet during 2003 (in each state) to proxy for the cross-sectional variation across states. And I use the growth rate in number of FinTech deals in UK as a proxy for the time variation. I use the product of these two variables to obtain an instrument for changes in number of robo-advisors at the state level between 2007-2019.

I study the effect of change in number of robo-advisors at the state on the change in number of financial advisors at a firm in the state, here. I consider changes instead of levels to avoid the immediate endogeneity concerns that would arise when dealing in levels with Bartik instruments. Again the specific details are provided in Appendix B.

[20] I also regress number of firms at the state level on the IV, and find an insignificant coefficient estimate (-18.72 with standard error of 22.46).

2.2.5 Empirical Specification

For the main analysis, I estimate the effect of number of robo-advisors on the number of financial advisors at a firm. A robo-advisory firm registered in a state can cater to all the customers within that state. As a result the effect (if any) of a new robo-advisory firm in a state will be felt by financial advisors across that state. Therefore, the first level of analysis is carried out at state level.

However, the analysis at the state level will abstract away from the effects at the individual firm level that can provide insights into the mechanism for the observed effects. Thus, all the analyses are performed at the firm level. That is, I study the response of a firm to the exposure of number of robo-advisors. In other words, I study the effect of number of robo-advisors at the state level on the number of financial advisors at the firm-state level.

I employ the two-stage least squares (2SLS) estimation provided in equations 1 for the state level analysis. The number of robo-advisors at the state-year ($R_{s,t}$) is instrumented using the interaction between indicator variables that denote states with stricter financial requirements and years post 2016 ($IV_{s,t}$) in the first-stage. The fitted-value for number of robo-advisors from first stage estimation ($\hat{R_{s,t}}$) is used to estimate the effect of robo-advisors on the number of financial advisors ($L_{s,t}$) in the second stage. β_2 estimates the effect of number robo-advisory firms on the number of financial advisors.

$$
\begin{aligned}
&\text{First Stage:}\\
&\qquad R_{s,t} = \beta_1 IV_{s,t} + X^{'}_{s,t}\gamma_1 + +\alpha_s + \alpha_t + \varepsilon_{s,t}\\
&\text{Second Stage:}\\
&\qquad L_{s,t} = \beta_2 \widehat{R_{s,t}} + X^{'}_{s,t}\gamma_2 + \alpha_s + \alpha_t + \varepsilon^{'}_{s,t}
\end{aligned}
\tag{1}
$$

The specification allows me to control for the state and year fixed effects. The state fixed effects will control for all the state specific characteristics that determine the stringency in adoption of financial requirements by individual states. To control for the factors that vary at state-by-time level and may have a confounding effect, I use economic variables (like number of employees in financial service sector, share of educated, GDP, unemployment, etc.) ($X_{s,t}$). Finally, standard errors are clustered at the state-level.

For studying the effect at the firm-state level, I again use the 2SLS procedure. The second stage in equation 1 is modified to reflect the firm-state level analysis. Specifically, the dependent variable is the number of financial advisors at the state level. And, I add firm and firm-by-time fixed effects. These will control for the firm level characteristics and time-varying firm level characteristics that effect the number of financial advisors at the firm level. I also control for the variation at firm-state-year, using the number of brokers ($X_{i,s,t}$) at each branch state of a firm. Finally, standard errors are clustered at the firm level.

2.2.6 Empirical Specification with Alternate IV

Here, I study impact of change in number of robo-advisory services on the change in number of financial advisors at firm-branch state. I instrument the change in number of robo-advisory services with the product of number of firms offering services through internet in 2003 across states and the yearly growth rate of FinTech deals in UK between 2007-2019. I employ the two-stage least squares estimation provided in equations 2 for this study:

$$
\begin{aligned}
&\text{First Stage:} \\
&\qquad \Delta R_{s,t} = \beta_3 IV_{s,t} + X^{'}_{s,t}\gamma_3 + \alpha_s + \alpha_t + \eta_{s,t} \\
&\text{Second Stage:} \\
&\qquad \Delta L_{i,s,t} = \beta_4 \widehat{\Delta R_{s,t}} + X^{'}_{s,t}\gamma_4 + \alpha_s + \alpha_t + \eta^{'}_{s,t}
\end{aligned}
\tag{2}
$$

Where, $\Delta L_{s,t}$ is the change in number of financial advisors in the state s during the period t. $\Delta R_{s,t}$ represents the change in number of robo-advisory service providers in the state s during the period t. β_4 is the estimate of interest, which captures the effect of change in robo-advisory firms on the change in number of financial advisors.

Here I control for state and year effects. I also control for state-by-time effects using time varying state characteristics as in equation 1. Standard errors are clustered at the state level. For the analysis at the firm-state level, second stage estimation is modified accordingly. Changes in the number of financial advisors at the firm-state level is used as a dependent variable. And all the controls used with the main IV for firm-state level analysis are employed here too.

3 Results and Discussion

3.1 Main Result

To understand the impact of robo-advisory firms penetration on the number of financial advisors at the state level, I estimate the specification 1. Column 1 Table 3 shows these estimates. Both the OLS (Panel A) and 2SLS (Panel C) estimates indicate the positive effect of number of robo-advisors on the number of financial advisors. 2SLS estimates indicate that there is an increase in number of financial advisors by about 800 when the number of robo-advisors at the state increase by one.

[Table 3 about here.]

Next, I look at the response of a firm at the state when it's exposure to the number of robo-advisors within that state increases. Column 2 in Table 3 shows these estimates. A Firm responds by increasing the number of financial advisors by about 1.13, on an average, when their exposure to number of robo-advisors increases by one. The positive effect of robo-advisors on financial advisors is robust to various controls (state level economic and industry variables, firm level variables, and firm-state level variables) and fixed effects (firm, state, year and firm $\times$ year).

The 2SLS coefficient estimate for firm-state level indicate that a new robo-advisor starting in a state leads to an increase in the number of financial advisors by about 640 at that state, on an average. This is very close to the number obtained using state level estimates. And gives confidence in the robustness of estimates obtained using different specifications. An increase in 640 financial advisors at the state level contributes to about 5% of the total number of advisors at a state, on an average. Thus the increase in financial advisors is economically meaningful too.

Table 3 also shows the estimation results obtained using an OLS (Panel A). The estimates obtained with an OLS also shows a positive effect. However, the magnitude of coefficient estimates is much smaller with an OLS as compared to the IV estimation. This indicates that OLS estimates are negatively biased. The negative bias in OLS estimates implies that the confounding omitted variable is correlated with the main dependent and independent in the opposite directions.

3.2 Validity of the IV

For an IV to be valid, it must satisfy relevance condition and exclusion restriction. Panel B in Table 1 shows the coefficient estimates obtained when the number of robo-advisors is regressed on the instrument. The coefficient estimates on the instrument are positive significant, indicating that the IV is correlated with the number of robo-advisors.

The F Statistic observed with state level analysis is 10.48. This indicates that the IV is not weak. Also I observe a very high F Statistic of about $2,460$ with firm-state level analysis. As most of the estimation in this study are at the firm-state level, the high F Statistic alleviates the concerns of a weak IV. A significant correlation between the IV and number of robo-advisors along with a high F Statistic means that the IV satisfies relevance condition.

Next, I turn to test if the IV satisfies exclusion restriction criterion. The setting allows me to check for parallel trends in average number of robo-advisors between different types of states over time. I estimate equation 3 and plot the coefficients on the $IV_{s,t}$ term, for this purpose. Figure 6 shows the plot. As can be seen the coefficient estimate on the IV is mostly driven by the post-2016 estimates.

$$R_{s,t} = \sum_{t=2012}^{2019} \beta_{1t} IV_{s,t} + X'_{s,t}\gamma_{11} + \alpha_t + \alpha_s + \varepsilon_{s,t} \tag{3}$$

[Figure 6 about here.]

Next, I assume that the shock occurred in 2014. I estimate the first stage regression of specification 1 for the period between 2011 and 2016. That is, I obtain first stage estimates in equation 1 with 2011-2013 as pre-treatment period and 2014-2016 as post-treatment period. I observe an insignificant coefficient estimate on the IV (coefficient estimate of 0.23 with 0.25 as standard error). The two tests performed here provide support to exclusion restriction criterion, and thus, plausible validity for the IV.

3.3 External Validity for the Results

To examine if the positive effect of robo-advisors on the number of financial advisors is robust, I construct a Bartik-like instrument. The details for the validity of Bartik-like instrument are provided in Appendix B. Here, I examine the effect of change in robo-advisors on the change in number of financial advisors with this Bartik-like instrument. Here, I consider the sample period between 2006 and 2019. And, I estimate the IV specification shown in equation 2.

Panel B in Table 4 shows that a change in the number of robo-advisory firms has a positive effect on the change in number of financial advisors. Specifically, a one unit increase in the number of robo-advisory firms increases the number of financial advisors by about 484 at the state level, and by about 1.25 at the firm-state level, on an average. The firm-state level estimate translates to an increase of financial advisors by about 425 at the state level.

[Table 4 about here.]

There is a consistency in the results obtained with firm-state level analysis and state level analysis with Bartik-like instrument. Keeping in mind the different estimation periods used with the Bartik-like IV (2006-2019) and the main IV (2012-2019), the results appear to be consistent between these two too. Also, the results obtained with Bartik-like instrument provide external validity to the results obtained using the main IV. Overall, the positive effect of number of robo-advisors on the number of financial advisors is robust.

3.4 Robustness with Various Controls

Altonji et al. (2005) and Oster (2019) argue that one can understand the importance of unobservable confounding variables by examining the coefficient estimates obtained by controlling for various observable covariates. A large movement in the coefficient estimates with addition of various observables is not ideal. Such movements indicate to the persistence of omitted variable bias. In order to examine that the results in this study are not influenced by unobservables I obtain estimates by dropping and/or adding controls at different levels.

Since my specification does not allow the addition of state-by-time fixed effects, the main concern is that any unobservable time varying state characteristics could be influencing my results. To address this concern, I obtain estimates only with industry level controls (employment in financial industry and total number of financial advisory firms in the state) and demand proxies (population aged greater than 25 and personal consumption expenditure on financial services at the state).

Column 1 in Table 5 shows these results. The magnitude of this coefficient estimate (1.01) is not statistically different from the coefficient estimate obtained using all time varying state controls (1.13 - refer to column 2 in Table 3). These results give confidence that the possibility of a state level time varying omitted variable driving the estimates is minimum.

[Table 5 about here.]

The second concern is that firm-by-state-by-year level variables could be driving the observed result. In order to alleviate this concern, I add the number of brokers at firm-state level as controls. Column 2 in the Table 5 shows these estimates. Again, the estimate (1.10) obtained is not statistically different from the baseline estimate (1.13 - refer to column 2 in Table 3). This result addresses the concern that an unobserved firm-by-state-by-year variable could be driving the estimates.

Column 3 of Table 5 shows the estimates obtained using time varying characteristics of a firm instead of firm-by-year fixed effects. This column also controls for number of brokers at firm-state. The difference in the magnitude of coefficient estimates between column 2 and 3 is not statistically different from zero. This estimates indicates that using time varying firm characteristics instead of firm-by-year fixed effects is not affecting the main result.

3.5 Effect on Other Employment Types

The results obtained till now are using the whole sample of firms, which include firms that provide brokerage and/or advisory services. To understand if the effect of robo-advisors is solely on the number of financial advisors, I study the effect on firms that provide financial advisory services (exclusive brokerage service providers are excluded). These results are presented in Column 1 of Table 6. The magnitude of coefficient estimate is much higher for these firms (4.06 vs. 1.13 obtained using the whole sample).

[Table 6 about here.]

As I observe that there is an effect of number of robo-advisors on the number of financial advisors, I turn to understand it's effect on other high-skilled employment types in financial advisory industry. I estimate the effect of number of robo-advisors on number of brokers and on the total number of high-skilled workers (sum of number of financail advisors and brokers). I find no effect of robo-advisors on the number of brokers and, on the total high-skilled employment at a firm (Columns 2 and 3 in Table 6). These results indicate that robo-advisors are affecting only the financial advisors labor market.

3.6 Heterogeneous Response

As has been evident from the results till now, robo-advisors has a positive effect on the number of financial advisors employed at a firm. But, the response may be different for different kinds of firms. To elucidate the heterogeneity in response I study the changes in number of financial advisors for two different types of firms. First, I estimate the response of small-advisory firms relative to large-advisory firms. Second, I estimate the response of firms that adopt robo-advisory technology relative to those firms that do not adopt robo-advisory technology.

For this, I interact an indicator variable that indicates the firm type with the number of robo-advisory service providers in the state, and use this as an independent variable in the specification 1. I follow the definition of SEC to define small advisory firms. SEC defines firms with less than $25 million in regulatory assets under management as small business firms. To categorize a firm as a firm with robo-advisory technology, I use the launch date for such services by the firm.

Table 7 shows the results from these estimations. Column 1 in Table 7 shows the results obtained for small firms. There is no significant size effect in a firms' response to the increase in robo-advisors. However, column 2 in Table 7 shows that firms that adopt robo-advisory services increase their number of financial advisors relative to other firms as their exposure to robo-advisory firms increases.

[Table 7 about here.]

Column 2 in Table 7 shows that the magnitude of response by firms adopting robo-advisory technology is much larger (22.11) than the average response of firms (1.13). Such strong response could be due to a couple of reasons. One, the firms that are adopting robo-advisory technology are (1) incumbent firms with employment numbers in the top ten percentile of the distribution and (2) start-up firms with more growth potential. Two, the addition of robo-advisory technology appears to be increasing the demand for financial advisors in these firms (evidence to this effect is presented below).

The combined effect of firms' profile along with an increase in demand for financial advisors from an investor who is utilizing robo-advisory services could explain the high magnitude of effect observed for firms with robo-advisory technology. In general, the response appears to be heterogeneous. However, the observation that robo-advisors have a positive effect on number of financial advisors holds on an average.

3.7 Mechanism

The results in this study has shown that the number of robo-advisors has a positive effect on the in number of financial advisors employed at a firm. Generally speaking, technology adoption can lead to either an increase or a decrease in human capital. If a technology adoption leads to a decrease in the number of employees for the same level of output, then the technology is a substitute for labor; and, if a technology adoption leads to an increase in the number of employees along with an increase in output levels, then the technology is a complement to the labor (Autor (2015)).

At the first glance, a positive relationship observed between the number of robo-advisors and financial advisors imply that robo-advisors and financial advisors are complements. In order to test for the complementarity between financial advisors and robo-advisors more rigorously, I should study the effect of robo-advisors on both financial advisors and level of output simultaneously. However, I cannot observe the level of output at the firm-state level (though I can observe AuM and number of accounts at the firm level).

Therefore, I take an alternate route to test if the financial advisors and robo-advisors are complements. When the technology and labor are complements there is an observable increase in the level of output. An alternative way to think about this is that there is an expansion in the market for services (output) with labor-complementing technologies. In the context of this study, there will be an expansion in the market for services provided by robo-advisors if robo-advisors are complements to financial advisors. This should also imply that there will be an expansion in the market for the services similar to the ones provided by robo-advisors.

An expansion in the market for such services implies that one will observe a stronger effect of robo-advisors on the firms that provide these services. That is, firms providing services similar to those provided by a robo-advisory firm will increase the number of financial advisors relatively more than other firms. This is because these similar service providing firms rely on financial advisors to provide such services, and an expansion in market for such services implies that they have to increase their number of financial advisors.

Here, I test this hypothesis by studying the effect of number of robo-advisors on three different types of firms: (1) firms that cater to individual investors, (2) firms that provide wrap fee programs, and (3) firms that provide pension services. Robo-advisory firms provide services that target individual clientele. Thus, services provided by firms with individual clientele are the closest to robo-advisory services.

Wrap service programs are a bundle of services that are offered by firms at a fixed fee. In that sense they are very similar to the services provided through robo-advisory technology, which offer fixed plans at a fixed fee. Finally, Fisch et al. (2018) discusses the increasing demand for robo-advisory programs that provide pension plans in the recent years. Thus, firms providing pension services are in the similar service space as a robo-advisory firm.

To study the effect of robo-advisors on these firms, I interact an indicator variable that represents the firm type with the number of robo-advisors and use this interaction term as an independent variable of interest in specification 1. Table 8 shows the estimates for this analysis. The estimate on interaction term is positive significant for all the cases. This indicates that firms offering services similar to those provided by robo-advisory firms are increase their financial advisors relatively more than other firms as their exposure to robo-advisory firms increases.

[Table 8 about here.]

The above results imply that the increase in financial advisors observed with an increase in robo-advisory firms may be due to expansion of market for such services. Another way to test the same hypothesis is to see the effect on firms that provide services dissimilar to the robo-advisory services. There should be no effect of robo-advisory services on such firms. To test this, I study the effect of robo-advisory services on firms that cater to high-net-worth (HNW) clientele.

Column 2 in Table 9 shows the estimates for this analysis. Consistent with the expansion in market for services similar to robo-advisory services, I find no effect of robo-advisory firms on the number of financial advisors at firms that cater to HNW clientele. Column 1 in Table 9 uses a more stringent condition to define a firm that caters to individual clientele. The corresponding results are consistent with the earlier results (column 2 of Table 8).

[Table 9 about here.]

An expansion in market for services similar to the robo-advisory services also implies that the demand for such services is increasing. Again, an increase in demand for similar services to robo-advisory services imply that there is an increase in demand for financial advisors (because non-robo-advisory firms use financial advisors to deliver similar services as robo-advisory firms). Specifically, there is an increase demand for financial advisors due to an increase in number of robo-advisors.

I test this hypothesis by utilizing the survey data on the usage of financial advisors from FINRA. I use an indicator variable that takes value one if an investor uses a financial advisor as the dependent variable. I estimate the effect of robo-advisors on this indicator variable using a 2SLS specification similar to the specification 1. These estimates are provided in column 1 of Table 10. I find that the probability of using a financial advisor at the investor-state level increases with an increase in the number of robo-advisors at the state level.

[Table 10 about here.]

I also estimate the probability that an investor uses financial advisor if the investor is using robo-advisory services. Columns 2 in Table 10 shows these results. This result indicate that there is an increase in the probability of using a financial advisor if the investor is utilizing robo-advisory services. This result is consistent with the findings in Rossi and Utkus (2020a). This result can also explain the large increase in financial advisors observed at firms with robo-advisory technology (refer columns 2 Table 7)

Overall, the results here indicate that there is an expansion in market for services that are similar to those provided by robo-advisory firms. This conclusion is corroborated with results that show (1) a relatively higher increase in number of financial advisors at firms providing services similar to robo-advisory services, and (2) an investor level increase in the probability of financial advisor usage with increase in number of robo-advisors.

3.8 Separation and Hiring

The increase in number of financial advisors observed with an increase in robo-advisors can be explained by either a decrease in separations or an increase in hirings. To test which of these channels can explain the increase in number of financial advisors, I study the effect of number of robo-advisors on the number of financial advisors leaving and entering the firms. I use specification 1 with separations and hirings at the firm-state level as dependent variables for this purpose.

I define separations at the firm-state level as the number of financial advisors that were present at the firm during the past year but not the current year. Similary, hirings is defined at the firm-state level as the number of financial advisors present at the firm during the current year but not in the past year. Table 11 shows the coefficient estimates obtained for this analysis.

[Table 11 about here.]

The results indicate that there is a decrease in number of financial advisors leaving the firm (column 1 Table 11). And there is an increase in number of financial advisors entering the firm (column 2 Table 11). Overall, these results indicate that the observed increase in number of financial advisors due to robo-advisors is due to the combined effect of decrease in separations and increase in hirings at the firm-state level.

3.9 Composition of Financial Advisors

Since the positive effect of robo-advisors on number of financial advisors can be explained by a combination of decrease in separations and an increase in hirings, the overall effect of robo-advisors on the composition of financial advisors is unclear. That is, there could be an overall increase in either experienced or inexperienced financial advisors due to the changes in influx and outflux of financial advisors.

To examine the effect of robo-advisors on the average experience level of financial advisors, I estimate specification 1 with average experience as a dependent variable.

Average experience is calculated using the experience levels of all the financial advisors present at a firm during the year. Column 1 in Table 12 shows these estimates. The results indicate that there is an increase in average experience of financial advisors at the firm level due to an increase in number of robo-advisors.

[Table 12 about here.]

3.10 Impact on Misconduct Behavior

As the robo-advisors have an effect on the composition of financial advisors, it is important to understand their effect on the misconduct behavior of financial advisors. I use an indicator variable that takes the value of 1 if there is a at least one misconduct complaint at the firm-state level during the year to define the misconduct behavior. This indicator variable is used as a dependent variable in the specification 1. And the coefficient estimates are shown in column 2 of Table 12.

The results indicate that robo-advisors have no effect on the misconduct behavior of financial advisors. These results combined with the observed increase in average experience of financial advisors could imply that the investors are benefiting from the advent of robo-advisors. That is, on an average, the investor is faced with an experienced financial advisor without incurring any hidden costs from changes to misconduct behavior. To a limited extent, this also implies that robo-advisors are improving the welfare of an investor.

4 Conclusion

In the recent years there has been an increase in the technology adoptions in service sector. This phenomenon has drawn researchers' attention to the effect of such technologies on the high-skilled labor market outcomes. In this paper, I focus on the effect of robo-advisors on the financial advisors labor market.

I employ a novel hand-collected data on robo-advisors within US market to study this effect. I complement this dataset with the data at both financial advisory firm level and individual financial advisor level. I employ an instrumental variable methodology to overcome the omitted variable bias to study my research question.

I observe that a unit increase in robo-advisory service providers leads to an increase in number of financial advisors by about 800 at the state level. And consistently an increase in number of financial advisors by about 1.13 at the firm level. These results are robust to addition of firm-state-year controls, various state-year controls and fixed effects.

The main result is consistent in terms of both direction and magnitude of response with an alternate Bartik-like IV too. Additionally, I observe that firms that adopt robo-advisory technology respond strongly to the increase in number of robo-advisors (relative to those that do not adopt). And in general, financial advisors and robo-advisors appear to be complements.

Further analysis on the plausible reasons for the observed complementarity between robo-advisors and financial advisors is undertaken. I observe that there is a stronger increase in financial advisors among the firms that offer services similar to those offered by a robo-advisor. I also observe an investor level increase in the demand for financial advisors with an increase in number of robo-advisory service providers.

These two results indicate that the expansion in market for financial services (due to robo-advisors) can explain the observed relationship between financial advisors and robo-advisors. I also find that a decrease in separation and an increase in hirings explains the positive relationship between financial advisors and robo-advisors. These dynamic effects are increasing the average experience of a financial advisor with no impact on misconduct behavior at the firm level.

Overall, the results in this paper suggests that robo-advisors have a positive effect on financial advisors labor market. Expansion in market for financial services due to robo-advisors is the mechanism that is driving this complimenarity between robo-advisors and financial advisors.

References

Acemoglu, D. (1998). Why do New Technologies Complement Skills? Directed Technical Change and Wage Inequality. *The Quarterly Journal of Economics*, *113*(4), 1055–1089.

Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature*, *40*, 7–72.

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2020). *AI and Jobs: Evidence from Online Vacancies* (Tech. Rep. No. w28257). Cambridge, MA: National Bureau of Economic Research.

Acemoglu, D., & Autor, H. D. (2010). Skills, Tasks and Technologies: Implications for Employment and Earnings. *NBER Working Paper No. 16082*.

Acemoglu, D., & Restrepo, P. (2017). Robots and Jobs: Evidence from US Labor Markets. *Woking Paper*.

Acemoglu, D., & Restrepo, P. (2018). Artificial Intelligence, Automation and Work. *NBER Woking Paper No. 24196*.

Altonji, G. J., Elder, E. T., & Taber, R. C. (2005). Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, *113*(1), 151–184.

Autor, H. D. (2015). Why are There Still So Many Jobs? The History and Future of Workplace Automation. *The Journal of Economic Perspectives*, *29*(3), 3–30.

Autor, H. D., Levy, F., & Murnane, J. R. (2000). Upstairs, Downstairs: Computer-skill Complementarity and Computer-labor Substitution on Two Floors of a Large Bank. *NBER Working Paper 7890*.

Autor, H. D., Levy, F., & Murnane, J. R. (2003). The Skill Content of Recent and Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333.

Back, C., Morana, S., & Spann, M. (2021). Do Robo-Advisors Make Us Better Investors. *Working Paper*.

Bessen, J. (2016). How Computer Automation Affects Occupations: Technology, Jobs and Skills. *Boston University School of Law, Law and Economics Research Paper*, 15–39.

Bessen, J., Impink, M. S., Seamans, R., & Reichensperger, L. (2018). The Business of AI Startups. In *Boston univ. school of law* (pp. 18–28).

Bianchi, M., & Brière, M. (2021). Robo-Advising for Small Investors. *Working Paper*.

Brenner, L., & Meyll, T. (2020). Robo-advisors: A Substitute for Human Financial Advice? *Journal of Behavioral and Experimental Finance*, *25*, 100275.

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What can Machines Learn, and What Does it Mean for Occupations and the Economy? *AEA Papers and Proceedings*, *108*, 43–47.

Chen, G. Y. (2016). The Rise of the Machines and the U.S. Labor Market. *Working Paper*.

Cortes, M. G., Jiamovich, N., & Siu, E. H. (2017). Disappearing Routine Jobs: Who, How, and Why? *Journal of Monetary Economics*, *91*, 69–87.

D'Acunto, F., Prabhala, N., & Rossi, G. A. (2019). The Promises and Pitfalls of Robo-Advising. *The Review of Financial Studies*, *32*(5), 1983–2020.

D'Acunto, F., & Rossi, G. A. (2020). Robo-advising. *Working Paper*.

D'Acunto, F., & Rossi, G. A. (2022). IT Meets Finance: Financial Decision Making in the Digital Era. *Working Paper*.

Dimmock, G. S., Gerken, C. W., & Nathaneil, P. G. (2018). Is Fraud Contagious? Coworker Influence on Misconduct by Financial Advisors. *The Journal of Finance*, *73*(3), 1417–1450.

Egan, M., Matvos, G., & Seru, A. (2019). The Market for Financial Advisor Misconduct. *The Journal of Political Economy*, *127*(1), 233–295.

Fan, L., & Chatterjee, S. (2020). The Utilization of Robo-Advisors by Individual Investors: An Analysis Using Diffusion of Innovation and Information Search Frameworks. *Journal of Financial Counseling and Planning*, *31*(1), 130–145.

Fisch, E. J., Labouré, M., & Turner, A. J. (2018). The Emergence of the Robo-Advisor. *PRC WP2018-12, Pension Research Council Working Paper*.

Fung, K. M. (2006). Are Labor-saving Technologies Lowering Employment in the Banking Industry? *Boston University School of Law, Law and Economics Research Paper*, *30*, 179–198.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review*, *110*(8), 2586–2624.

Grennan, J., & Michaely, R. (2020). Artificial Intelligence and High-Skilled Work: Evidence from Analysts. *Working Paper*.

Jiang, W., Tang, Y., Xiao, R., & Yao, V. (2021). Surviving the FinTech Disruption. *Working Paper*.

Kim, D. S., Cotwright, M., & Chatterjee, S. (2019). Who are Robo-advisor Users. *Journal of Finance Issues*, *18*(2), 33–50.

Moon, S. K., & Suh, P. (2021). Startup (Dis)similarity and types of Early-stage Financing. *Working Paper*.

Oster, E. (2019). Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business and Economic Statistics*, *37*(2), 187–204.

Parsons, A. C., Sulaeman, J., & Titman, S. (2018). The Geography of Financial Misconduct. *The Journal of Finance*, *123*(5), 233–295.

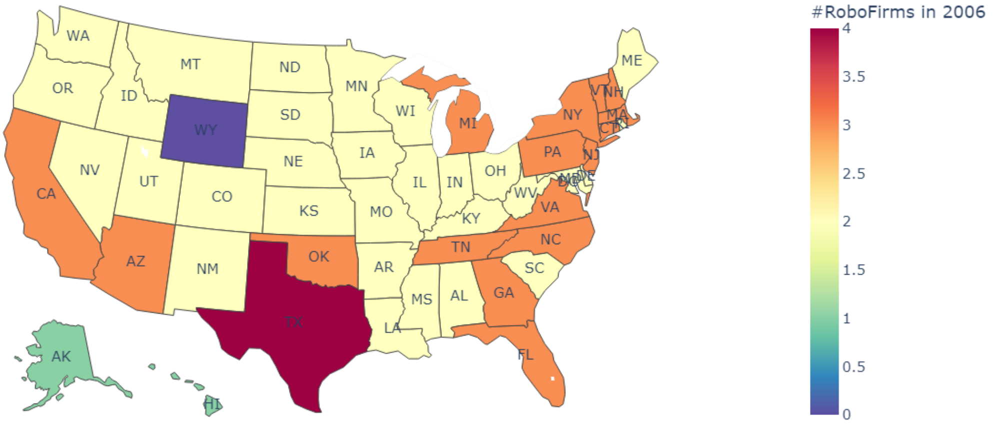
Rossi, G. A., & Utkus, S. (2020a). The Needs and Wants in Financial Advice: Human versus Robo-advising. *Working Paper*.

Rossi, G. A., & Utkus, S. (2020b). Who Benefits from Robo-advising? Evidence from Machine Learning. *Working Paper*.

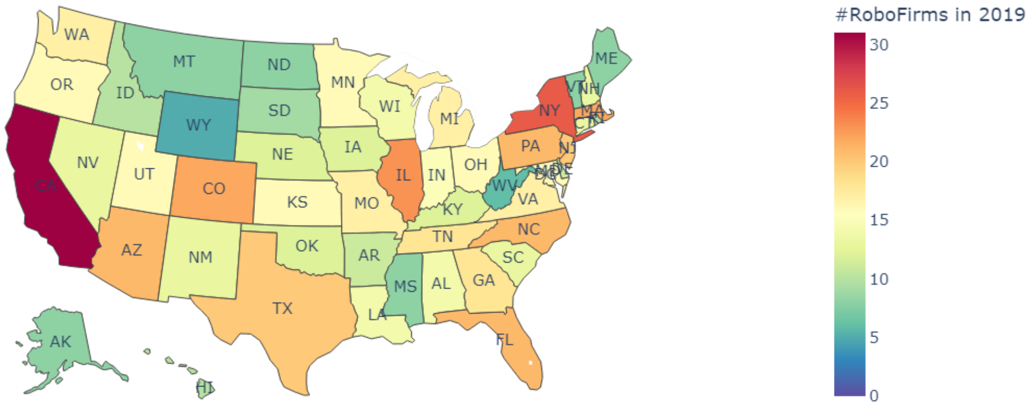
Todd, T. M., & Seay, M. C. (2020). Financial Attributes, Financial Behaviors, Financial-advisor-use Beliefs, and Investing Characteristics Associated with having used a Robo-advisor. *Financial Planning Review*, *3*(3), e1104.

Webb, M. (2019). The Impact of Artificial Intelligence on the Labor Market. *Working Paper*.

Figures

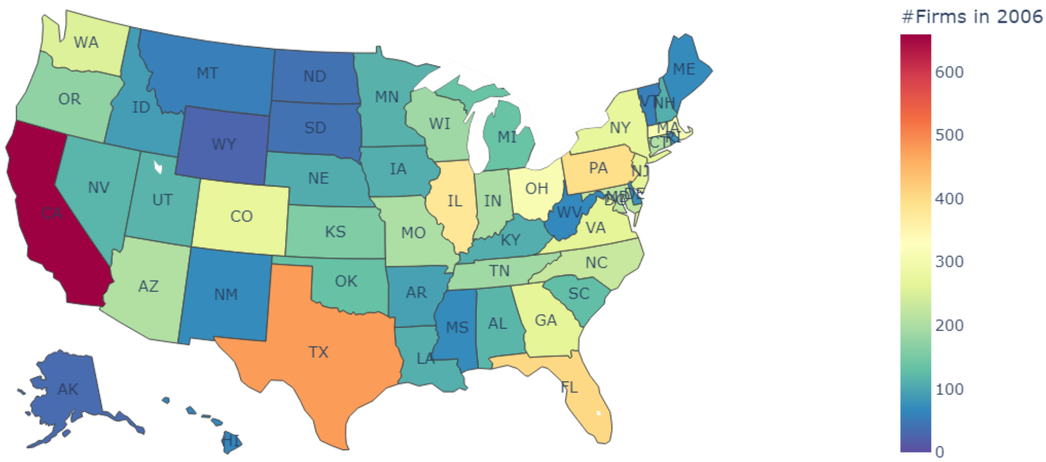


(a) Distribution during 2006

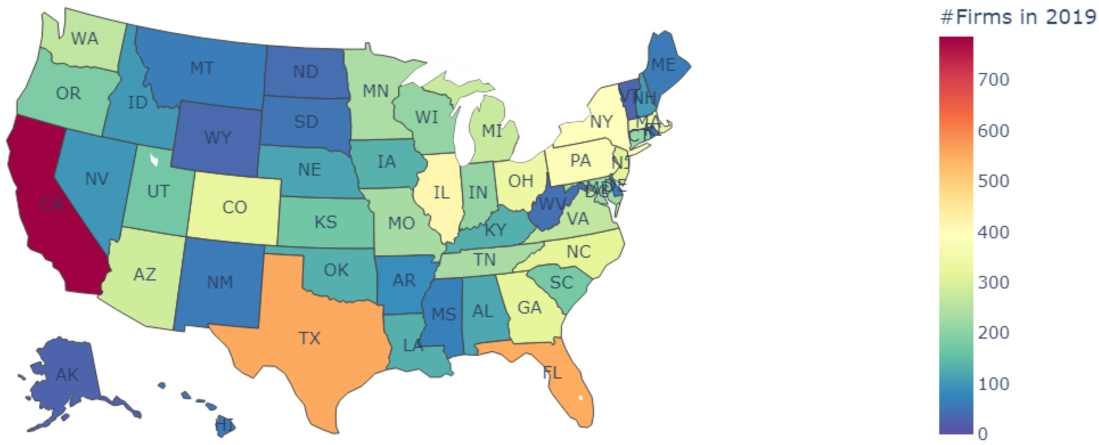


(b) Distribution during 2019

Figure 1: Distribution of Firms Offering Robo-advisory Services across US States during 2006 and 2019



(a) Distribution during 2006



(b) Distribution during 2019

Figure 2: Distribution of Financial Advisory Firms across US States during 2006 and 2019

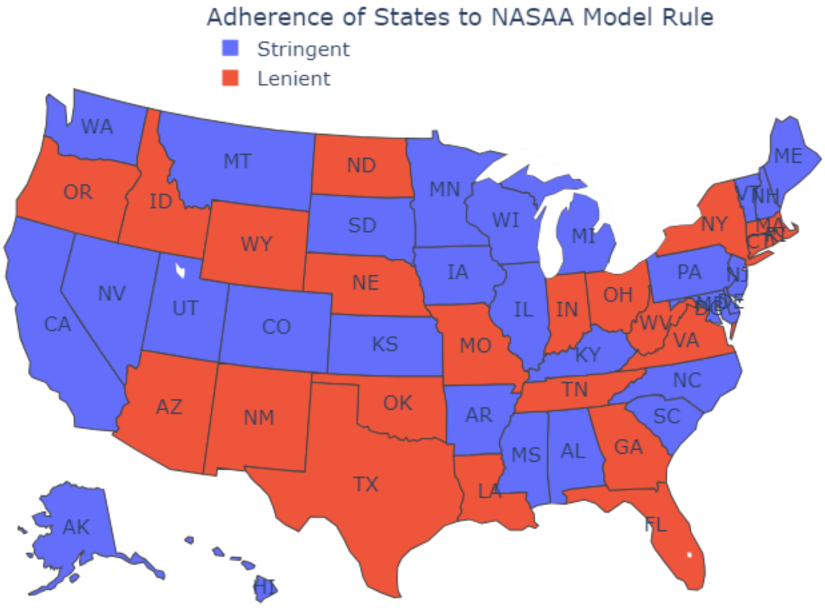


Figure 3: Adoption of NASAA Model Rule 202(d)-1 by Various States

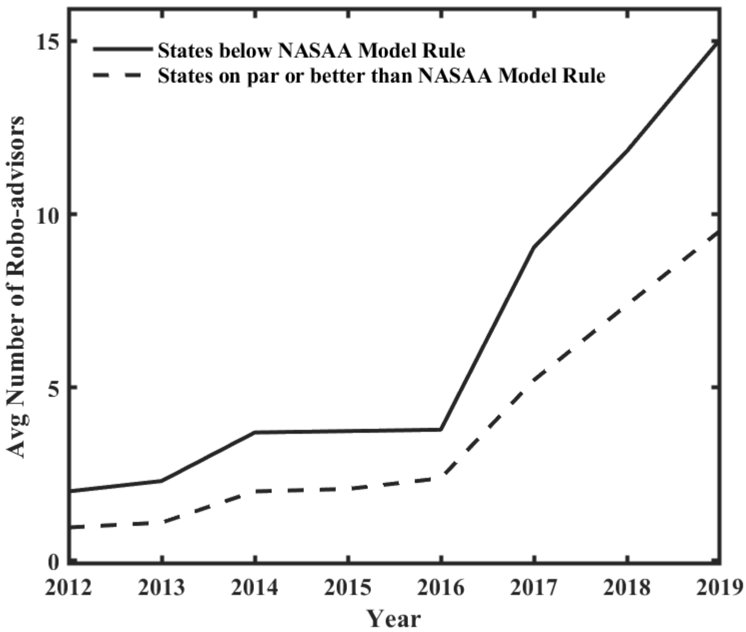


Figure 4: Average Number of Robo-advisors in States with Different Levels of Adoption of NASAA Recommendations on Firms' Financial Requirements

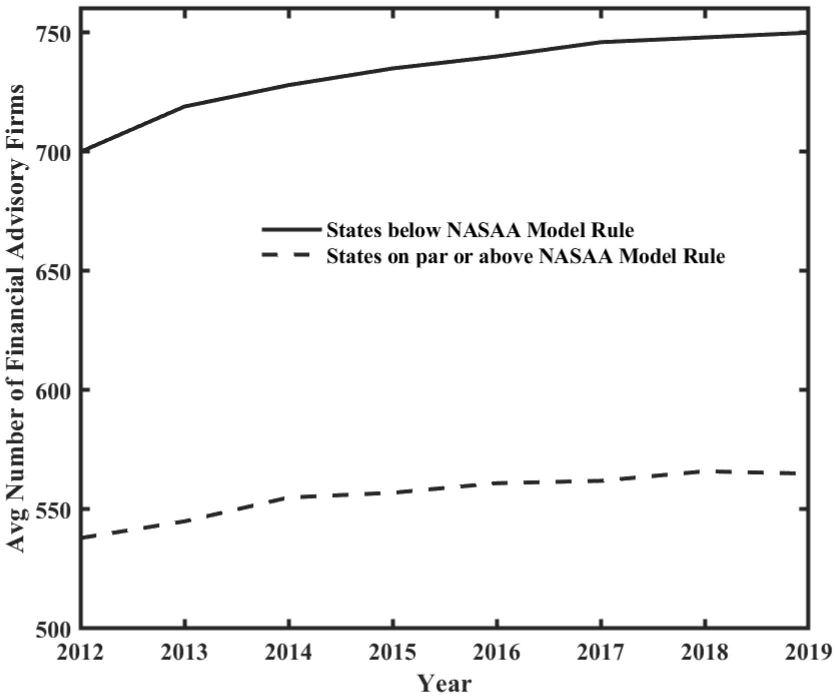


Figure 5: Average Number of Financial Advisory Firms in States with Different Levels of Adoption of NASAA Recommendations on Firms' Financial Requirements

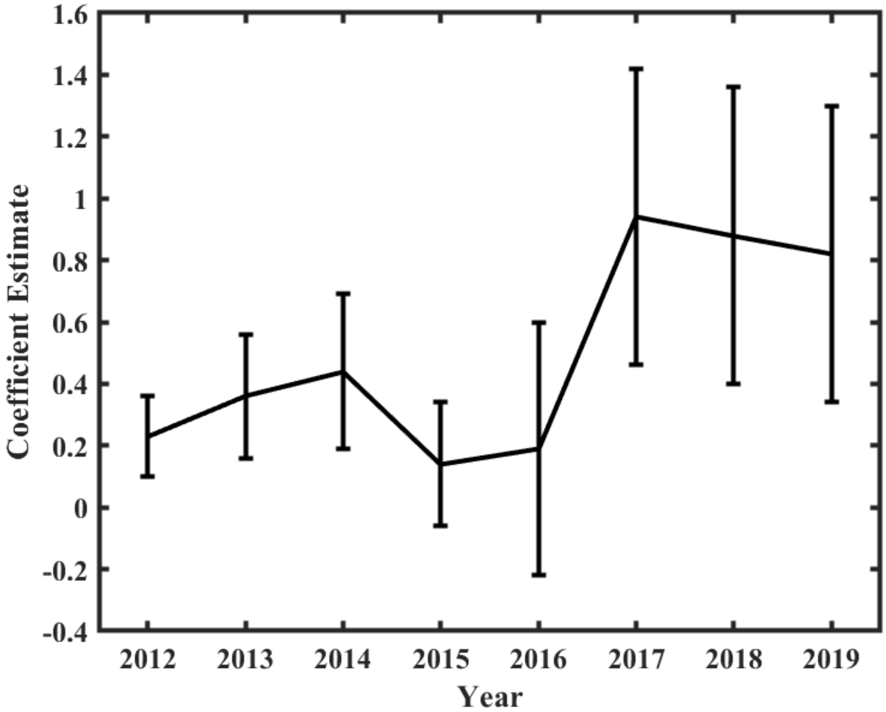


Figure 6: Coefficient Estimates on the Instrumental Variable Plotted over Years - Obtained by Estimating Equation 3.

Tables

Table 1: Break-down of Various Types of Firms that Provide Robo-advisory Services

	#Firms
Started as Robo-advisory Firm	98
Incumbent Firms that Started Robo-advisory Services	36
Offer Services only to other Registered Investment Advisors*	27
Exempt Reporting Advisers†	13
Total	174

*These firms do not provide services to individual investors, and are not registered with Securities Exchange Commission. †They act as an adviser solely for either venture capital funds or private funds.

Table 2: Summary Statistics

Panel A		
	2006	2019
% of Firms with at least 50% Individual Clients	59.27	39.08
% of Firms with at least 50% High Net Worth Indvidual Clients	19.04	4.33
% of Firms with Compensation as % of AuM	96.64	96.64
% of Firms offering Pension Services	65.94	48.12
% of Firms offering Wrap Fee Program*	34.43	60.21
% of Firms selling Financial Products	6.11	6.88
% of large-advisory Firms†	57.67	66.04

Panel B‡					
	Mean	Std Dev	Min	Median	Max
#Advisors	9.78	41.13	1	2	3170
Change in #Advisors	-0.04	10.52	-1996	0	2318
#Robo-advisors	5.88	5.93	1	3	25
Change in #Robo-advisors	0.25	1.82	-9	0	11
#Firms	422.43	326.96	1	340	1462
#Internet Adv Firms in 2003	9.16	6.46	1	7	24
Growth in FinTech Deals in UK	0.19	0.18	-0.01	0.20	0.60

*Rule 204-3(f) of the Investment Advisers Act of 1940 defines a wrap fee program as a"program under which any client is charged a specified fee or fees not based directly on transactions in a clientâs account for investment advisory services (which may include portfolio management or advice concerning the selection of other advisers) and execution of client transactions." This fee is usually a fixed percentage of the clients' AuM and is charged based on the bundle of services provided. †large-advisory firms have regulatory assets and management of at least $100 million. ‡ All the variables shown here are at the state-quarter level, except for the Growth in FinTech Deals in UK.

Table 3: Impact of Robo-advisors on the Number of Financial Advisors at State and Firm-State Levels

Panel A: Ordinary Least Square Estimates		
	State-year	Firm-state-year
	$\#FA_{s,t}$	$\#FA_{i,s,t}$
$R_{s,t}$	472.44***	0.18**
	(82.30)	(0.08)
Panel B: First-stage Estimates		
	$R_{s,t}$	$R_{s,t}$
$IV_{s,t}$	0.81***	0.43***
	(0.25)	(0.01)
F Statistic	10.48	2,460
Panel C: Second-stage Estimates		
	$\#FA_{s,t}$	$\#FA_{i,s,t}$
$\hat{R}_{s,t}$	797.81**	1.13**
	(389.43)	(0.52)
State-Year Controls	Y	Y
Firm FE		Y
State FE	Y	Y
Year FE	Y	Y
Firm×Year FE		Y
Observations	408	305,716

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

#FA represents the number of financial advisors. $IV_{s,t}$ is the instrumental variable obtained using the interaction between an indicator variable that takes 1 for states with lax financial requirements and an indicator value that takes 1 when the year is 2016 and after. All the regressions have controls at financial industry and state level. Total number of employees in the financial sector and number of financial advisory firms comprise of industry conditions at the state-year level. Personal consumption expenditure on financial services and population aged greater than 25 are the proxies to control for state level demand for financial services. Gross domestic product, unemployment rate, share of college educated, share of female employees in all the sectors comprise the state economic conditions that vary with year. Standard errors are clustered at state level to obtain column 1 estimates, and at firm level to obtain column 2 estimates.

Table 4: Impact of Robo-advisors on the Number of Financial Advisors at State and Firm-State levels: Estimated Using Bartik-like Instrument over the Period 2006-2019

Panel A: First-stage Estimates		
	State-year	Firm-state-year
	$\Delta R_{s,t}$	$\Delta R_{s,t}$
$IV_{s,t}$	0.05***	0.03***
	(0.01)	(0.01)
F Statistic	14.59	17.48
Panel B: Second-stage Estimates		
	$\Delta \text{FA}_{s,t}$	$\Delta \text{FA}_{i,s,t}$
$\Delta R_{s,t}$	483.20***	3.94***
	(146.03)	(0.81)
State-by-time Controls	Y	Y
Firm FE		Y
State FE	Y	Y
Year FE	Y	Y
Firm×Year FE		Y
Observations	392,222	2,443

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

#FA Firms is the number of financial advisory firms. All the regressions have controls at financial industry and state level. Total number of employees in the financial sector and number of financial advisory firms comprise of industry conditions at the state-year level. Personal consumption expenditure on financial services and population aged greater than 25 are the proxies to control for state level demand for financial services. Gross domestic product, unemployment rate, share of college educated, share of female employees in all the sectors comprise the state economic conditions that vary with year.

Table 5: Robustness of the Effect of Robo-advisors on the Number of Financial Advisors at a Firm with Additional Controls

Second-stage Estimates			
	$\#FA_{i,s,t}$	$\#FA_{i,s,t}$	$\#FA_{i,s,t}$
$\hat{R}_{s,t}$	1.01**	1.10**	1.10*
	(0.52)	(0.52)	(0.60)
$\#Brkrs_{i,s,t}$		0.24***	0.27***
		(0.06)	(0.06)
$\log(1+AuM)_{i,t}$			-0.19***
			(0.04)
$\log(1+Acc)_{i,t}$			0.72***
			(0.16)
Industry Controls	Y	Y	Y
Demand Proxies	Y	Y	Y
Economic Variables		Y	Y
Firm FE	Y	Y	Y
State FE	Y	Y	Y
Year FE	Y	Y	Y
Firm×Year FE	Y	Y	
Observations	305,716	305,716	210,936

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

#FA represents the number of financial advisors, and #Brkrs represent the number of brokers at a firm in each branch state. log(1+AuM) is calculated a the natural logarithm of one plus discretionary regulatory assets under management at the firm. log(1+Acc) is calculated a the natural logarithm of one plus discretionary regulatory number of accounts held by the firm. $IV_{s,t}$ is the instrumental variable obtained using the interaction between an indicator variable that takes 1 for states with lax financial requirements and an indicator value that takes 1 when the year is 2016 and after. Total number of employees in the financial sector and number of financial advisory firms comprise of industry conditions at the state-year level. Personal consumption expenditure on financial services and population aged greater than 25 are the proxies to control for state level demand for financial services. Gross domestic product, unemployment rate, share of college educated, share of female employees in all the sectors comprise the state economic conditions that vary with year. Column 2 controls for firm-by-state-by-time variation with the number of brokers (#Brkrs). All the regressions control for firm, state and year fixed effects. While firm-by-year fixed effects are used to obtain column 1 and 2 estimates, firm-by-year control variables (AuM and Accounts) in column 3. Standard errors are clustered at the firm level.

Table 6: 2SLS Estimates Impact of Robo-advisors on the Number of Financial Advisors and Brokers at a Firm

Second-stage Estimates			
	Firms that provide Advisory Services	All Firms	All Firms
	$\#\text{FA}_{i,s,t}$	$\#\text{Brkr}_{i,s,t}$	$\#\text{Emp}_{i,s,t}$
$\hat{R}_{s,t}$	4.06***	0.12	0.69
	(1.38)	(0.67)	(0.83)
$\#\text{Brkrs}_{i,s,t}$	0.25***		
	(0.06)		
State-by-time Controls	Y	Y	Y
Firm FE	Y	Y	Y
State FE	Y	Y	Y
Year FE	Y	Y	Y
Firm×Year FE	Y	Y	Y
Observations	284,916	305,716	305,716

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

#FA represents the number of financial advisors, #Brkrs represent the number of brokers, and #Emp represents the combined number of financial advisors and brokers at a firm in each branch state. Total number of employees in the financial sector, number of financial advisory firms, personal consumption expenditure on financial services, population aged greater than 25, gross domestic product, unemployment rate, share of college educated, share of female employees in all the sectors comprise the state controls that vary with year. All the regressions control for firm, state, year and firm-by-year fixed effects. Standard errors are clustered at the firm level.

Table 7: Heterogeneity in Response to the Number of Robo-advisory Firms

	Small-advisory Firms	Firms that Provide Robo-advisory Services
	$\#\text{FA}_{i,s,t}$	$\#\text{FA}_{i,s,t}$
$R_{s,t}$	1.10*	3.49***
	(0.61)	(0.37)
$\mathbf{I}\{Small = 1\} \times R_{s,t}$	0.00	
	(0.36)	
$\mathbf{I}\{Robo = 1\} \times R_{s,t}$		22.11**
		(10.35)
Firm-Year Controls	Y	Y
Firm-State-Year Control	Y	Y
State Level Controls	Y	Y
Firm FE	Y	Y
State FE	Y	Y
Year FE	Y	Y

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

$\mathbf{I}\{S = 1\}$ indicates small business firms. SEC defines small business firms as those that have regulatory assets under management of less than \$25 million. $\mathbf{I}\{Robo = 1\}$ indicates firms that provide robo-advisory services. Firm-Year Controls include natural logarithm of one plus discretionary regulatory assets under management and natural logarithm of one plus discretionary number of accounts at the firm level. Firm-State-Year Control is the number of brokers at the firm-state. Total number of employees in the financial sector, number of financial advisory firms, personal consumption expenditure on financial services, population aged greater than 25, gross domestic product, unemployment rate, share of college educated, share of female employees in all the sectors comprise the state controls that vary with year. Standard errors are clustered at the firm level.

Table 8: Response by Firms that Provide Services Similar to Robo-advisory Services

	Firms Offering Advisory Services to Individual Clientele $\#FA_{i,s,t}$	Firms Offering Wrap Service Programs $\#FA_{i,s,t}$	Firms Offering Pension Services $\#FA_{i,s,t}$
$R_{s,t}$	1.10*	1.01*	1.00*
	(0.60)	(0.58)	(0.60)
$\mathbf{I}\{Indv = 1\} \times R_{s,t}$	1.13***		
	(0.24)		
$\mathbf{I}\{Wrap = 1\} \times R_{s,t}$		0.82***	
		(0.28)	
$\mathbf{I}\{Pension = 1\} \times R_{s,t}$			0.60**
			(0.24)
Firm-Year Controls	Y	Y	Y
Firm-State-Year Control	Y	Y	Y
State Level Controls	Y	Y	Y
Firm FE	Y	Y	Y
State FE	Y	Y	Y
Year FE	Y	Y	Y

Clustered standard errors in the parentheses
*** p<0.01, ** p<0.05, * p<0.1

$\mathbf{I}\{Indv = 1\}$ indicates firms that have cater to predominantly individual clientele. $\mathbf{I}\{Indv = 1\}$ takes value 1 if the firm has more than 50% as individual clientele. $\mathbf{I}\{Wrap = 1\}$ indicates firms that offer wrap service programs. $\mathbf{I}\{Pension = 1\}$ indicates firms that offer pension services. Firm-Year Controls include natural logarithm of one plus discretionary regulatory assets under management and natural logarithm of one plus discretionary number of accounts at the firm level.Firm-State-Year Control is the number of brokers at the firm-state. Total number of employees in the financial sector, number of financial advisory firms, personal consumption expenditure on financial services, population aged greater than 25, gross domestic product, unemployment rate, share of college educated, share of female employees in all the sectors comprise the state controls that vary with year. Standard errors are clustered at the firm level.

Table 9: Response by Firms that Cater to Individual and High-net-worth Clienetele

	Firms Offering Advisory Services to Individual Clientele $\#\text{FA}_{i,s,t}$	Firms Offering Advisory Services to HNW Clientele $\#\text{FA}_{i,s,t}$
$R_{s,t}$	1.10*	1.01*
	(0.60)	(0.58)
$\mathbf{I}\{Indv1 = 1\} \times R_{s,t}$	0.82***	
	(0.27)	
$\mathbf{I}\{HNW = 1\} \times R_{s,t}$		-0.18
		(0.18)
Firm-Year Controls	Y	Y
Firm-State-Year Control	Y	Y
State Level Controls	Y	Y
Firm FE	Y	Y
State FE	Y	Y
Year FE	Y	Y

Clustered standard errors in the parentheses

*** p<0.01, ** p<0.05, * p<0.1

$\mathbf{I}\{Indv1 = 1\}$ takes value 1 if the firm has more than 75% as individual clientele. $\mathbf{I}\{HNW = 1\}$ takes value 1 if the firm has more than 75% as high-net worth (HNW) clientele. Firm-Year Controls include natural logarithm of one plus discretionary regulatory assets under management and natural logarithm of one plus discretionary number of accounts at the firm level. Firm-State-Year Control is the number of brokers at the firm-state. Total number of employees in the financial sector, number of financial advisory firms, personal consumption expenditure on financial services, population aged greater than 25, gross domestic product, unemployment rate, share of college educated, share of female employees in all the sectors comprise the state controls that vary with year. Standard errors are clustered at the firm level.

Table 10: Impact of Robo-advisors on the Demand for Financial Advisory Services

	2SLS	OLS
	$\mathbf{I}\{UseFA = 1\}_{j,s,t}$	$\mathbf{I}\{UseFA = 1\}_{j,s,t}$
$R_{s,t}$	0.35***	
	(0.09)	
$\mathbf{I}\{UseRobo = 1\}_{j,s,t}$		0.06***
		(0.02)
State-Year Controls	Y	Y
Individual Characteristics	Y	Y
Individual-Year Characteristics	Y	Y
State FE	Y	Y
Year FE	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

$\mathbf{I}\{UseFA = 1\}_{j,s,t}$ takes value of 1 if the individual j in state s utilizes either financial advisory or brokerage services during period t. $\mathbf{I}\{UseRobo = 1\}_{j,s,t}$ takes value of 1 if the individual j in state s utilizes either financial advisory or brokerage services during period t.

Table 11: Effect of Robo-advisors on the Number of Financial Advisors Separated and Hired at the Firm-State

	$\text{Separation}_{i,s,t}$	$\text{Hiring}_{i,s,t}$
$R_{s,t}$	-0.20**	0.40**
	(0.09)	(0.20)
Firm-State-Year Control	Y	Y
State-Year Controls	Y	Y
Firm FE	Y	Y
State FE	Y	Y
Year FE	Y	Y
Firm×Year FE	Y	Y

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Separation is defined as the number of financial advisors who were present at the firm during the previous year but are not at the firm during the current year. Hiring is defined as the number of financial advisors who are present at the firm during the current year but are not at the firm during the past year. Firm-State-Year Control is the number of advisors and brokers at the firm-state. Total number of employees in the financial sector, number of financial advisory firms, personal consumption expenditure on financial services, population aged greater than 25, gross domestic product, unemployment rate, share of college educated, share of female employees in all the sectors comprise the state controls that vary with year. Standard errors are clustered at the firm level.

Table 12: Effect of Robo-advisors on the Average Experience of Financial Advisors and the Misconduct Behavior of the Financial Advisors at the Firm-State

	Avg $\text{Exp}_{i,s,t}$	$\text{Misconduct}_{i,s,t}$
$R_{s,t}$	0.37***	0.00
	(0.12)	(0.00)
Firm-Year Controls	Y	Y
Firm-State-Year Control	Y	Y
State-Year Controls	Y	Y
Firm FE	Y	Y
State FE	Y	Y
Year FE	Y	Y

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Avg Exp is calculated as the average experience of all financial advisors at firm-state. Misconduct is an indicator variable that takes 1 if there is at least one misconduct complaint at the firm-state. Firm-Year Controls include natural logarithm of one plus discretionary regulatory assets under management and natural logarithm of one plus discretionary number of accounts at the firm level. Firm-State-Year Control is the number of advisors and brokers at the firm-state. Total number of employees in the financial sector, number of financial advisory firms, personal consumption expenditure on financial services, population aged greater than 25, gross domestic product, unemployment rate, share of college educated, share of female employees in all the sectors comprise the state controls that vary with year. Standard errors are clustered at the firm level.

Appendices

Appendix A Robo-Advisory Firms

The first robo-advisory firms started in 2006. The number of firms entering the robo-advisory space has seen an increase from 2013. The number of incumbent firms offering robo-advisory services has seen an increase from 2015. Figure A1 shows the evolution of robo-advisory service firms between 2006 and 2019. Figure A2 shows the snapshot of distribution of individuals clients across various kinds of firms during 2019. As can be observed from this figure, firms that offer robo-advisory services cater predominantly to individual clients.

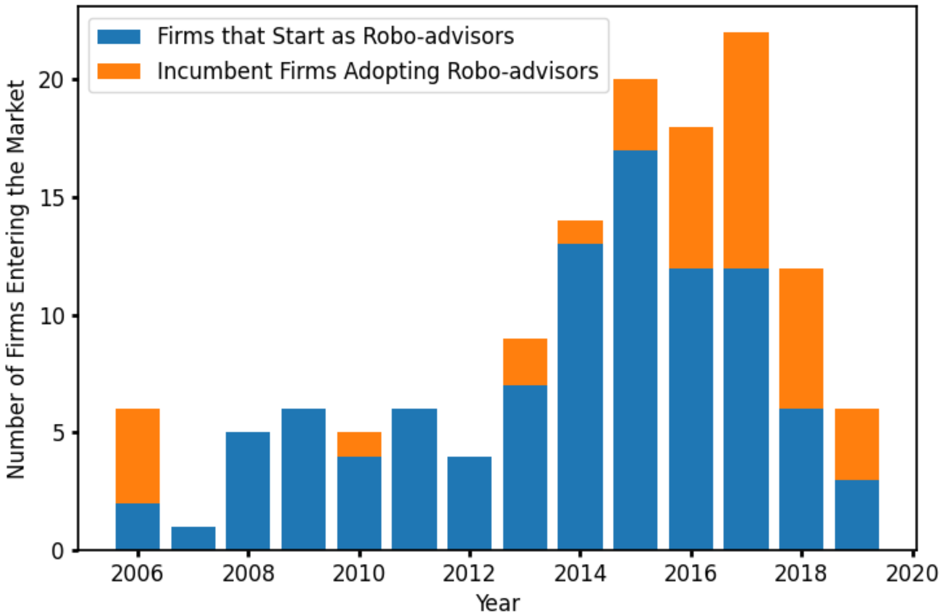


Figure A1: Number of Firms Entering the Robo-advisory Service Space between 2006 and 2019

Figure A3 shows the snapshot of distribution of various types of firms during 2019. As can be seen from this figure over 60% of firms that offer robo-advisory services are large-advisory firms. Almost all the firms that offer robo-advisory services are wrap service program providers. Around 30% of the firms that offer robo-advisory services are also pension consultants.

Figures A4, A5 and A6 show the evolution of average number of financial advisors, discretionary regulatory AuM and number of discretionary accounts, respectively. It can be observed that the incumbent firms that are adopting robo-advisory services have

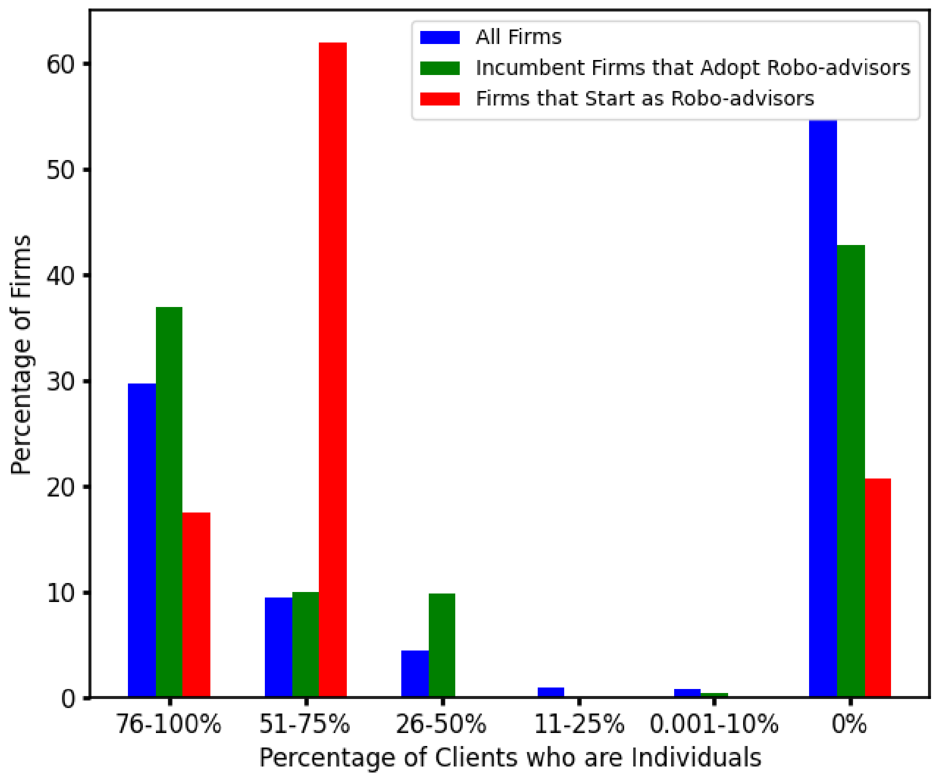


Figure A2: Percentage of Individual Clients Catered to by Various Types of Firms during 2019

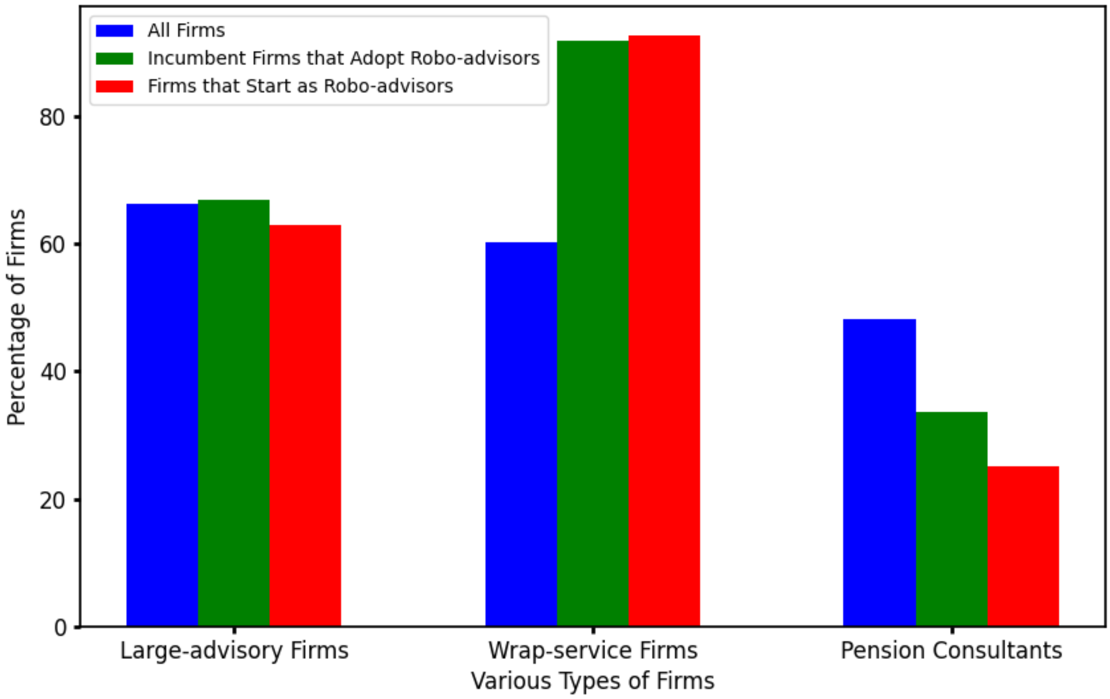


Figure A3: Percentage of Various Types of Firms during 2019

higher number of financial advisors as compared to the industry, on an average. Firms that start as robo-advisory firms have lower number of financial advisors as compared to the industry, on an average. Similar pattern can be observed for discretionary regulatory AuM and number of discretionary accounts.

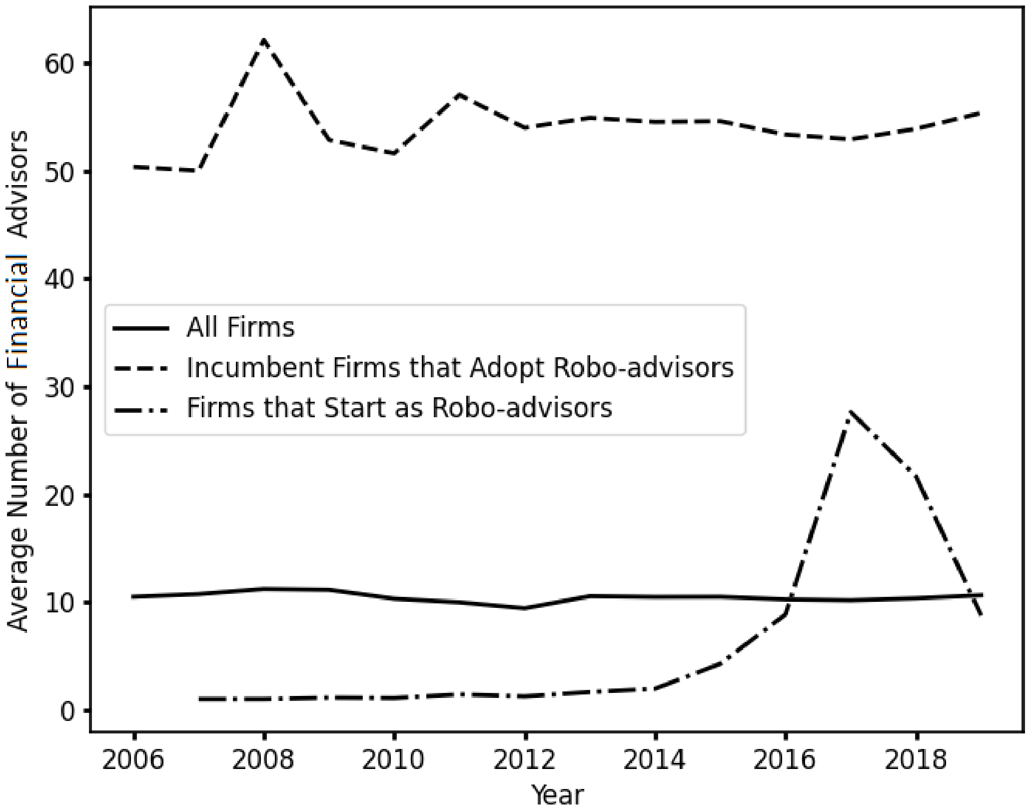


Figure A4: Average Number of Financial Advisors across Various Types of Firms between 2006 and 2019

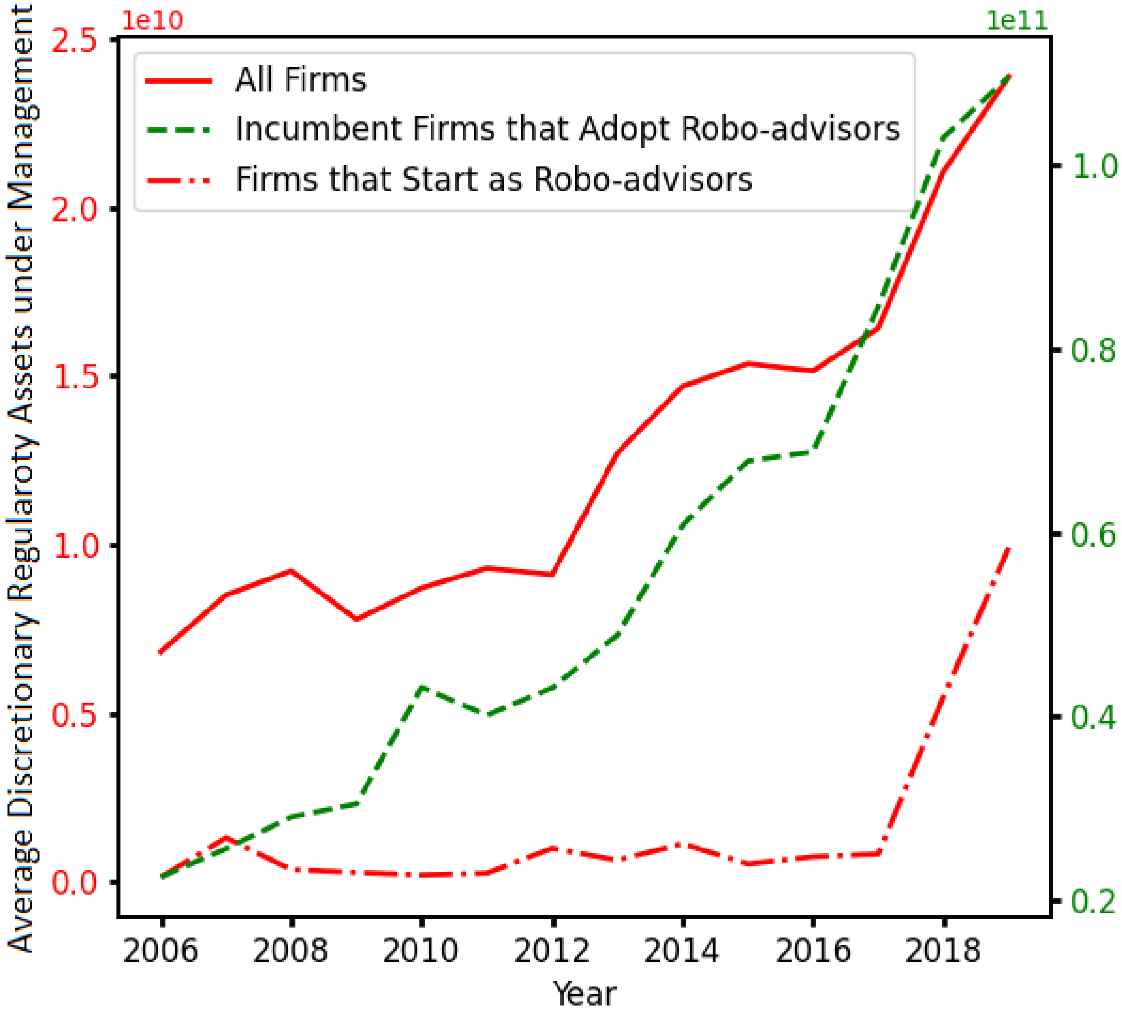


Figure A5: Average Discretionary Regulatory Assets under Management across Various Types of Firms between 2006 and 2019

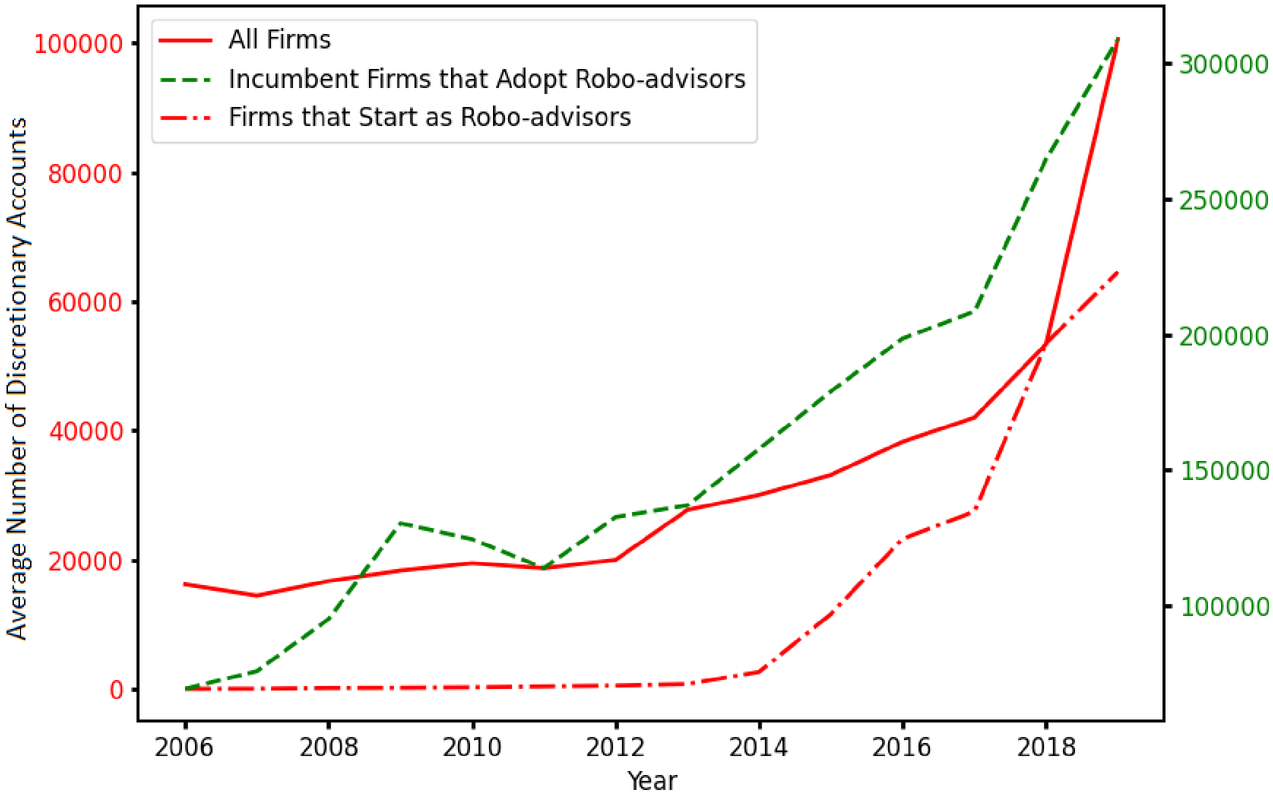


Figure A6: Average Number Discretionary Accounts across Various Types of Firms between 2006 and 2019

Appendix B Bartik-like Instrument

B.1 Construction of Bartik-like Instrumental Variable

For this, I start by rewriting change in robo-advisors, $\Delta R_{s,t}$, as follows:

$$\Delta R_{s,t} = R_{s,t} - R_{s,t-1} = R_{s,t-1} \times \frac{\Delta R_{s,t}}{R_{s,t-1}} = R_{s,t-1} \times G_{s,t}.$$

Here, $G_{s,t}$ is the growth in robo-advisory services at location s and period t; and $R_{s,t-1}$ is the number of robo-advisory service providers at location s and period $t-1$.

Then, I decompose the growth in robo-advisory services at a location as the sum of growth at the national level ($G_{US,t}$) and growth component at that specific location which is beyond the national growth rate($\widetilde{G}_{s,t}$):

$$G_{s,t} = G_{US,t} + \widetilde{G}_{s,t}.$$

Ideally, in the above decomposition $G_{US,t}$ and $\widetilde{G}_{s,t}$ are orthogonal to each other only under special condition. The orthogonality arises when all the idiosyncratic shocks at the state level are i.i.d (individually independently distributed). To see when the orthogonality assumption for the above decomposition is valid, consider $G_{US,t}$. $G_{US,t}$ is a sum of growth across all states during t:

$$G_{US,t} = \sum_{s \in US} \left(G_{s,t} + \widetilde{G}_{s,t}\right).$$

When $\widetilde{G}_{s,t}$ are i.i.d, $\sum_{s \in US} \widetilde{G}_{s,t}$ will be zero. And, $G_{US,t} = \sum_{s \in US} G_{s,t}$. Thus, $G_{US,t}$ is uncorrelated with state level shocks only when these shocks are i.i.d. The i.i.d assumption may be valid when s is large. And, when there is no cross-correlation between different states. When the i.i.d. assumption is valid, employing $G_{US,t}$ in the place of $G_{s,t}$ in evaluating $\Delta R_{s,t}$ implies that exogeneity condition is satisfied between the growth term and change in number of robo-advisors at the state level.

In the context of this study, it is probably reasonable to assume that the demand shocks across states are i.i.d. However, the supply shocks may not be i.i.d. For example, Moon and Suh (2021) show that venture capitalists make geographically diversified investments in similar industries. So, an increase of investments in robo-advisors in one particular state could be correlated with an increase of investment in another state. This leads to a spatial correlation in the supply of robo-advisors across states. To avoid this spatial correlation, one potential solution is to decompose the growth rate of robo-advisors into growth rate of FinTech[21] ($G_{FinTechUS,t}$) and growth component of robo-advisors that is beyond the growth rate of FinTech ($\widetilde{G}_{US,t}$):

$$G_{US,t} = G_{FinTechUS,t} + \widetilde{G}_{US,t}.$$

Again, when the above decomposition leads to two orthogonal components, $G_{FinTechUS,t}$ can be a good proxy for growth in robo-advisory services. In which case, $\widetilde{G}_{US,t}$ is independent of other industry growth rates within US. However, in reality there may be a cross-correlation across industries within FinTech, which implies there is a correlation between $G_{FinTechUS,t}$ and $\widetilde{G}_{US,t}$. For example, Moon and Suh (2021) show that angel investors make geographically concentrated investments across dissimilar industries. That is, when there is an increase in investments in one particular industry of FinTech, there could also be a corresponding increase in investment in robo-advisors.

To avoid such potential violations to exogeneity condition, I use the FinTech growth rate in UK as a proxy for US. The relevance of using FinTech growth rate in UK as a proxy for growth rate of robo-advisors at state-level in US arises due to factors that are common to both the growth rates. That is, Investment trends in FinTech in another developed country (UK) will be correlated with that in US through the common factors impacting global trends of investment in FinTech. The common factors that determine global trends are uninfluenced by the incentives provided/subsidies available at individual countries to boost their FinTech growth. For example, US provided tax incentives for technology firm start-ups during 2016. Such incentive is seen as an encouragement for FinTech firms, specifically. A growth in FinTech firms due to incentives provided by the government will actuate spatial and with-in FinTech industry correlations.

Therefore, the spatial and with-in FinTech industry correlations that may become important when considering US FinTech growth rates as a proxy for state-level robo-advisory growth rates. Because the common factors driving global trends in FinTech investment are important when considering UK FinTech growth rates as a proxy for within US state-level robo-advisory growth rates, the spatial and with-in FinTech industry correlations may become irrelevant.

One plausible reason when these correlation may still be relevant is when the common factors driving FinTech investment in US and UK are the incentives/subsidies for FinTech growth in US. For example, investors seek geographic diversification across countries and increase their investment in both US and UK when incentives/subsidies are introduced in US. In this case, my proxy will fail to have satisfied exogeneity condition. However,

[21] Robo-advisors are part of a broader FinTech industry.

the effect of such a scenario is likely to be minimal here. This is because, an investor seeking geographic diversification need not always invest in UK. And, definitely not all the investors will invest only in UK when they invest in US. To the extent that correlation in investment between US and UK is minimal, it is reasonable to argue that using UK FinTech growth rate may not violate exogeneity condition.

The final proxy for growth in robo-services at a location — growth of FinTech in UK — possibly abstracts away from local confounding factors that could be correlated with both demand and supply effects of robo-advisory services and gives an exogenous variation in the changes to number of robo-advisory firms at that location. This will mostly eliminate any concerns about the correlations between component of growth in FinTech services at the US level and local factors that may still effect the *local supply* of robo-advisory services. Also, the final proxy yields a very parsimonious estimate for local growth in robo-advisory services.

$$G_{s,t} \approx G_{FinTechUK,t}.$$

To proxy for $R_{s,t-1}$, I rely on the change to ADV form implemented by SEC during 2001. This change required the firms that were offering services through internet to report that they were 'Internet Firms' starting mid of 2002. This change itself is not intended to effect the number of such firms — as there are no other impositions on firms that report to be either 'Internet Firms' or not — but allows for the identification of such firms for the first time.

I use the number of firms that were providing advisory services through internet in 2003[22] at the state level, to obtain heterogeneity in the level of robo-advisory firms at various locations.The logic to use the number of internet firms in 2003 to proxy for robo-advisory service providers is that states that exhibited high (low) preference for internet advisory services during 2003 may also be the same states that exhibit high (low) preference for advisory services through mobile apps (robo-advisors) during the current times.

The number of internet firms in 2003 is expected to be correlated with the *level* of robo-advisory firms at various states over time. This choice as a proxy for $R_{s,t-1}$ hopefully allows for the disassociation between the factors that impact *levels* of robo-advisory firms and those that impact *changes in level* of robo-advisory firms. However, there could still be concerns about the exogeneity of this component of the IV. I discuss this issue in more detail in the following paragraphs. I discuss the various tests I perform to alienate these

[22]The firms started reporting if they were 'Internet Firms' only from the mid of 2002. In order to avoid a situation where the number of internet firms is underestimated due to some selected firms not filing during the later part of 2002, I choose 2003 as the year of choice.

concerns in the Results and Discussion section.

To summarize the IV, I use the product of number of internet firms in 2003 ($I_{s,2003}$) at a location s and growth in the FinTech startups in UK over time as an IV for the change in firms offering robo-advisory services at a location and time. That is, the IV is given by the right hand side expression below.

$$\Delta R_{s,t} = R_{s,t-1} \times G_{s,t} \approx I_{s,2003} \times G_{FinTechUK,t}. \tag{A1}$$

The final IV has a similar form as what Goldsmith-Pinkham et al. (2020) refer to as *Bartik-like instrument*. Goldsmith-Pinkham et al. (2020) argue that the main concern of such instruments is the validity of exclusion restriction assumption on IV. In the context of an empirical strategy that uses changes in independent and outcome variables they say, "the key question researchers should have in mind is whether the correlates of the levels of the shares predict changes in the outcome. For the empirical strategy to be valid, it is fine if the level of the correlates are related to the level of the outcome.

In the context of my IV, the number of internet firms during 2003 correspond to the shares referred in the above quote. Therefore, to argue for the validity of exclusion restriction assumption for the IV, I have to establish that correlates of the number of internet firms during 2003 do not predict the changes in number of financial advisors during my study period. To this end I use the tests and directions provided in Goldsmith-Pinkham et al. (2020).

B.2 Validity of Bartik-like IV

Panel A in Table 4 shows the first stage estimates of equation 2. These results show that there is positive significant correlation between the IV and change in the number of robo-advisory firms. Also, an F Statistic of 25.55 (column 3, Panel B in Table 2) alleviates the concerns that the IV may be weak. These results show that the relevance assumption on the IV is valid.

Next, I conduct tests to check if this IV satisfies the exclusion restriction criterion. The IV used in this study has a similar form as a Bartik-like instrument in Goldsmith-Pinkham et al. (2020). As highlighted in Goldsmith-Pinkham et al. (2020), the main concern with such instruments is the use of level variable (number of internet firms in 2003, here) as one of the component in the IV construction. This is the main challenge to the validity of exclusion restriction assumption. To establish the validity of exclusion restriction I have to show that the number of internet firms in 2003 does not impact the change in number of financial advisors (either directly or through other correlates).

I exploit the similarity in the form of IV used in this study and the Bartik-like instruments referred to in Goldsmith-Pinkham et al. (2020) to validate the exclusion restriction assumption. Goldsmith-Pinkham et al. (2020) provide various tests that can help validate this assumption. The first test they suggest is to check for the correlation of IV with initial period characteristics (2003, here). Because the number of internet firms present at each state during 2003 is a component of the IV, variation in the IV could be mainly due to this component. If that is the case then the correlates of this component will explain the IV. This would cause a omitted variable bias with specification 2 and violate the exogeneity condition.

To check if the IV used in this study is not prone to this problem, I check to see how much of variation in the IV can be explained using the economic characteristics during 2003. To perform this test, I run a simple regression with the number of internet firms during 2003 and IV as dependent variables and the economic characteristics during 2003 as independent variables. Table A1 shows these results. R-squared value is compared between columns 1 and 2, and between columns 3 and 4. These results show that though the economic characteristics explains significant variation in the level of internet firms during 2003 (39%), they do not explain much variation in the IV (9%) itself.[23]

Table A1: Correlation between Level of Internet Firms and Characteristics during 2003

	#Internet Firms	IV	#Internet Firms	IV
Share of Educ	0.40**	0.07***	0.39**	0.08***
	(0.17)	(0.02)	(0.18)	(0.02)
Share of Female Empl	-2.80***	-0.45***	-3.33***	-0.56***
	(0.74)	(0.08)	(0.94)	(0.10)
Share of Empl	2.77***	0.44***	3.43***	0.60***
	(0.82)	(0.09)	(1.10)	(0.12)
GDP Per Capita	-45.85	-10.25*	-38.98	-8.14
	(48.62)	(5.25)	(53.55)	(5.54)
Share of Empl in Fin Serv			0.82	0.07
			(2.05)	(0.21)
Consmptn Fin Serv Per Capita			-1052.73	-261.99
			(2282.96)	(240.83)
Share of Pop Age >= 25			42.03	9.07*
			(43.78)	(4.66)
R-squared	0.38	0.09	0.39	0.09

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[23]Variations of these economic characteristics do not alter the results.

Next Goldsmith-Pinkham et al. (2020) point out that Bartik-like IV is a product of two components: one explaining the cross-sectional variation (the level variable) and the other explaining the time variation (the growth variable). In this sense, the specification (2SLS specification in equation 2 here) becomes similar to a differences-in-differences setting. For exogeneity assumption in such cases, parallel pre-trends assumption should hold. They suggest the use of controls as the correlates of levels variable during the initial period (2003, here) interacted with the time fixed effects to check for the same.

If there is a significant difference in the coefficient estimate of interest with and without these controls, then the exogeneity condition is not valid. The logic is that if the addition of these controls (interaction of time-invariant initial period characteristics with time fixed components) can alter the coefficient estimates, then there may be some confounding factors that could be correlated with the IV and can explain the IV. This again leads to an omitted variable bias.

Table A2 shows the results obtained with and without these controls. The coefficient estimate obtained without controls do not include any controls from Table 4 too. IV is the only independent variable in column 1. The difference in the coefficient estimates between columns 1 and 2 is statistically insignificant. The results from Tables A1 and A2 provide possible validity of the exclusion restriction for the IV used in this study.

Table A2: Coefficient Estimates from 2SLS Regressions with and without 2003 Level Variables Interacted with Time as Controls

	Controls not included	Controls included	Diff in Coefficient Estimates
$\Delta R_{s,t}$	1.27***	1.24***	0.03
	(0.34)	(0.37)	

Robust standard errors, clustered at state, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The setting of my study offers another option to test for the validity of exclusion restriction assumption. The presence of levels in component is the main concern for the validity of exclusion restriction assumption. If this assumption has to hold, use of a level component from another time period should not yield a significantly different coefficient estimate for the variable of interest. For this study, I can check this using level of internet firms during 2004 and 2005. Table A3 shows these results. As evidenced from this table, the use of different level components in the IV do not lead to statistically significant differences in the coefficient estimate.

The results from Tables A1, A2 and A3 give confidence that the IV used in this study most probably does not violate the exclusion restriction assumption. As has also been discussed above, the coefficient estimates from columns 1 through 3 of Panel B in

Table A3: Coefficient Estimates from 2SLS regression using the IVs Constructed using Number of Internet Advisor Firms from various Base Years

	2003	2004	2005
	$\Delta L_{i,s,t}$	$\Delta L_{i,s,t}$	$\Delta L_{i,s,t}$
$\Delta R_{s,t}$	1.25***	1.34***	1.42***
	(0.29)	(0.30)	(0.32)
Difference		0.09	0.08

Robust standard errors, clustered at state, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 indicate the possibility of no omitted variable bias due to time-varying state level characteristics. This further adds strength to the results on validity of exclusion restriction. Combining these results with the results on relevance of the IV (Panel A in Table 4), I can argue for the validity of the IV used in this study to a reasonable degree.