Deputizing Financial Institutions to Fight Elder Abuse

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Abstract

Permissive laws deputize financial professionals to screen for misbehavior without providing explicit incentives. These are very common in financial markets. To evaluate their effectiveness, we exploit the staggered adoption of the 2016 Model Act provisions intended to curb elder abuse. We find a drop in reports of abuse by financial professionals to the Department of Treasury and, separately, in financial crimes against the elderly as monitored by the FBI. The effect is stronger for high-value crimes and where elderly are isolated. Our results highlight the role financial professionals play in combating social problems and the impact of permissive policies.

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1. Introduction

Regulators frequently deputize financial professionals to help screen for illegal activities, without providing explicit rewards for detection or punitive actions for missing malfeasance. This permissive type of governance is common in the finance industry either because 1) the scale of a problem is so large that it makes rewarding all monitors infeasible, or 2) the misconduct is sufficiently insidious that it is not appropriate to hold the financial professionals culpable for failing to detect crimes. Examples where permissive governance is used include the detection of money laundering, terrorism financing, and fraud (Levinson, 2008).

But, do permissive laws work in the finance industry? In the absence of explicit incentives, carrots or sticks, what is the economic and social value of deputizing professionals to help regulators identify misconduct? To date, little is known about this because large-scale, quasi-natural experiments are rare (Zingales, 2015).

We address these questions in the setting of fighting elder financial abuse. This type of elder exploitation is pervasive and growing. According to the U.S. Department of Treasury, elder abuse involved $21.8 billion in suspicious activity during 2013-2019 (FinCEN, 2019). Likewise, DeLiema et al. (2020) find that 8.7% of older Americans were victims of fraud in the past five years. This issue will only become more important as the elderly population grows from 15.2% to 23.4% of the total population in the next 40 years (Vespa, 2018).

Elder abuse is also pernicious and difficult to police. This is because the perpetrators are often people close to the victim like family members and caregivers. And the losses can be devastating. For example, the average amount stolen by family members amounts to 28% of victims' net worth, excluding their home equity (FinCEN, 2019).

To combat this problem, in 2016 the North American Securities Administrators Association (NASAA) voted to adopt the *NASAA Model Legislation or Regulation to Protect Vulnerable Adults from Financial Exploitation* (hereinafter, "Model Act"). The regulation granted financial professionals two new authorities. First, the new laws granted professionals the power to reach out to a trusted contact to discuss red flags and confirm mental and physical health status. Prior to the Model Act, strict privacy laws impeded this (Berdychowski, 2019). Second, professionals were given the authority to halt disbursements that appear suspicious for financial abuse. However, the designers of the Model Act made it permissive and did not create an obligation for financial professionals to act, either through rewards or punitive actions.

By 2020, thirty states adopted the Model Act provisions. Since state regulators adopted the Model Act in a staggered fashion, we use a dynamic, staggered difference-in-differences (DiD) specification to estimate the effectiveness of financial professionals as monitors in societies (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Baker, Larcker, and Wang, 2021). Our identifying assumption is that states' timing of adoption is independent of factors that might otherwise affect elder financial abuse.

We take a variety of measures to substantiate this assumption. We show that whether and when a state adopts Model Act provisions is unrelated to its previous financial exploitation cases, the size of the elderly population, and other observable characteristics. Our dynamic specification always reports the pre-adoption event-time estimates to gauge whether pre-trends are parallel. We conduct the Goodman-Bacon (2021) and Callaway and Sant'Anna (2021) decompositions to analyze sources of variations that contribute to our estimates.

Using two measures of elder financial exploitation, we find that this permissive policy appears to be effective at reducing financial exploitation of the elderly. The first is the county-level, monthly counts of elder abuse cases from the U.S. Department of Treasury, 80% of which result in an actual financial loss (CFPB, 2019). The second is the state-level, monthly counts of actual crimes against the elderly that were reported by local law-enforcement agencies to the National Incidence-Based Reporting System (NIBRS), which is managed by the Federal Bureau of Investigation (FBI).

We estimate that the Model Act provisions led to a reduction in the monthly number of elder financial abuse cases reported by financial professionals by 3% (7%) of a standard deviation by the first (second) year. We find similar drops using the log number of abuse cases and the per capita number of abuse cases as the outcome as well as when estimating a Poisson model (Cohn et al., 2021). These meaningful magnitudes speak to effects within the set of abuse that go through the hands of financial professionals, rather than the entire universe of elder financial abuse.

The effect is stronger in counties with more deputies per capita, when deputies serve wealthier clients, and for financial abuse more likely to be intermediated by the deputies. Interestingly, brokers appear to be less effective deputies than investment advisers. Furthermore, consistent with social isolation being a leading risk factor for abuse (Podnieks, 1992; Choi et al., 1999; Bernatz et al., 2001), the effect is stronger for socially isolated elderly persons, measured using the Facebook social connectedness index and the number of religious congregations per capita (Alves and Wilson, 2008; Lichtenberg et al., 2013; James et al., 2014; Lichtenberg et al., 2016; DeLiema, 2018).

This drop in reported cases of elder financial exploitation could be due to a few reasons. The new authorities may allow financial professionals to stop abuse faster and earlier, reducing the number of cases reaching the mandatory reporting threshold of $5,000. Additionally, family members and other perpetrators may learn in conversations with advisors or when enrolling in trusted contact systems about the new protections on the account, which alters the perceived riskiness of fraud and deters them from attempting abuse. Relatedly, as the deputies take their role seriously and set up trusted contact systems and procedures for halting disbursements, their actions can act as a deterrent.

Using the crime data reported by local law-enforcement agencies to NIBRS, we find that there was a significant drop in financial crimes against the elderly following the passage of the Model Act. The drop is stronger for higher value crimes. Using this dataset helps us rule out alternative explanations for the drop in reported abuse by financial professionals (our first dependent variable). For example, it might be that the quality of screening improved, which led to a drop in reports. If reaching out to a trusted contact clarified the suspicious case and made reporting by financial institutions unnecessary, this could account for a drop in elder financial abuse reports, absent any change in actual malfeasance. However, this alternative mechanism would not account for the drops we identify in the actual crimes in NIBRS.

Our findings could be driven either by the actions of financial professionals, the deterrence of potential criminals, or both. Consistent with both channels, we find that the drops are non-immediate and build up over time. It takes time for regulators to host information sessions, for financial firms to train their professionals, for financial firms to put systems in place (e.g., getting clients to provide trusted contacts), and for perpetrators to learn about the new safeguards.[1]

Finally, it is possible that the magnitudes of the effects of deputization in this paper underestimate the potential role of deputization in other settings. First, we cannot observe the drop in attempted abuse that exceeds the $5,000 mandatory reporting threshold to the Department of Treasury but is later interrupted. Second, a growing literature documents that some financial professionals engage in frequent misconduct and even prey on the elderly themselves (e.g. Dimmock and Gerken, 2012; Dimmock, Gerken, and Graham, 2018; Charoenwong, Kwan, and Umar, 2019; Egan, Matvos, and Seru, 2019). Thus, it is reasonable to expect that deputies in an industry with less misconduct may be even more effective. Luckily, we find no evidence that financial professionals use their new authorities to abuse the elderly, as there is no evidence of an increase in regulatory actions against advisers. In general, a large literature examines and reveals the misconduct of financial professionals. We are one of the few papers that examine the ability of financial professionals to prevent financial fraud, which represents an important contribution of finance to society.

2. Background

2.1. Elder Financial Exploitation

Elder financial exploitation, or elder financial abuse, is defined by the U.S. Government Accountability Office as the "illegal or improper use of an older adult's funds, property, or assets" (GAO, 2011). Such exploitation is pervasive and economically costly. According to the U.S. Department of Treasury, between October 2013 and August 2019, reports of elder financial exploitation submitted by financial professionals involved $21.8 billion in suspicious activity (FinCEN, 2019). This issue will likely become more prevalent as the elderly population grows in the next 40 years

[1]If professionals did not take this role seriously, rational perpetrators would learn this and the laws would have no cumulative and persistent deterrent effect. Anecdotal evidence, however, does suggest that financial professionals do participate. For example, the head of Alabama's securities division informed us that nine out of ten cases are handled by reaching out to a trusted contact and using the ability to halt a disbursement as a last resort.

(Vespa, 2018).

Why are the elderly particularly vulnerable to financial exploitation? Two interrelated sets of factors are at work. The first set is health-related. The aging process brings about cognitive and physical changes that elevate the risks of financial exploitation. The changes can include cognitive impairment, poor physical health, functional impairment, and dependency on others. According to the Alzheimer's Association, around 15-20% of people 65 years of age or older have Mild Cognitive Impairment (MCI), and about a third of persons with MCI develop dementia within five years (ALZ, 2019).

The second set of factors are related to financial and retirement trends. Americans over the age of 50 currently account for 77% of financial assets in the United States (DOJ, 2018). Their wealth, combined with greater financial autonomy upon retirement brought by a general shift from defined benefit to defined contribution plans, makes them popular targets of financial exploitation.

Elder financial exploitation can be divided into three broad categories: scams by strangers, scams by professionals, and exploitation by family members and trusted others. Typical scams by strangers include lottery scams, "grandparent" scams (for example, an older adult is called and told that his or her grandson is in jail and needs money immediately), and charity scams (i.e. falsely soliciting funds for good causes). Scams by professionals include predatory lending, annuity schemes, Medicare scams, and identity theft (e.g. fraudulently opening a credit card in an elder person's name). Common ways family members exploit older adults include stealing checks, exploiting joint bank accounts, withholding assets from needed care and medical services, and threatening to abandon or harm unless the older person transfers money.

The Consumer Financial Protection Bureau's (CFPB) analysis of a random sample of 1,051 elder financial exploitation cases revealed that 51% are perpetrated by strangers, 36% by family members, 25% by caregivers, and 7% by fiduciaries (the percentages add up to more than 100% because reports of elder financial exploitation may indicate multiple types of suspects) (CFPB, 2019). Both the probability and the amount of the losses are substantially higher when the perpetrator is a known person ($50,200) rather than a stranger ($17,000). In 7% of cases, the loss exceeded $100,000.

These magnitudes are meaningful for most retirees in the United States. In addition, several studies examine elder abuse cases across different demographic groups and find mixed results. DeLiema et al. (2012) find that low-income Hispanic immigrants are disproportionally victimized, whereas DeLiema et al. (2020) do not find higher incidence of abuse against females or Hispanics.

2.2. Financial Professionals

The financial professionals deputized in our setting include a broad set of agents, including money managers, retirement planners, brokers, and investment advisers. As we describe in Section 3, five states expressly deputized *all* types of financial professionals (Delaware, Kentucky, Texas, Virginia, and Washington), while other states primarily deputized brokers and investment advisers, who provide a wide variety of services. Brokers and advisers constitute 9.1% of total employment of the finance and insurance sector, and SEC-registered investment advisers manage about 25% of global wealth.[2]

About 85% of investment adviser representatives are also registered as brokers. The reverse is not true—only about 50% of broker representatives are dual-registered as investment advisers. Both broker-dealers and investment advisers could be employees of large financial institutions, such as bank holding companies. Below we provide a more detailed description of these deputies.

2.2.1. Investment Advisers

In the United States, firms known as registered-investment advisers (RIAs) employ investment-adviser representatives (IARs), who engage in the business of advising about securities, managing clients' wealth, and constructing personalized financial plans. These plans may include not only investments but also savings, budget, insurance, and tax strategies. RIAs may be standalone

[2] According to sources in Bureau of Labor Statistics, Investment Adviser Public Disclosure (IAPD), and BrokerCheck, in 2016, there were 350,731 unique advisers and 701,181 unique brokers. Approximately 85% of advisers are dual-registered as brokers (298,181). The entire finance industry employed 8,203,000 individuals, so that advisers and brokers make up (350,731+701,181-298,181)/8,203,000 = 9.5% of the finance industry. In addition, as of 2014, investment adviser firms registered with the SEC reported managing approximately $61.9 trillion in assets for their clients, and total global wealth in 2014 is estimated to be $251 trillion. See https://www.govinfo.gov/content/pkg/FR-2015-09-01/pdf/2015-21318.pdf and https://onlinelibrary.wiley.com/doi/full/10.1111/roiw.12318.

firms or divisions of larger financial institutions, such as bank holding companies (e.g. Morgan Stanley Wealth Management managed $735 billion in assets in 2017 per its Form ADV). The SEC regulates investment advisers. RIAs and IARs have a fiduciary duty to their clients, requiring advisers to put their clients' interests first. Clients include individuals, high-net-worth persons, pooled-investment vehicles (e.g., hedge funds, and mutual funds), pension funds, and governments. Common names for investment advisers include asset managers, investment counselors, investment managers, portfolio managers, and wealth managers.

2.2.2. Broker-dealers

FINRA oversees broker-dealers, which employ brokers. The Securities Exchange Act of 1934 defines a broker-dealer as any "company engaged in the business of buying and selling securities on behalf of its clients, for its own account (as dealer), or both." Broker-dealers may be standalone securities firms or divisions of larger financial institutions, such as bank holding companies. Broker-dealers typically charge commissions and product fees, whereas registered investment advisers charge fees based on assets under management (AUM). Also, brokers are held to a weaker "suitability standard," which requires a broker to take into account a client's financial situation and investment needs but does not require that they put the client's interests before their own. Conflicts of interest are potentially higher for brokers than advisers.

3. Legislation Protecting Elders

There are two regulatory changes that similarly granted financial professionals serving an elderly client the authority to reach out to trusted contacts and if needed, the power to halt disbursements of funds. Both regulations are permissive (not requiring participation) rather than mandatory, and do not provide explicit incentives. Before these rules were passed, professionals were already required to report suspicious disbursements to the U.S. Treasury. But, because monies were often hard to recover during investigations, simple reporting did little to limit financial loss.[3] The two rules

[3]See interview with Michael Pieciak (Deputy Commissioner, Vermont Securities Division, NASAA) during the SEC Meeting of the Advisory Committee on Small and Emerging Companies.

vary in the types of financial professionals covered and certain other terms of implementation. We summarize these differences in Table 1 and in detail below.

[Insert Table 1 Here]

3.1. The Model Act

The Model Act originated as an initiative of the NASAA's Committee on Senior Issues and Diminished Capacity. On September 29, 2015, a draft of the Model Act was released for a 30-day public comment period. On January 22, 2016, NASAA members voted to approve the Model Act. By the end of 2020, 30 states had adopted provisions similar to the Model Act in a staggered fashion.

The NASAA Model Act applies to both broker-dealers and registered investment advisers, including certain qualified employees (e.g. broker-dealer agents, investment adviser representatives, and persons serving in a supervisory, compliance, or legal capacity for a broker-dealer or investment adviser). The key provisions enhancing the ability of these financial professionals to protect the elderly are the authority to reach out to a specified trusted contact and the authority to delay disbursements of funds.

Prior to the Model Act, strict privacy laws impeded advisers' efforts to consult with trusted contacts of their clients in suspicious cases (Berdychowski, 2019). Now, professionals may make statements like "staff have reason to believe that the account holder may be the current target of a scam — you might want to speak to the account holder to see if he or she will give details to aid you in providing helpful advice" (NAFCU, 2020). The trusted contact authority is distinct from a power of attorney, which requires elderly to cede control over their finances. Because the deputizing policies are permissive, there is also never any obligation for the financial professionals to reach out to a trusted contact even after the rule (for example, if the financial professional believes the trusted contact to be the perpetrator).

Broker-dealers and investment advisers may delay disbursement of funds from a senior's account for up to 15-25 days if they reasonably believe that such disbursement will result in the financial exploitation of the senior. The broker-dealer or investment adviser halting the disbursement must direct that the funds be held in temporary escrow pending resolution of the disbursement decision. If a disbursement is delayed, the broker-dealer or investment adviser must initiate an internal investigation of the suspect disbursement and provide the results of such investigation to the state securities administrator and Adult Protection Services (APS) agencies. At the discretion of the state securities regulator or APS agencies, the broker-dealer or investment adviser may extend the delay for an additional 10 days if necessary. The ability to delay a disbursement of funds allows for an investigation to occur prior to any loss of funds due to exploitation. The head of Alabama's securities division informed us that nine out of ten cases are handled by reaching out to a trusted contact and using the ability to halt a disbursement as a deterrent.

We identify state-level acts, laws, statutes, and regulations that are based on the Model Act or contain similar provisions to the Model Act across U.S. states. For each state, we obtain the name of the relevant legislation or regulations, the passage date, and the effective date from the state's legislature website. Figure 1 shows graphically the staggered adoption of the Model Act or similar provisions across U.S. states.

[Insert Figure 1 Here]

As shown in Table 2, as of December 2020, twenty-seven states have enacted legislation that contains many of the provisions found in the Model Act between 2016 and 2020. Prior to the passage of the Model Act in 2016, three additional states—Delaware, Missouri, and Washington—already enacted laws that contain provisions similar to the Model Act. Thus, there are thirty states with provisions similar to the Model Act.

[Insert Table 2 Here]

Although state-level legislation was often inspired and guided by the Model Act, states exercised autonomy in determining the exact scope of the legislation. For example, although the majority of the states adopting the Model Act enacted regulations that applied to broker-dealers and investment advisers, five states expanded the scope to include all financial institutions (DE, KY, TX, VA, and WA) and two states limited the scope to include only broker-dealers (MO and RI).

3.2. FINRA Rules 2165 and 4512

State regulation of broker-dealers exists in parallel with regulations of FINRA, a federally-sanctioned self-regulatory organization. In February 2017, FINRA proposed new FINRA Rule 2165, "Financial Exploitation of Specified Adults", and amendments to FINRA Rule 4512, "Customer Account Information". The Securities and Exchange Commission (SEC) approved them both in March 2017. The new rules became effective on February 5, 2018.

The amendments to FINRA Rule 4512 require broker-dealers to make reasonable efforts to implement a "trusted contact" system. FINRA Rule 2165 allows broker-dealers to place temporary holds on disbursements of funds or securities from a senior customer's account when there is a reasonable belief that financial exploitation is taking place. The latter rule is permissive rather than mandatory. As FINRA states in its regulatory notice: "The rule creates no obligation to withhold a disbursement of funds or securities in [suspicious] circumstances." Upon placing a hold, FINRA Rule 2165 requires the broker-dealer to immediately initiate an internal review of the facts and circumstances.

To summarize, the essence of the FINRA Rules 2165 and 4512 is similar to that of the Model Act, but FINRA Rules 2165 and 4512 only apply to brokers as opposed to a broader range of financial professionals and are implemented nationally.

4. Data and Sample

4.1. Financial Crimes Enforcement Network (FinCEN)

We obtained data on elder financial exploitation from the Suspicious Activity Reports maintained by the U.S. Department of Treasury's Financial Crimes Enforcement Network (FinCEN). As established by the federal Bank Secrecy Act of 1970, financial institutions including banks, money service businesses, and insurance companies must file Suspicious Activity Reports with FinCEN if they know or suspect that a transaction has no apparent lawful purpose or is not the sort in which the particular customer would normally be expected to engage. Violations of Bank Secrecy Act provisions can result in criminal penalties. Apart from these mandated institutions, as of December 2002, rule 31 CFR § 1023.320 also requires reporting by standalone broker-dealer firms (not a subsidiary of any bank holding companies, which are required to report already). In 2015, it was proposed that standalone investment advisery firms also become mandatory reporters to FinCEN, but the rules were never adopted. However, approximately 85% of investment advisers are dual-registered as brokers and are thus already required to report. Additionally, advisers largely work for or with financial institutions that are already subject to such reporting requirements. For example, advisers may work in a division of a bank holding company, execute trades through broker-dealers to purchase or sell client securities, and direct custodial banks to transfer assets. Important to our empirical design, these reporting requirements to FinCEN by financial professional did not change with a state's adoption of the Model Act or with FINRA's adoption of Rules 2165 and 4512.

In April 2012, FinCEN introduced electronic suspicious activity reporting with a designated category for "elder financial exploitation." We collect the total number of reported cases in a county in a month. The count is broken down by the type of reporting institution and the financial product involved (e.g. fund transfer). Reports are tied to the county in which the victim resides.[4]

Figure 2 shows the trend in reported abuse. Because there is a large increase in total reports of elder abuse in the months immediately following the reporting category's introduction in 2012, we start the sample in January 2014 (as indicated by the red vertical line).

[Insert Figure 2 Here]

We show that time fixed effects address the remaining aggregate increase in reports after 2014. In Figure 3, we remove the national trend in reported abuse and plot the remaining trend across states till June 2016, which is just before the Model Act becomes effective in the earliest adopting states. We find no differential remaining trends for any states.

[4] According to FinCEN, counties are defined by zip codes as provided by the filing institution indicating where the suspicious activity occurred.

[Insert Figure 3 Here]

Our results are robust to varying the sample start year or sample end year (Internet Appendix Table A7 and A8). In our main specifications, we also estimate and control for county-level linear pre-trends. However, this common robustness test is ultimately not important for our results, as Internet Appendix Figure A2 repeats Figure 3 without controlling for linear trends, and again shows no evidence of linear pre-trends.[5] Finally, Internet Appendix Table A6 finds no evidence that the growth in reporting at the state-level between 2012 and 2016 is correlated with when states adopt the Model Act provisions.

Reporting suspicious activity is mandatory when a suspicious transaction involves at least $5,000 in funds or assets. If such a suspicious disbursement is attempted or occurs, then it must be reported. The rule changes we examine provide financial professionals with new tools to deter attempted abuse. Reports would fall if abuse is interrupted earlier, before reaching the $5,000 reporting threshold. Family members could learn in conversations with advisers or from mailed informationals about the new protections on the account, which deters them from attempting abuse. Strangers (like robo scammers or Nigerian scammers) may learn that deputies make it more difficult to get an elderly person to disburse funds, and therefore the deputization may have a deterrent effect.

4.2. National Incident-Based Reporting System (NIBRS)

In addition to the FinCEN database, which contains suspicious elder financial abuse cases reported by financial institutions, we also use data from the National Incident-Based Reporting System (NIBRS) to corroborate our findings (Kaplan, 2022). NIBRS is a crime reporting system maintained by the Federal Bureau of Investigation (FBI), and it is used by local, state, and federal law enforcement agencies to report crimes in the United States. For example, in 2013, there were 6,328 participating law enforcement agencies in the US and the agencies cover about one-third

[5] The level differences in Internet Appendix Figure A2 are a result of states being difference sizes. The linear pretrends remove these level differences, centering states at 0.

of US total population.[6] We downloaded the victim and property data for each financial crime that occurred against an elderly person (age above 65) for the years 2010-2020. We only analyze incidences in which we can identify that the actual monetary loss is above zero. The data include the date of the crime, as well as the state in which it occurred. From NIBRS, we also downloaded data on financial crimes against individuals between 50 and 64 years of age, and use them as a control group. Internet Appendix Figure A1 shows the nationwide trend in financial crimes against the elderly. As in Figure 2, which shows trends in reports to the U.S. Treasury by financial professionals, there is also a general increase in financial crimes against the elderly in the NIBRS database.

4.3. Investment Advisers and Brokers

Because the Model Act deputizes investment advisers, we obtain individual-level data on investment adviser representatives from the SEC's Investment Adviser Public Disclosure (IAPD) database. Representatives are required to file Form U4 with the IAPD annually or when there are material changes. The data is survivorship-bias free for at least the past ten years. The data include the firm an adviser works for, the branch office the adviser works in (city, state), and the dates an adviser worked at that branch. Full employment and registration histories are available. Thus, these data allow us to calculate a time series of the per capita number of investment advisers in a county. We also have the date, resolution, and a detailed description of any regulatory action taken against an adviser.

We also obtain data on registered investment adviser (RIA) firms through a Freedom of Information Act filed with the SEC. RIAs are required to file Form ADV annually, which records information such as firm ownership structure, total asset under management, number of employees, clientele composition (individual vs. institution), locations, conflicts of interests, and a variety of disclosures such as customer complaints and regulatory actions.

Because FINRA's rule change and the Model Act both empower broker-dealers and broker

[6] https://ucr.fbi.gov/nibrs/2013/resources/nibrs-participation-by-state.

representatives, we gathered similar data from the BrokerCheck database that we gathered for investment advisers from the IAPD. We again have the ability to know which firm a broker works for, what branch the broker works in, and for what dates the broker worked there.

Both the IAPD and BrokerCheck are managed by FINRA and thus use the same identifiers for individuals. We can therefore observe which investment adviser representatives are dual-registered as brokers.

4.4. Social Connectedness Measures

4.4.1. Facebook Social Connectedness Index

We use a new dataset from Facebook to measure the strength of social ties in a county. The Social Connectedness Index is constructed using aggregated and anonymized information from the universe of friendship links between all Facebook users as of April 2016 (Bailey et al., 2018). The Social Connectedness Index between two locations i and j is defined as:

$$Social\ Connectedness_{i,j} = \frac{Facebook\ Connections_{i,j}}{Facebook\ Users_i \times Facebook\ Users_j} \tag{1}$$

Here, $Facebook\ Users_i$ and $Facebook\ Users_j$ are the number of Facebook users in locations i and j, and $Facebook\ Connections_{i,j}$ is the number of Facebook friendship connections between users in the two locations. $Social\ Connectedness_{i,j}$, thus, measures the relative probability of a Facebook friendship link between a given user in location i and a given user in location j. When i is equal to j, this index measures the social connectedness within a county. Locations are assigned to users based on not only public profile information (such as the stated city), but also device and connection information. Only friendship links among Facebook users who have interacted with Facebook over the prior 30 days are considered.

Facebook usage rates are high in the United States. Even among adults that are 65 years of age or older, the average usage rate is about 56% (Bailey et al., 2018). For younger adults, the usage rate is 87% on average.

4.4.2. U.S. Religion Census

We use data from the 2010 U.S. Religion Census to measure the number of religious congregations and religious adherents in each county. These proxies for religiosity are standard in the literature (e.g. Hout and Greeley, 1998; Grullon et al., 2009). Every decade, the Association of Statisticians of American Religious Bodies (ASARB) compiles data from national surveys on religious affiliation in the United States. Based on the results from these surveys, the ASARB prepares the "U.S. Religion Census: Religious Congregations and Membership Study", which reports county-by-county data on the number of congregations and total adherents by religious affiliation. A congregation is generally defined as a group of people who meet regularly (typically weekly or monthly) at a preannounced time and location. Congregations may be churches, mosques, temples, or other meeting places. Adherents include all people with an affiliation to a congregation, such as children, members, and attendees who are not members.

4.4.3. Social Capital Index

We obtained county-level Social Capital Composite Index developed by the Social Capital Project from the U.S. Joint Economic Committee. This index captures information on volunteering, public meeting attendance, non-profit organization participation, and more. This composite index is constructed from four sub-indexes at the county level: a family unity subindex, a community health subinex, a institutional health subindex, and a collective efficacy subindex. We use a version of this index released in April 11, 2018.[7]

4.5. Control Variables

We use data on counties from the U.S. Census Bureau as control variables. These data include the number of persons 65 years of age or older. These data also provide the gender makeup, ethnic composition, average retirement income, and total income for individuals 65 years of age or older.

We also use data from a major credit bureau, Experian, that tracts a random sample of 1% of adults. For individuals in a county 65 years of age or older, we determine the average credit

[7] The data is downloaded here: https://www.lee.senate.gov/scp-index.

score, fraction subprime, fraction low income, average age, fraction married, and household debt-to-income ratio.

4.6. Summary Statistics

Our sample includes monthly observations for 3,139 counties from January 2014 to December 2020, resulting in 263,676 total county-month observations. Our dynamic DiD regressions keep observations four years before and after the month of treatment for treated counties so that our tables generally show 245,169 county-month observations.

Table 3 presents summary statistics for the counties in our sample. The average number of reported senior financial exploitation cases in a county-month is 1.3, with a standard deviation of 4.1. Because aggregate reports of elder abuse are increasing during our sample period (see Section 4.1 for a discussion), by the end of our sample, the average number of cases in a county-month is 2.4, with a standard deviation of 5.9. Approximately 80% of county-months have zero reported cases.[8] The 99th percentile of reported senior financial fraud in a county-month is 29. The per capita number of abuse cases is on average 6.4 per 100,000 persons 65 years of age or older, and the 90th percentile is 16.9 cases per 100,000 elderly persons. This rate of elder financial exploitation is similar to the rate of gun deaths, and twenty times more frequent than voter fraud.[9] We winsorize these variables at the 1^{st} and 99^{th} percentile in all OLS specifications to reduce skewness and alleviate the influence of outliers.

[Insert Table 3 Here]

In terms of access to financial professionals, the average number of investment advisers (brokers) per 1,000 individuals is 0.5 (0.8). There is a large distribution in access to financial professionals as the standard deviations of these variables are at least twice as large as their means.

[8]We show our results hold in a state-month panel with essentially no state-months with zero reported cases.

[9]The rate of gun deaths in the U.S. in 2017 was 12 per 100,000 people, the highest rate since the 1990s. See https://worldpopulationreview.com/state-rankings/gun-deaths-per-capita-by-state. A Brennan Center for Justice report pegs the rate at 0.0003%. The equivalent measure of elder financial exploitation is 0.0064% (6.4/100,000 × 100), or ten times more frequent. See https://www.brennancenter.org/sites/default/files/2019-08/Report_Truth-About-Voter-Fraud.pdf

In an average county, roughly 18% of the population is 65 years of age or older. This statistic varies substantially across counties as the standard deviation is 4.6%. In terms of the economic conditions, the counties average about ninety-thousand dollars in household income and about twenty-two thousand dollars in retirement income. The average credit score is about 725. About 19% of the elderly population is subprime on average (credit score below 660) and have an average debt-to-income ratio of approximately 6.5%.

Table 3 Panel B breaks out the county-month abuse cases by the product or instrument involved, regulator overseeing the reporting financial institution, and the industry of the reporting financial institution. About 24% of elder financial exploitation reports involve fund transfers, which are directly targeted by one of the Model Act's new authorities: disrupting suspicious disbursements of funds. About 10% of abuse involves credit cards, which are less likely to involve investment advisers and brokers. About 72% of reports are made by depository institutions, which include bank holding companies that employ brokers and advisers. About 26% of reports are from money services businesses, which tend to not employ broker or advisers. Only 1.5% of reports are from pure broker-dealers, likely because major broker-dealers are housed within bank holding companies.

Table 3 Panel C provides summary statistics for the NIBRS crime data reported by local law enforcement agencies. The sample only includes financial crimes involving a non-zero amount of money that is lost. There are about 51 cases on average against persons above 65 years of age in a state-month. The standard deviation in case counts is 60 cases per state-month. Counts range at the 10th percentile from 5 cases per state-month to the 90th percentile being 144 cases per state-month. We also break down the number of cases when the monetary loss exceeds the median loss of $700.

5. Results

5.1. Empirical Specification

We employ a generalized difference-in-differences (DiD) approach. This approach exploits the staggered passage of regulations across states empowering financial professionals to reach out to trusted contacts and to halt suspicious disbursements of funds from the accounts of the elderly.

More specifically, in our main specifications, we exploit differences across states in the timing of passage of the NASAA Model Act. Table 2 and Figure 1 show variations in the treatment dates across states. Later, we also examine the Model Act's interaction with FINRA Rules 2165 and 4512, which are directed at brokers only and apply nationally.

We estimate models of the following two forms:

$$OUTCOME_{ct} = \alpha + \beta POST_{st} + \gamma' \mathbf{X}_{ct} + \eta_c + \eta_t + \epsilon_{ct} \tag{2}$$

and

$$OUTCOME_{ct} = \alpha + \beta_h \mathbb{1}(t - \text{Treatment Date}_s = h) + \gamma' \mathbf{X}_{ct} + \eta_c + \eta_t + \epsilon_{ct} \tag{3}$$

Here, we index county by c, state by s, and month by t. In Equation 2, $POST_{st}$ is an indicator variable that equals to one in the month the Model Act goes into effect in a state, permitting financial professionals to reach out to trusted contacts and halt suspicious disbursements. The β on $POST_{st}$ measures the static effect of deputization. $\mathbf{X}_{ct}$ denotes a vector of time-varying county demographic and economic characteristics, such as the number of persons 65 years of age or older in a county. The controls are measured for the elderly persons in a county and detailed in Footnote 10.[10] We confirm that these time-varying controls are not "bad controls" by showing that our main results are similar excluding these controls in Internet Appendix Table A2. We include county fixed effects, denoted by η_c, to absorb any unobserved persistent county characteristics. We also

[10]Here is the list of county-year controls and reasoning:

1. "Log Pop Above 65", captures the size of the elderly population.
2. "Vantage Score", captures the general financial health. A higher score may suggest a wealthier base of elderly to exploit.
3. "Fraction Married", captures the extent to which the elderly are socially isolated.
4. "Fraction of Subprime", indicates the amount of assets available to exploit.
5. "Fraction of Low Income", indicates the amount of assets available to exploit.
6. "Average Age", may be correlated with the degree of cognitive impairment in that county.
7. "Male", DeLiema et al. (2020) finds females more subject.
8. "Household income", may indicate the amount of financial resources available to exploit.
9. "Household Debt-to-Income", may indicate the amount of available funds to exploit.
10. "Bachelor or Higher", may indicate the educational attainment of the elderly and the family members.

include year-month fixed effects, denoted by η_t, to account for nationwide trends, such as the general increase in reports of elder financial exploitation during our sample period (see Figure 2 and the related discussion in Section 4.1). For additional robustness, we also estimate and control for county-level linear trends in elder abuse, estimated during the pretreatment period and projected forward through the treatment period per Goodman-Bacon (2021). We cluster standard errors at the state level because Bertrand et al. (2004) recommends clustering at the state level in DiD models with state-level treatment to account for serial-correlation. Bertrand et al. (2004) writes, "This technique works well when the number of groups is large (e.g., 50 states) but fares more poorly as the number of groups gets small." Our sample covers all 50 states and the District of Columbia.

In Equation 3, we show the dynamics of the DiD coefficients as Goodman-Bacon (2021) cautions against only relying on a "single coefficient two-way fixed effects specification to summarize time-varying effects." h is the event time, which is only defined for states treated by December 2020. We estimate these dynamics for the four years before and after the month the policy becomes effective in a state. For compactness in the presentation of our regression tables, when estimating Equation 3, we estimate the effect for the semi-annual (six-month) intervals before and after the month a state adopts the Model Act. In addition, as in Callaway and Sant'Anna (2021), we omit the indicator immediately before a state adopts the Model Act.

5.2. Main Effects

We find that deputizing financial professionals appears to be effective at deterring financial exploitation of the elderly. Table 5 shows the results. In columns (1) to (3), the outcome variable is the count of elder financial exploitation in a county-month. Column (1) shows that the static effect is a 0.186 drop in the number of abuse cases per county-month, which represents 4.5% (0.186/4.1) of a standard deviation in abuse and 14.3% (0.186/1.3) of the mean. These magnitudes speaks to effects within the set of abuse that goes through the hands of financial professionals, rather than the entire universe of elder financial abuse.

[Insert Table 5 Here]

Table 5 Column (2) shows the dynamic effect. At the first (second) year following treatment, the decline in abuse is 0.115 (0.296) cases per county month, which is about 3% (7%) of a standard deviation and 9% (23%) of the mean. Because we are examining count data, in Column (3), we also examine whether the results hold using a Poisson specification as advised in Cohn et al. (2021). We see a similar decline in elder abuse over time. Column (4) shows a decline when we change the outcome to the natural log of one plus the number of abuse cases to reduce any skewness in the count data. Column (5) also shows a decline when we change the outcome to the number of elder financial exploitation cases per capita (per 100,000 persons 65 years of age or older). We also find similar and often more significant results when we repeat these same specifications on the subset of abuse involving fund transfers (see Columns (6) to (10)). Abuse involving fund transfers may be more directly affected by the policy because fund transfers are more likely to involve a deputized financial professional and one of the new authorities is meant to interrupt suspicious disbursements.

To help visualize the results in Table 5, we plot the coefficients of the dynamic specifications in Figure 4. The plots make clear that there is no evidence that treated and control counties have different trends in abuse prior to treatment across a variety of specifications of the outcome variable (e.g., count, log, or per capita). Also, the plots show that the effect of the policy is increasing over time. While we show the dynamics four years after treatment, it is more appropriate to focus on the more immediate effects because the number of treated states used to estimate the effect farther out from treatment is much smaller. As such, the standard errors of the estimated effects farther out from treatment are meaningfully larger.

[Insert Figure 4 Here]

The effect may be non-immediate for a few reasons. First, it takes time for regulators to spread the word through information sessions, for financial firms to develop protocols for implementation, and for firms to provide training. State securities divisions have been organizing seminars for financial professionals to inform them about the rule change. For example, in 2019, Colorado's securities division held 14 industry facing events using both webinars and in-person presentations. These events are targeted to front line financial professionals who have regular contact with clients.

Likewise, Michigan's Corporations, Securities and Commercial Licensing Bureau also held two outreach seminars during 2018. The seminars had the primary goal of introducing investment advisers and broker-dealers to the new rules, discussing how these rules would affect their businesses, and how to handle suspected elder abuse within their client base. See the NASAA 2019 and 2020 Investment Adviser Section Report for more details. Additionally, the deterrence effect of allowing financial professionals to reach out to trusted contacts and to halt transactions may take time to become known among the perpetrators.

Because we find that the treatment effect is increasing over time, this trend is less consistent with the possibility that the policy created an empty threat and deputies did not act at all. In that case, we would likely observe an initial temporary decline caused by the threat of the new regulations, and a subsequent reversal when rational perpetrators would soon learn that financial professionals are not performing as deputies. Instead, we find that the treatment effect persists and increases over time.

5.3. Main Effects, Using Crime Data from NIBRS

We evaluate changes in not only suspicious elder abuse cases reported by financial institutions, but also actual criminal activities reported by local law enforcement agencies against the elderly that resulted in financial losses. We leverage the detailed age information about victims in NIBRS and compare changes in criminal activities against individuals between 50 and 64 years old and against individuals 65 years old and above. Specifically, we estimate equations of the following form:

$$OUTCOME_{sat} = \alpha + \beta_h \mathbb{1}(t - \text{Treatment Date}_s = h)\mathbb{1}(Age \geq 65) + \eta_s t + \eta_s a + \eta_a t + \epsilon_{sat} \quad (4)$$

Here, we index state by s, age group (above 65, or between 50 and 64) by a, and month by t. We include state-by-month fixed effects so that we are comparing incidences in a given state in a given month across groups of individuals above and below 65. We also include state-by-age group fixed effects to control for level differences in incidences, and age group-by-month fixed effects to control for national trend in incidences across age groups.

Figure 5 shows a drop in monetary crimes against the elderly, and this effect builds up over time as in Figure 4. Prior to the rule change, there is no evidence of differences in crimes against those persons above 65 and those persons 50 to 64 years of age in a state-month.

[Insert Figure 5 Here]

Table 6 Columns (1) and (2) show drops in crimes against the elderly. The estimated decline in crimes in Column (1) at the first (second) year following treatment is about 3.3% (6.1%) of a standard deviation, or 3.9% (7.2%) of a mean. These magnitudes relative to the mean are smaller than the drop in reports to the Treasury but still economically meaningful. The difference in magnitudes could be due to differences in the types of data. For example, the NIBRS data include actual crimes instead of suspicious activities, involve monetary losses, and does not have a reporting threshold requirement.

Table 6 Columns (3) and (4) provide evidence that the drop is stronger for crimes involving larger monetary amounts. Crimes involving larger amounts are more likely to be intermediated by financial professionals and thus benefit from expanding the authorities of the financial professionals. Specifically, in Columns (3) and (4), we separately estimate equation 4 for crimes involving above and below median financial losses (about $700). The effects are substantially higher for larger value crimes, which are more likely to involve an adviser or a broker.

These findings corroborate our main results and help us rule out alternative explanations related to reporting changes. For example, reaching out to a trusted contact may clarify the suspicion, making a report unnecessary. This could account for a drop in elder financial abuse reports. However, this alternative mechanism would not account for drops in actual crimes in NIBRS.

[Insert Table 6 Here]

5.4. Identification Assumptions and Robustness Tests

The key identifying assumption underlying our empirical strategy is that states' timing of adoption is independent of factors that might otherwise affect elder financial abuse. We take a variety of measures to substantiate this assumption, which are discussed below.

5.4.1. Is policy adoption endogenous?

We explicitly model the policy adoption decisions across states and find that the decision does not seem to be driven by observable state characteristics. In Figure 6, we show graphically that the timing of adoption is unrelated to many key variables, including the rate of elder abuse, the proportion of adults 65 years of age or older, the average income of the elderly, and the population of a state. In Internet Appendix Table A3 Panel A, we confirm this result with regressions and show that adoption timing is unrelated to additional covariates (average credit score, % of elderly who are subprime, % of elderly who are low income, number of elderly, % of elderly who are male, % of elderly who are married, debt-to-income ratio of the elderly, and educational attainment). Overall, there is no strong relation between a variety of state characteristics and *when* a state adopts the Model Act.

[Insert Figure 6 Here]

The exact timing of adoption in a relatively short time window may plausibly be exogenous because of idiosyncratic conventions by state legislators, which meet at different times of the year and set different effective dates for new laws. Also, state legislators in some states may not be able to fully pass a policy by the end of the legislative session in a given year because of unrelated obligations. For instance, in Florida, by September 2019, the bill had passed through Florida's House of Representatives twice, but not Florida's Senate, due to busier than usual legislative sessions (Berdychowski, 2019)

Importantly, as discussed more below, the main variation driving our estimates of the effect comes from comparing treated and never-treated states, so an important consideration is the extensive margin—whether the choice to adopt the policies at all by 2020 is related to variables of interest.

Internet Appendix Table A3 Panel B shows no significant relation between the aforementioned state characteristics and *whether* a state adopts the Model Act provisions by 2020.

5.4.2. Parallel Pre-Trend

Figure 4 shows no unusual changes in elder financial exploitation prior to the rule change, and a noticeable drop only following the rule change. The figure shows evidence of parallel pre-trends using four different specifications. The figure also shows similar evidence using the sub-sample of abuse cases involving fund transfers, which are more targeted by the policy. In Internet Appendix Figure A3, we show similar evidence at the monthly frequency. Figure 5 likewise shows no unusual changes in financial crimes against the elderly in the NIBRS data managed by the FBI prior to the rule change.

5.4.3. Decomposing the Treatment Effects per Goodman-Bacon (2021) and Callaway and Sant'Anna (2021)

To help give more context to the empirical design, we also run the Goodman-Bacon decomposition and analyze the weights underlying our staggered DiD regressions. As Goodman-Bacon (2021) notes, the two-way fixed-effect estimator is a weighted average of all potential 2×2 DiD estimates, where the weights are determined by both the size of the treated group and the timing of the treatment. In running the decomposition, we open the black box of the two-way fixed-effect estimator and dig deeper into the comparisons that contribute to the coefficient in our main table.

Table 7 and Internet Appendix Figure A4 show the results of the decomposition for the static effect estimate in Column (1) of Table 5 of -0.186. Most of the variation used to estimate β results from the cleanest comparison of treated states to never treated states. Specifically, "Treated vs Never Treated", which compares states that adopted the policy at some point during the sample period and those that did not. The average estimate derived from this source of variation is -0.246 and has a weight of 74.4%.

[Insert Table 7 Here]

A heavy weight on the comparison "Treated vs Never Treated" is advantageous, because in the presence of dynamic treatment effects, coefficient estimates could be biased (Goodman-Bacon 2021). For example, comparisons that involve "Early Treated" vs "Later Control" may attenuate the estimated effect, as there could be negative drifts in elder abuse cases for the later treated states after treatment. This drift would bias the coefficient downwards, and the magnitude of the bias depends on the sample period length and the dynamic effects. This reasoning may explain why the effect estimated using these comparisons is only -0.024 cases per county per month. A similar issue arises when comparing the later treated states to all previously treated states ("Later Treated" vs "Earlier Control"). When the states treated earlier in the sample are used as controls for the states treated later in the sample, and to the extent that there are any dynamics in the treatment effects, this will attenuate the estimated coefficient—potentially even flipping the sign of the estimate. Again, this may explain why the effect estimated using these comparisons is positive 0.049 cases per county per month.

Relatedly, we implement the procedure in Callaway and Sant'Anna (2021) to estimate the average treatment effect of the policy in event time using only the never-treated states as control states. Figure 7 shows that for both the total number of elder abuse cases and the number of abuse cases involving fund transfers, there are apparently similar pre-trends between the treated and control states and a divergence after treatment, with abuse cases dropping.

[Insert Figure 7 Here]

That said, Wooldridge highlights that by discarding data, the Callaway and Sant'Anna (2021) procedure is less efficient (Wooldridge, 2021). Also, using only the never-treated states as controls could potentially bring other concerns. For example, they may be fundamentally different from the treated states. We present evidence alleviating this concern: the adoption model estimated in Internet Appendix Table A3 Panel B shows that the adoption decision is uncorrelated with state economic and demographic characteristics. To further mitigate this concern, we perform a matching procedure to ensure that the treated and control counties are observably similar, and repeat our analysis on the matched sample. We discuss this procedure in detail below.

5.4.4. Matched Sample Analysis

We show that the effect is robust to forming matched samples based on counties' pre-treatment characteristics. Matching should ensure that counties achieve covariate balance on observed attributes and hopefully also brings them closer on unobserved dimensions to help reduce the risk of non-parallel trends. While we show parallel *pre*-treatment trends in Figure 4, the parallel trend assumption — that treated and control groups would have experienced parallel changes *post*-treatment — is inherently untestable.

We use the following minimum distance matching procedure: for each county, we calculate its geometric distance to all other counties based on the vector of control covariates in Footnote 10 and elder abuse, all measured as of December 2015.[11] So that each covariate receives an equal weight, we standardize them to have a mean of zero and a standard deviation of one. Next, for each county, we select a pair-county that has the smallest geometric distance, is located in a different state, and receives treatment at a different point in time.

We perform the DiD regressions, including a set of matched-pair fixed effects to ensure that treatment effects are identified from within-pair comparisons. We limit the sample to the 25% of matches with the closest geometric distances. Table 8 Panel A shows that the dynamic estimates using matched county pairs are statistically significant and economically similar to those presented in Table 5 for both total elder abuse cases in a county-month and for abuse involving fund transfers. Table 8 Panel B is a covariate balance table, which shows that paired counties are similar in observable aspects.

[Insert Table 8 Here]

5.4.5. Could changes in reporting drive the results?

The nature of our data is reports of elder financial abuse cases by financial professionals, rather than the entire universe of actual elder financial abuse cases, which is inherently unobservable.

[11]Geometric distance is the square root of the sum of the squares of the differences in covariates between two counties. Mathematically, the geometric distance metric is $d_{ij} = \sqrt{(x_{1i} - x_{1j})^2 + (x_{2i} - x_{2j})^2 + ... + (x_{Ni} - x_{Nj})^2}$, where x_1, x_2, ..., x_N are standardized covariates, and i and j denote counties.

Alleviating concerns about a change in reporting quality by financial professionals is that we find similar results using financial crimes against the elderly that are independently investigated and confirmed by local law enforcement agencies. The latter dataset contains crimes that resulted in actual financial losses for seniors. Nevertheless, in this section, we address in detail several concerns that could arise from differences or changes in reporting.

First, one may worry that general trends in county-month abuse reporting by financial professionals vary for treated counties versus never treated counties for reasons other than the deputization. While we showed that the trends in abuse reporting are identical between these counties prior to treatment, we cannot observe the counterfactual after treatment. However, we can exploit the available breakout of county-month abuse reports by instrument and reporting institution to control for categories that are less likely to be affected by the new rules. Doing so, we are able to control for the aggregate trend in elder abuse at a county-month level, thereby better isolating the effects of the policy. Specifically, Table 9 Column (1) shows that the drop in abuse involving fund transfers is robust to controlling for the number of abuse reports from money services businesses, which do not hire investment advisers and brokers, the primary deputies.[12] Column (2) shows a decline in abuse involving fund transfers after controlling for the county-month number of abuse cases involving credit cards, which are less likely to be under the purview of an adviser or broker.

[Insert Table 9 Here]

Relatedly, we can directly compare abuse categories that should be more and less affected by deputization. Doing so, we find that the results are unique to reports of elder financial exploitation that are more likely to be affected by the policy. Internet Appendix Table A11 shows evidence of a decline in elder abuse reports from depository institutions (bank holding companies) and some evidence of a drop in abuse reports from standalone securities firms (broker-dealer firms) but no such decline in reports from money services businesses. Interestingly, reports from depository institutions and securities firms are primarily related to theft by family members and caregivers,

[12]https://www.fincen.gov/money-services-business-definition.

while reports from money services businesses are primarily related to overseas scams (FinCEN, 2019).

Second, reporting to the FinCEN database by financial professionals is mandated for all transactions that involve more than $5,000, and failure to report could result in criminal penalties for financial institutions. This reporting requirement and the reporting threshold did not change with a state's adoption of the Model Act.

While there is no evidence of underreporting of abuse cases to the FinCEN database, it remains a possibility. Consequently, the frequency and magnitude of elder abuse could be even higher. Any underreporting is unlikely to be a problem for our analysis for a few reasons. First, if underreporting existed, the new rules would have raised awareness about elder abuse and likely decreased such underreporting. This resulting increase in reporting would work against our finding that the new laws decreased elder financial abuse. Second, for underreporting to be a confounding factor for our analysis, the underreporting pattern would have to be correlated with the staggered adoption of the *Model Act* across states or with whether a state adopts Model Act. That is, underreporting would have had to increase when states adopted the *Model Act* to result in our observed drop in elder financial exploitation. This is unlikely since the preexisting reporting requirements to the U.S. Treasury did not change. Third, given the evidence in Table 9, any underreporting would have to be related differentially to fund transfers relative to abuse reported by money services businesses and abuse related to credit cards in the same county-month. Lastly, we also find a drop in financial crimes reported by local law enforcement agencies to the FBI's NIBRS database.

Admittedly, Figure 2 shows that reports of elder financial exploitation have been increasing since 2014. However, Figure 3 shows that we largely remove such aggregate increase in reports from our analysis with time fixed effects. In Figure 3, we plot the state-level elder abuse case trends (up to year 2016, the earliest adoption year of Model Act across states) after removing the aggregate time trend, and there is no remaining pre-trend for any states.

In addition, we use regression analysis to show that the rate by which reporting of elder financial exploitation increased across states during the sample period is not correlated with the timing of adoption of the Model Act. Specifically, in Internet Appendix Table A6, we regress the number of months until a state adopts the Model Act on the state-level growth in reporting from 2012 to 2016. There is no relation.

While there was no concomitant change in the reporting requirements of suspicious activity to FinCEN (our main source of data), some states adopting the Model Act started to mandate reporting to Adult Protective Services (APS) and sharing records with state regulators. Importantly, these changes in reporting requirements are independent of the reporting requirements to FinCEN. Judy Shaw, the president of the NASAA, which designed the Model Act, explained to us that "reporting to APS is separate and in addition to FinCEN requirements. Some of the state APS reporting requirements have been in place for years, some, like Maine, have been put in place as a result of adoption of the NASAA Model Act."

Lastly, there is no drop in suspicious activity reports unrelated to financial exploitation. Internet Appendix Table A10 Columns (1) and (2) show no effect of the policy change on suspicious activity reports related to insider trading and terrorism financing. Hence, it is unlikely that reporting to FinCEN shifted more generally. And, the effect is not driven by one state; Internet Appendix Figure A5 shows that the static effect documented in Table 5 Column (1) is robust to dropping any state. And, we also show that the effects are robust to changing the sample start or end year in Table A7 and Table A8, respectively.

5.4.6. Collapsing at more aggregate levels to reduce sparsity

Because elder abuse at the county-month level is somewhat sparse, with 80% of county-month observations being zero, we collapse the dataset at the state-month level and repeat our DiD analysis. After collapsing the data, only 4% of state-months have zero reports. Despite removing a substantial amount of variation, Internet Appendix Table A5 shows that we also find a significant drop in the state-month number of reports across the same formulations of the outcome variable as in Table 5. In fact, Column (2) shows a significant drop in abuse cases after six months rather than one year. Lastly, the drop in reports of financial crimes from local law enforcement agencies to NIBRS occurs at the state-month level, and that panel has essentially no state-month observations with zero reports.

5.4.7. Confounding regulatory changes

A related regulatory change aimed at protecting seniors is the *Senior Safe Act*. This act became federal law on May 24, 2018. It provides financial institutions with immunity for reporting potential exploitation of a senior citizen to regulators. It does not provide any tools (like the ability to reach out to a trusted contact or halt a suspicious disbursement).

This rule change cannot explain our results because it is a national rule change. Additionally, our results are primarily identified by comparing treated and never-treated counties (see Table 7), which were affected by the *Senior Safe Act* at the same time. In Internet Appendix Table A8, we find similar results when only including sample months prior to 2018. We are unaware of any other confounding events or rule changes that took place simultaneously with the adoption of these policies and that were adopted in a staggered fashion.

5.5. The Presence of Deputies, and the Types of Deputies

The rule change should be more effective in treated counties with a higher concentration of deputies, all else equal, if abuse falls because of their actions. We take advantage of our data from the SEC's IAPD and FINRA's BrokerCheck databases to characterize the heterogeneity in investment advisers and brokers across counties.

We study this question using a triple DiD design, in which we interact $Post_{st}$ with measures of these county attributes. Importantly, we also control for the interaction of $Post_{st}$ with each existing control variable listed in Footnote 10, which reduces the possibility that the interaction of interest is driven by an omitted factor (Yzerbyt et al., 2004). For example, when interacting $Post_{st}$ with the per capita number of advisers in a county, we also interact $Post_{st}$ with the controls related to the number of elderly, the average level of educational attainment, and income. This approach addresses the concern that the per capita number of deputies is correlated with these other county attributes and we are just capturing a larger effect in wealthier counties, for example.

Table 10 presents the results. Consistent with abuse falling because of deputization, Table 10

Columns (1) and (2) show that the drop in elder abuse is greater in counties with more investment adviser representatives per capita and more brokers per capita. The interaction terms are both negative and highly significant. Note that the measures of advisers and brokers per capita are standardized prior to forming the interactions. A standard deviation increase in the presence of deputies per capita predicts about a 0.85 larger decline in abuse cases per month. While the coefficients may suggest that counties with low deputies see an increase in abuse, this interpretation is incorrect. In an alternative specification with an indicator variable that equals one if the county has a high per capita presence of deputies, only the indicator loads negatively. Relatedly, in Internet Appendix Table A13, we show that there is no effect in counties with no deputies.

[Insert Table 10 Here]

The similarity in the coefficients in Table 10 Columns (1) and (2) is expected because there is a high correlation in the per capita number of advisers and brokers across counties. Nevertheless, it is interesting to examine whether the policy is more related to the presence of advisers than to the presence of brokers. Column (3) shows that the relation with brokers per capita is not robust to controlling for the presence of advisers per capita. Specifically, the coefficient on number of brokers per capita is smaller in magnitude (-0.337) relative to that on the number of advisers per capita (-0.578). Also, only the coefficient on the number of advisers per capita is statistically significant. Relatedly, Column (4) shows that the effect is not related to the per capita presence of pure brokers (brokers who are not dual-registered as advisers). Specifically, the coefficient on the number of pure brokers per capita is only -0.183, while the coefficient on the number of advisers per capita (including dual-registered advisers) is -0.75.

With the caveat that our measures of advisers and brokers per capita are highly correlated, this dichotomy in the effect between investment advisers and brokers is consistent with brokers having a more arms-length and transactional relationship with clients than investment advisers.[13] Brokers are more likely to assist with one-off transactions, compensated accordingly with commissions,

[13] See https://www.investor.gov/home/welcome-investor-gov-crs and https://www.sec.gov/rules/interp/2019/ia-5248.pdf.

fixed fees, or hourly compensation. Also, brokers serve more clients—Form ADV data shows that investment advisery firms employing an above the median number of advisers dual registered as brokers service 60% more clients per employee on average in 2015. By contrast, advisers have a fiduciary duty to their clients that requires them to both understand their clients' situations and objectives and to put their client's interests first. Advisers are more likely to provide regular financial planning advice and, thus, are more likely to develop deeper and more intimate relationships with clients, which improves their ability to detect suspicious activity.

Several pieces of additional evidence support the possibility that brokers are less effective deputies for this policy. Internet Appendix Table A4 shows that the drop in elder abuse is not significantly weaker in states that adopt the Model Act after FINRA Rules 2165 and 4512 (the coefficient on the interaction of *Post* and *FINRA Passed* is statistically indistinguishable from zero). Given the similarity in between these FINRA rules and the NASAA Model Act, this finding may be due to the fact that the FINRA legislation is specific to brokers. Also, Internet Appendix Table A11 finds a strong drop in abuse reported by bank holding companies (Column 1) and a less significant drop in abuse reported by pure broker-dealers (Column 3). Broker-dealer firms tend to employ brokers only, and bank holding companies employ both advisers and brokers. We caveat, however, that Table 3 Panel B shows that only 1.5% of abuse reports come from pure broker-dealer firms so that this lack of a significant decline may simply be because there are not enough reports from such firms with which to evaluate the policy. It is important to highlight that large broker-dealers primarily exist within bank holding firms, which make up the bulk of reports. But, since reports are separated out for pure broker-dealers, it may be informative to examine those separately.

An alternative interpretation for the dichotomy in the effect across investment advisers and brokers is that in communities with more advisers, there was more elder financial exploitation and therefore deputization had a larger impact. However, the opposite seems to be the case. Internet Appendix Table A12 Column (3) shows a positive relation between the presence of brokers and elder abuse rates prior to the rule change, while the proportion of investment advisers is negatively related to abuse rates.

In addition to variation in the effect of deputization across types of financial professionals, we also observe differences within the set of investment advisers. Table 11 column (1) shows a larger drop in abuse when investment advisers serve wealthier clients. This may be because those clients provide more fee revenues and because those advisers know their clients better and thus what is suspicious. Alternatively, abuse against wealthier clients is more likely to exceed the $5,000 threshold, above which reporting to FinCEN is mandatory; consequently, a change in abuse because of the policy is more measurable in counties serving wealthier clients. Less consistent with the compensation motive for deputies to take action is the evidence in column (5), which indicates no relation between the decline in abuse and whether advisers in a county tend to charge hourly fees, commissions, or fixed fees for services.[14]

[Insert Table 11 Here]

5.6. Heterogeneous Effects by Existing Safeguards and Social Incentives

This section examines whether the effects of deputization vary with existing protections within social communities. Prior work finds that the risk of fraud increases for emotionally and socially isolated elderly persons (Alves and Wilson, 2008; Lichtenberg et al., 2013; James et al., 2014; Lichtenberg et al., 2016; DeLiema, 2018). For this reason, a client's relationships with others in the community may matter for the effectiveness of the policy. Stronger social ties might suggest that others in the community have offered protection to the elderly ex ante, and therefore deputization could be less effective, because it is less needed. In other words, social connections may serve as a substitute of the new regulation.

Table 12 column (1) shows that the effect of deputization is significantly weaker in more connected counties, measured using the Social Connectedness Index from Facebook that captures

[14] These analyses use data from the Form ADV filed annually by each registered investment adviser firm with the SEC. For each county, we match all individual advisers with their firm's characteristics and then take an average, so that a county's measures are weighted by the number of individual advisers working for a firm (or branch of a firm) operating in that county.

the probability that two members of a county are friends on Facebook. Column (2) also shows that the effect of deputization is weaker in counties with more religious congregations per capita (Lim and Putnam, 2010). A larger number of congregations can foster intimate relationships through frequent interactions and may indicate a higher desire by people in a community to seek meaningful connections.[15] Supporting this assumption, the correlation between our Facebook measure of social connectedness and this measure of congregations per capita exceeds 0.7. (By contrast, the correlation between the Facebook measure and the per capita number of religious adherents is only 0.2.) Note that we control for variation in the effect related to the number of advisers per capita and related to the covariates in Footnote 10 by including interactions of $Post$ with these measures as advised by Yzerbyt et al. (2004). Evidently, more isolated elderly persons benefit marginally more from a policy that strengthens their relationship with their financial professional, whereas more socially-connected elderly persons benefit less.

[Insert Table 12 Here]

In Column (4), we further examine whether the effect varies with the county-level Social Capital Index. This index captures information on volunteering, public meeting attendance, non-profit organization participants per capita, and more. To the extent that social capital describes the set of values or norms shared by members in a community and fosters cooperation, these values, norms, and cooperation should offer protections to seniors ex ante. Our results are consistent with this hypothesis: In areas with a higher social capital index, the effects are weaker.

Another type of safeguard may be a more ethical community. Adam Smith emphasized the influence of religious morality in engendering feelings of guilt or pride as a motivator of proper behavior (Smith, 2010). Though still a question of debate, there is empirical evidence supporting the role of religion in deterring unethical behaviors in economics and finance (e.g. Guiso et al., 2003; Grullon et al., 2009). The weaker effect in areas with more religious congregations per capita

[15] We focus on religious congregations, not other types of organizations, because it is difficult to think of any non-religious organizations in the US that are comparable in scale and scope of membership base (Lim and Putnam, 2010).

could be consistent with that form of protection ex ante. However, column (5) suggests that the effect is more negative when the number of religious adherents per capita is higher.

5.7. Alternative Explanations

While the policies are permissive, financial professionals may perceive them as mandatory because regulators might increase oversight of the industry if financial professionals do not act. In other words, the adoption of the new laws may signal increased regulatory concern with elder financial exploitation and thus the potential for increased oversight and monitoring of advisers and brokers. If this were the case, then we would expect professionals to not only protect the elderly more, but also decrease their other egregious activity. We examine this possibility in Internet Appendix Table A14 by gathering all of the disclosures individual advisers and brokers must make regarding regulatory actions and misconduct. In columns (1) and (2), we do not observe a statistically significant increase in disclosures of regulatory actions taken against advisers and brokers following adoption of the Model Act. If regulators became more active, we would have expected an increase in regulatory actions. Due to data limitations, we conduct these tests on the subsample of advisers that are dual-registered as brokers, which comprise 85% of the entire universe of advisers. This sample restriction should bias our results towards finding supportive evidence for the monitoring hypothesis because Charoenwong et al. (2019) shows that the behavior of brokers is more sensitive to changes in regulatory oversight than the behavior of advisers.

Relatedly, Sunstein (1996) and McAdams (1997) suggest that laws signal societal values to a community, express generally-held beliefs about what is right and wrong, and shape desirable social norms. Hence, deputies may again not perceive the new regulations as permissive but rather mandatory. For example, laws banning smoking signal to smokers a societal consensus that exposing others to smoke is offensive, triggering smokers to refrain from smoking in public places, even in the absence of enforcement. Similarly, we might expect that the laws we study in this paper signal or strengthen a negative societal perception of elder abuse, motivating financial professionals to serve as protectors. This hypothesis would suggest that *both* investment advisers and brokers should similarly engage in halting suspicious transactions and preventing abuse, given that they would be equally exposed to the law-induced change in the perception of abuse. However, this mechanism is unlikely to be the main explanation because Section 5.5 suggests that the policy is more related to investment advisers than to brokers.

Lastly, deputies may act to manage their reputations. However, we find little support for this possible mechanism in the data. Because of strict privacy laws, there is essentially no media coverage of financial professionals disrupting elder abuse. We searched Factiva's news database to analyze the frequency with which the local and national media cover an adviser's or broker's efforts to protect elders from financial exploitation. We searched for articles that include the following set of words: "adviser" or "advisor", "halt" or "delay", and "financial abuse" or "financial exploitation." We find only 67 such articles released during 2015 to 2020 across the United States. This frequency is equivalent to an average of 0.3 articles per state per year. Inspection of these articles reveals that none specifically mention a particular adviser or broker by name. Instead, the articles only include general discussions of the problem of elder financial exploitation or the new regulation. As such, publicizing through the media does not appear to be a way in which individual advisers or brokers manage their reputations about the extent to which they protect elders from financial exploitation. We use various other combinations of texts to identify articles. We present the detailed texts, dates, regions, and timestamps of the searches in the Appendix Table A15. Neither the SEC's IAPD website nor FINRA's BrokerCheck website discloses such information regarding brokers and advisers.

6. Conclusion

While financial professionals are often called upon to monitor for crimes and misbehavior in societies, there is little evidence that financial professionals are effective monitors, and whether this represents an important contribution to societies (Zingales, 2015). The monitoring tasks are so challenging that financial professionals are often not culpable for failing to detect crimes, and the scale of the tasks makes it infeasible for regulators to reward completely the agents who act and to punish those who do not. For these reasons, before implementing the new rules to curb elder financial exploitation, it was unclear whether empowering financial professionals to be monitors would be effective. As is often the case with these permissive policies, the new rules do not include penalties for not participating or monetary incentives for catching abusers, but instead relied on existing social or market mechanisms.

Our results suggest that permissive laws that deputized financial professionals were successful in reducing the abuse of seniors, especially for those who are most socially isolated. Overall, our findings give hope for the use of permissive laws in the future in other venues.

References

Alves, Linda M., and Steve R. Wilson, 2008, The effects of loneliness on telemarketing fraud vulnerability among older adults, Journal of Elder Abuse & Neglect 20, 63–85.

ALZ, 2019, 2019 Alzheimer's disease facts and figures, Technical report, Alzheimer's Association.

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong, 2018, Social connectedness: Measurement, determinants, and effects, Journal of Economic Perspectives 32, 259–80.

Baker, Andrew, David Larcker, and Charles Wang, 2021, How much should we trust staggered difference-in-differences estimates?, Technical report, Working Paper.

Berdychowski, Bernadette, 2019, Advisors may be first to notice elder abuse. Why don't more delay disbursements?, FinancialPlanning .

Bernatz, SI, SJ Aziz, and L. Mosqueda, 2001, Financial abuse, in Mezey MD, ed., The Encyclopedia of Elder Care (Springer Publishing Co).

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, 2004, How much should we trust differences-in-differences estimates?, The Quarterly Journal of Economics 119, 249–275.

Callaway, Brantly, and Pedro H.C. Sant'Anna, 2021, Difference-in-differences with multiple time periods, Journal of Econometrics 225, 200–230.

CFPB, 2019, Suspicious activity reports on elder financial exploitation: Issues and trends, Technical report, Consumer Financial Protection Bureau.

Charoenwong, Ben, Alan Kwan, and Tarik Umar, 2019, Does regulatory jurisdiction affect the quality of investment-adviser regulation?, American Economic Review 109, 3681–3712.

Choi, Namkee G., Deborah B. Kulick, and James Mayer, 1999, Financial exploitation of elders: Analysis of risk factors based on county adult protective services data, Journal of Elder Abuse & Neglect 10, 39–62.

Cohn, Jonathan B., Zack Liu, and Malcolm Wardlaw, 2021, Count data in finance. Working Paper.

DeLiema, Marguerite, 2018, Elder fraud and financial exploitation: Application of routine activity theory, The Gerontologist 58, 706–718.

DeLiema, Marguerite, Martha Deevy, Annamaria Lusardi, and Olivia S Mitchell, 2020, Financial fraud among older americans: Evidence and implications, The Journals of Gerontology: Series B 75, 861–868.

DeLiema, Marguerite, Zachary D. Gassoumis, Diana C. Homeier, and Kathleen H. Wilber, 2012, Determining prevalence and correlates of elder abuse using promotores: Low-income immigrant latinos report high rates of abuse and neglect, Journal of the American Geriatrics Society 60, 1333–1339.

Dimmock, Stephen G, and William C Gerken, 2012, Predicting fraud by investment managers, Journal of Financial Economics 105, 153–173.

Dimmock, Stephen G, William C Gerken, and Nathaniel P Graham, 2018, Is fraud contagious? Coworker influence on misconduct by financial advisors, Journal of Finance 73, 1417–1450.

DOJ, 2018, Resources for financial institutions to prevent and protect against elder financial exploitation, Technical report, Department of Justice.

Egan, Mark, Gregor Matvos, and Amit Seru, 2019, The market for financial adviser misconduct, Journal of Political Economy 127, 233–295.

FinCEN, 2019, Elders face increased financial threat from domestic and foreign actors, Technical report, U.S. Department of Treasury.

GAO, 2011, Stronger federal leadership could enhance national response to elder abuse, Technical report, Government Accountability Office.

Goodman-Bacon, Andrew, 2021, Difference-in-differences with variation in treatment timing, Journal of Econometrics 225, 254–277.

Grullon, Gustavo, George Kanatas, and James Weston, 2009, Religion and corporate (mis)behavior, SSRN 1472118 .

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2003, People's opium? Religion and economic attitudes, Journal of Monetary Economics 50, 225–282.

Hout, Michael, and Andrew Greeley, 1998, What church officials' reports don't show: Another look at church attendance data, American Sociological Review 63, 113–119.

James, Bryan D., Patricia A. Boyle, and David A. Bennett, 2014, Correlates of susceptibility to scams in older adults without dementia, Journal of Elder Abuse & Neglect 26, 107–122.

Kaplan, Jacob, 2022, Jacob kaplan's concatenated files: National incident-based reporting system (nibrs) data, 1991-2020., Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor] Accessed 2022-05-09.

Levinson, Bruce, 2008, Unwarranted deputization: Increased delegation of law enforcement duties to financial institutions undermines American competitiveness, SSRN 2711938 .

Lichtenberg, Peter A., Laurie Stickney, and Daniel Paulson, 2013, Is psychological vulnerability related to the experience of fraud in older adults?, Clinical Gerontologist 36, 132–146.

Lichtenberg, Peter Alexander, Michael A. Sugarman, Daniel Paulson, Lisa J. Ficker, and Annalise Rahman-Filipiak, 2016, Psychological and functional vulnerability predicts fraud cases in older adults: Results of a longitudinal study, Clinical Gerontologist 39, 48–63.

Lim, Chaeyoon, and Robert D Putnam, 2010, Religion, social networks, and life satisfaction, American Sociological Review 75, 914–933.

McAdams, Richard H, 1997, The origin, development, and regulation of norms, Michigan Law Review 96, 338–433.

NAFCU, 2020, Mitigating elder financial abuse risk, Technical report, National Association of Federally-Insured Credit Unions.

Podnieks, Elizabeth, 1992, National survey on abuse of the elderly in canada, Journal of Elder Abuse & Neglect 4, 5–58.

Smith, Adam, 2010, The theory of moral sentiments (Penguin).

Sunstein, Cass R, 1996, On the expressive function of law, University of Pennsylvania Law Review 144, 2021–2053.

Vespa, Jonathan, 2018, The u.s. joins other countries with large aging populations, Technical report, U.S. Census Bureau.

Wooldridge, Jeffrey, 2021, Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators, Working Paper .

Yzerbyt, Vincent Y., Dominique Muller, and Charles M. Judd, 2004, Adjusting researchers' approach to adjustment: On the use of covariates when testing interactions, Journal of Experimental Social Psychology 40, 424 – 431.

Zingales, Luigi, 2015, Presidential address: Does finance benefit society?, The Journal of Finance 70, 1327–1363.

Figure 1. Staggered Adoption of the Model Act Across States

The map shows the staggered adoption of the Model Act across states through December 2020 as listed in Table 1.

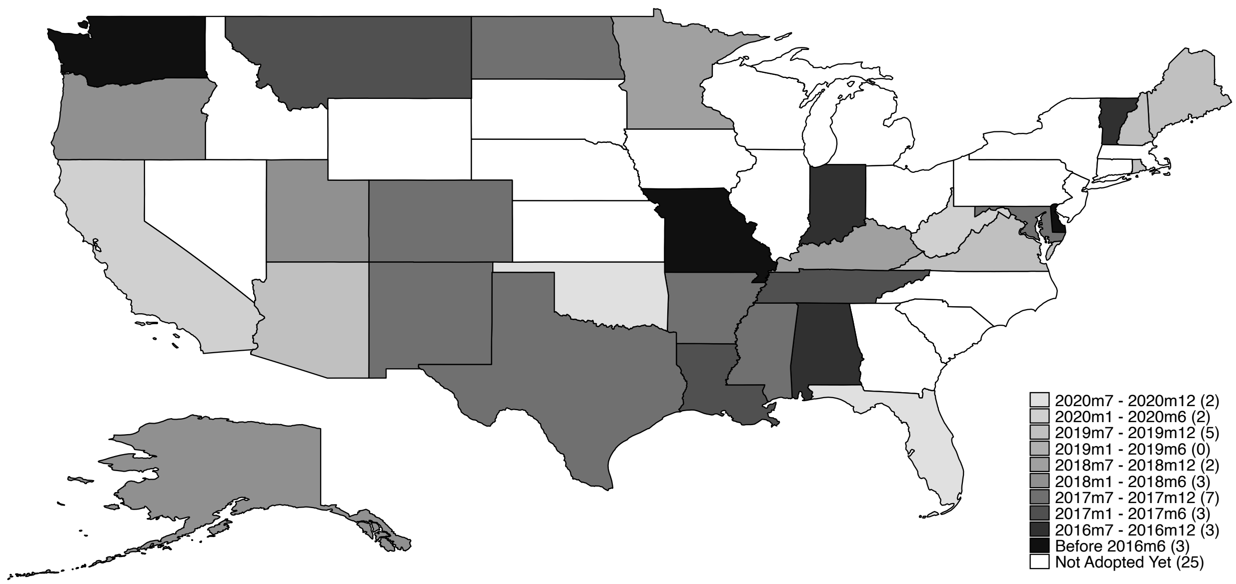


Figure 2. Elder Financial Exploitation by Month

This figure depicts, for each month ("m"), the natural logarithm of the total number of suspicious activity reports submitted to FinCEN that are flagged as related to elder financial exploitation in the United States. The category for suspicious activity reports involving elder financial exploitation was introduced at FinCEN in 2012. To remove the steep rise in reports due to the new category introduction, all of our empirical work starts at the red vertical line at January 2014. Thus our main sample period is January 2014 to December 2020. In Internet Appendix Table A7, we show that our results are robust to varying the sample start dates.

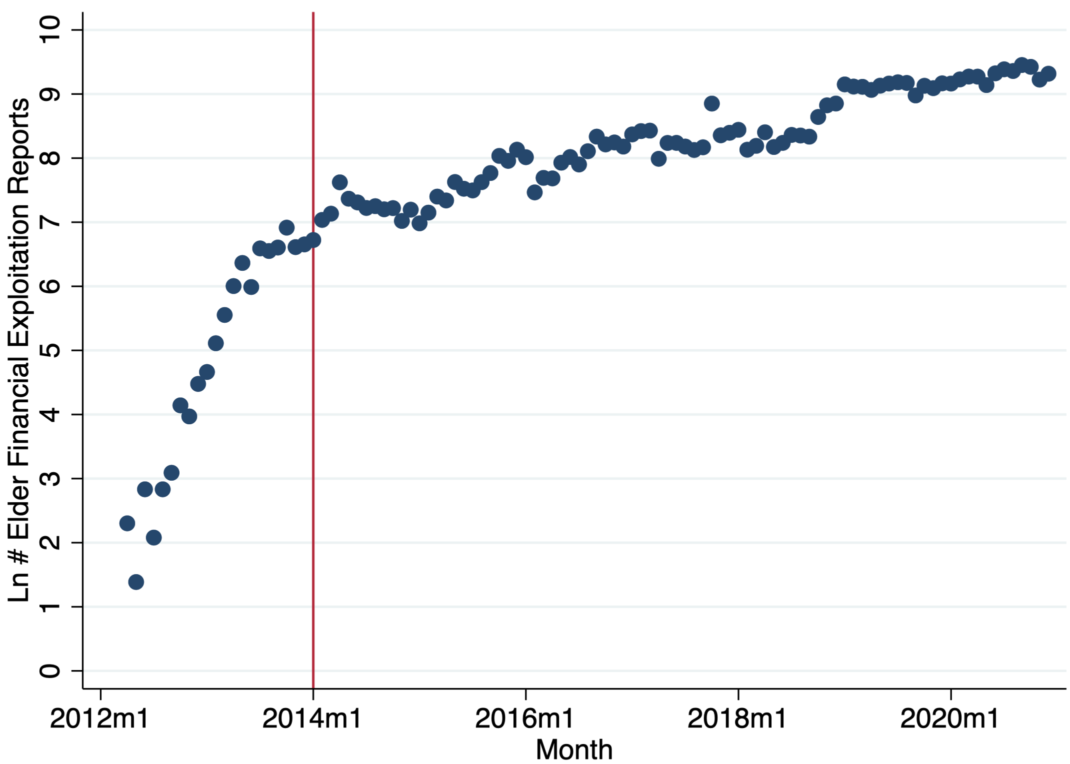


Figure 3. State Trends in Elder Financial Abuse Prior to Deputization

This figure shows the trends in the monthly, state-level number of elder financial exploitation reports. We first estimate the nationwide monthly trend in elder financial exploitation reports (depicted in Figure 2) with year-month fixed effects and remove this trend. We also estimate and remove a state-specific linear trend estimated using pre-treatment data per Goodman-Bacon (2021). In our regression analyses, we likewise estimate and control for county-specific linear trends. Please see Internet Appendix Figure A2 for the same figure without removing the linear trend. The sample for this figure begins in January 2014 and ends in June 2016, which is just before the NASAA Model Act becomes effective for the earliest adopters. We exclude Delaware, Missouri, and Washington, which adopted provisions similar to the Model Act prior to 2016.

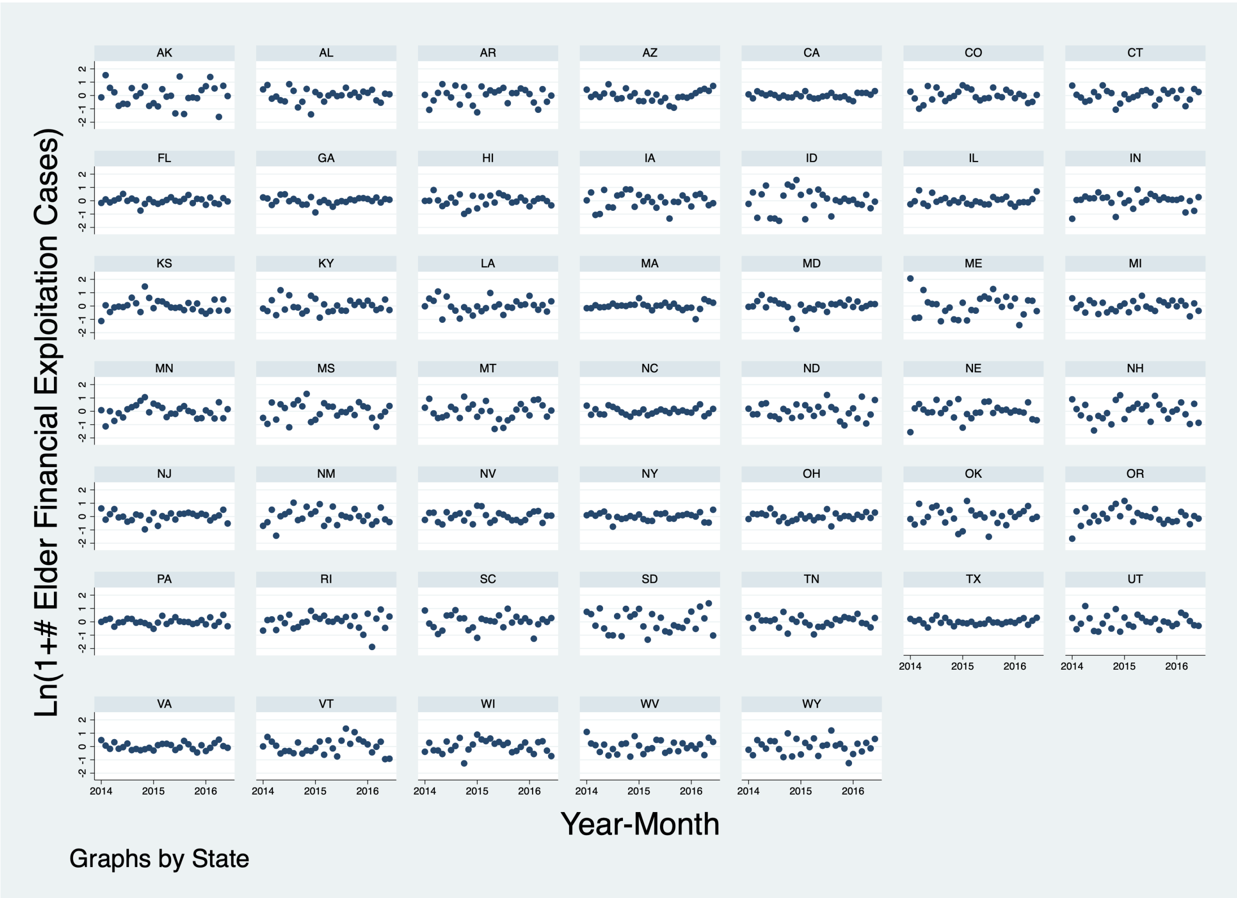
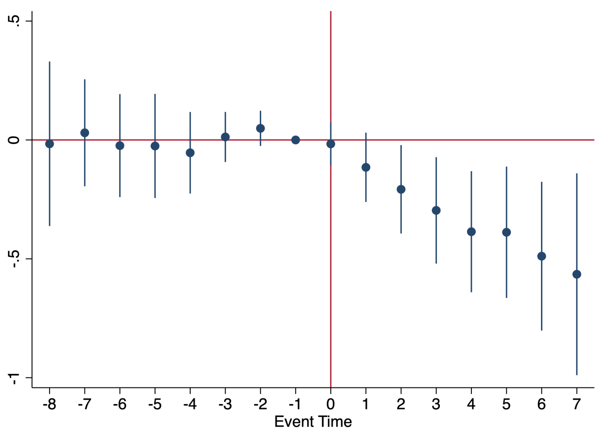


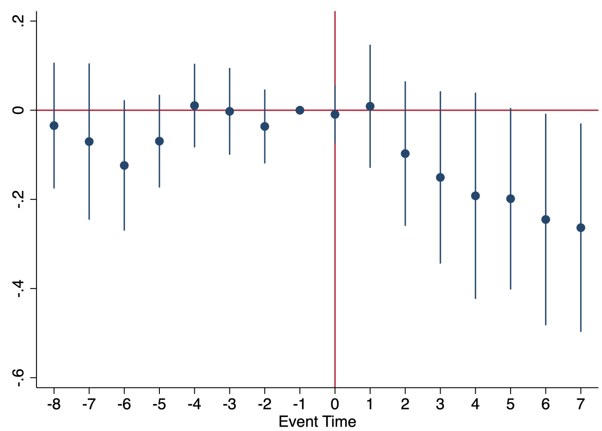
Figure 4. Effect of Deputization on Elder Financial Exploitation

The event-time figure shows the dynamic effect of deputizing financial professionals on elder financial exploitation around the month a state adopts the Model Act. We plot the coefficients on the event-time indicators from the dynamic difference-in-differences regression in Equation 3. Note that to simplify the figures and tables, we estimate the effect using monthly data for the six month intervals up to four years before and after the month of adoption. Thus, the effect estimated at $t = 0$ denotes the average effect in months zero to five since adoption. The red vertical line at $t = 0$ indicates the beginning of treatment for a county. Figures (a), (c), and (d) are estimated using Ordinary Least Squares (OLS) regressions, while Figure (b) is estimated using a Poisson regression. Figures (e)-(h) repeat the event-time plots using only elder financial exploitation involving fund transfers. Note that if a state does not adopt the Model Act by 2020, then the event time indicators are all zero. Year-month and county fixed effects are included. The time-varying county controls in Table 3 are also included. We show 90% confidence intervals based on standard errors clustered by state. We omit the indicator for the six months before the month of treatment.

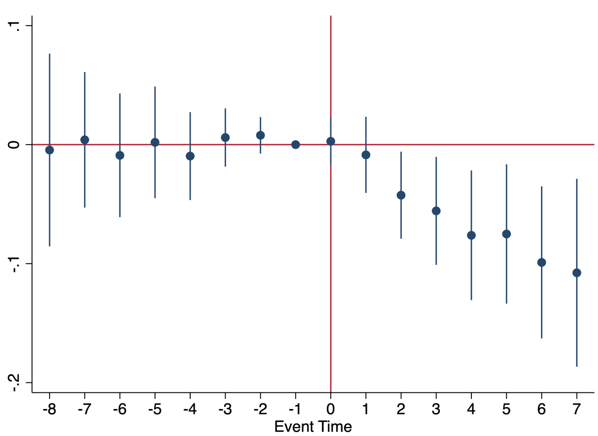
Y=Elder Financial Exploitation Cases



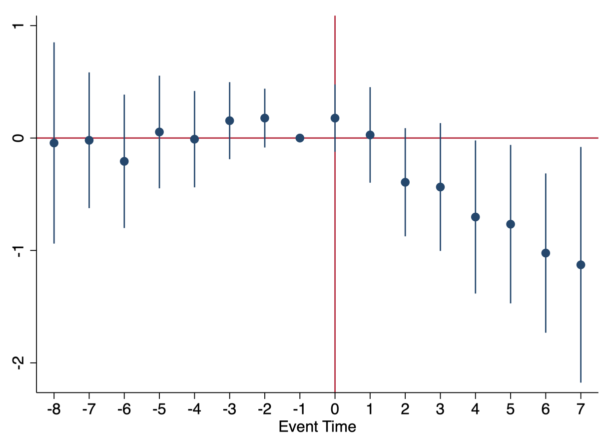
(a) Y (OLS)



(b) Y (Poisson)

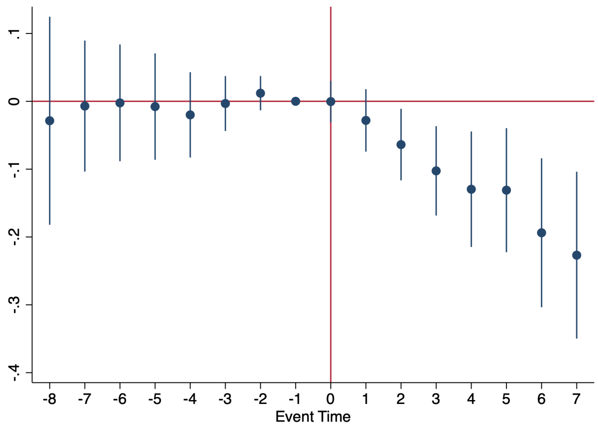


(c) Ln(1+Y)

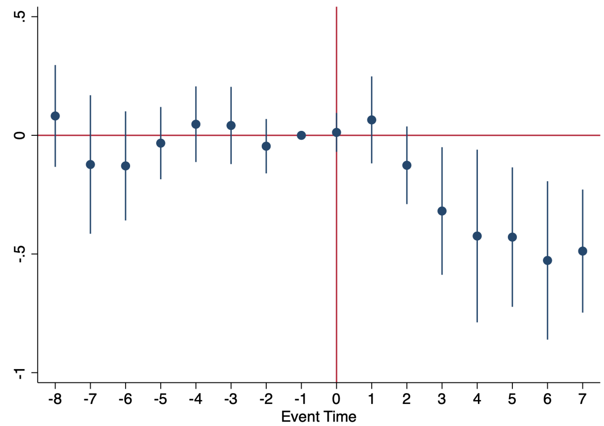


(d) Y/Pop. 65+×100,000

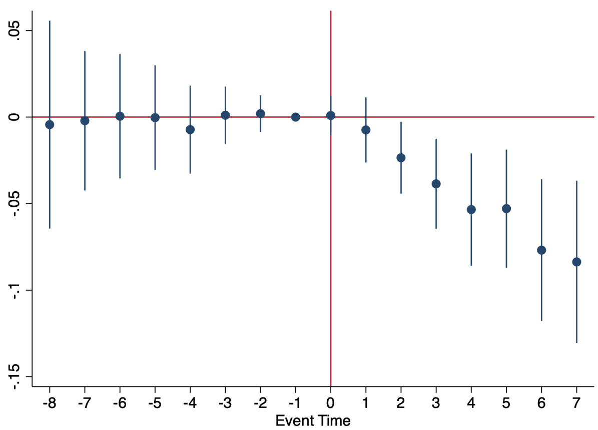
Z=Elder Financial Exploitation Cases *Involving Fund Transfers*



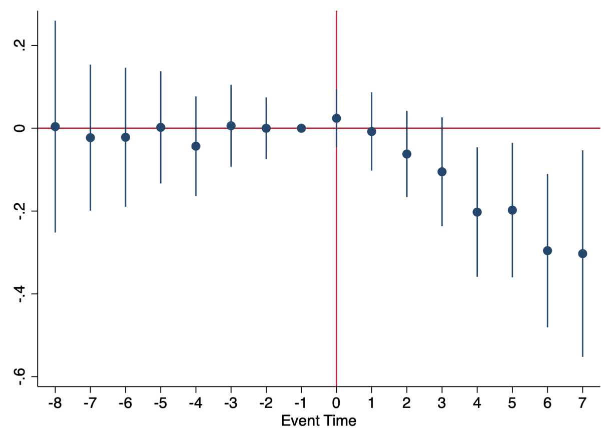
(e) Z (OLS)



(f) Z (Poisson)



(g) Ln(1+Z)



(h) Z/Pop. 65+×100,000

Figure 5. Effect of Deputization on Elder Financial Exploitation, Using Incident-Level Crime Data from NIBRS

This figure uses data from the FBI's National Incident-Based Reporting System (NIBRS) for the years 2010 to 2020. NIBRS data are incident-level data for each crime that is reported to the police agency. We know the state in which the crime occurred and date. We construct a state-month panel. Because we have a victim's age, we form two age groups: elderly (persons 65 years of age or older) and non-elderly (persons 50 to 64 years of age). The outcome is the number of crimes involving a positive amount of money for each age group and month. As in the previous figures, we estimate the effect using monthly data for the six month intervals up to four years before and after the month of adoption. Thus, the effect estimated at $t = 0$ denotes the average effect in months zero to five since adoption. The red vertical line at $t = 0$ indicates the beginning of treatment for a state. Note that if a state does not adopt the Model Act by 2020, then the event time indicators are all zero. State-by-month fixed effects are included to capture overall differences in trends in incidents across states. Identification comes from comparing the elderly in a state to the non-elderly in a state in the same month. We control for fixed differences in the amount of crimes against the elderly and non-elderly in a state. We also control for national trends in crimes against the elderly and non-elderly. We show 90% confidence intervals based on standard errors clustered by state.

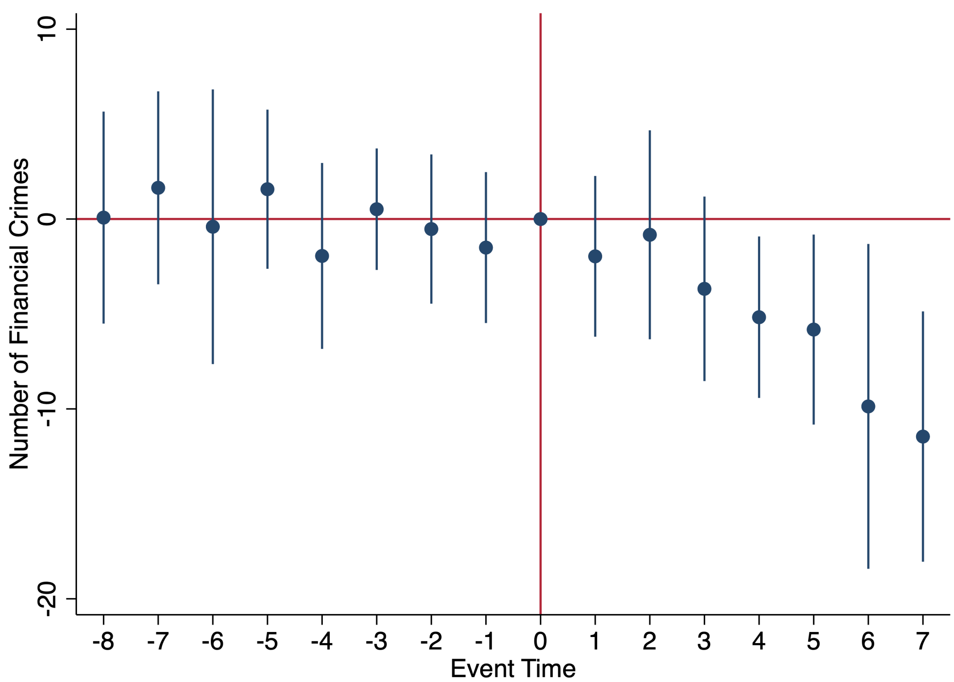


Figure 6. Do state characteristics predict the timing of adoption?

This figure shows scatter plots of the timing of states' adoption of the Model Act against states' characteristics, for the 30 states that adopted the Model Act by December 2020. The corresponding regression results are reported in panel A of Internet Appendix Table A3. The variable plotted on the y-axis, *Group of Adoption*, is equal to 1 for the earliest adopting state(s), 2 for the second earliest adopting state(s), and so on. State labels are displayed next to each data point. The coefficients and p-values of the slopes are reported at the top-right corner of each figure. *Number of Elder Exploitation Cases Per 1000* measures the number of elder financial exploitation cases per 1,000 people in a state that are age 65 and above. *Frac Pop Above 65* measures the fraction of the population in a state that is age 65 and above. *Average Household Income* measures the average household income in a state. *Log State Population* is the natural logarithm of population in a state. All variables on the x-axis are measured as of 2015, the year before the Model Act was finalized.

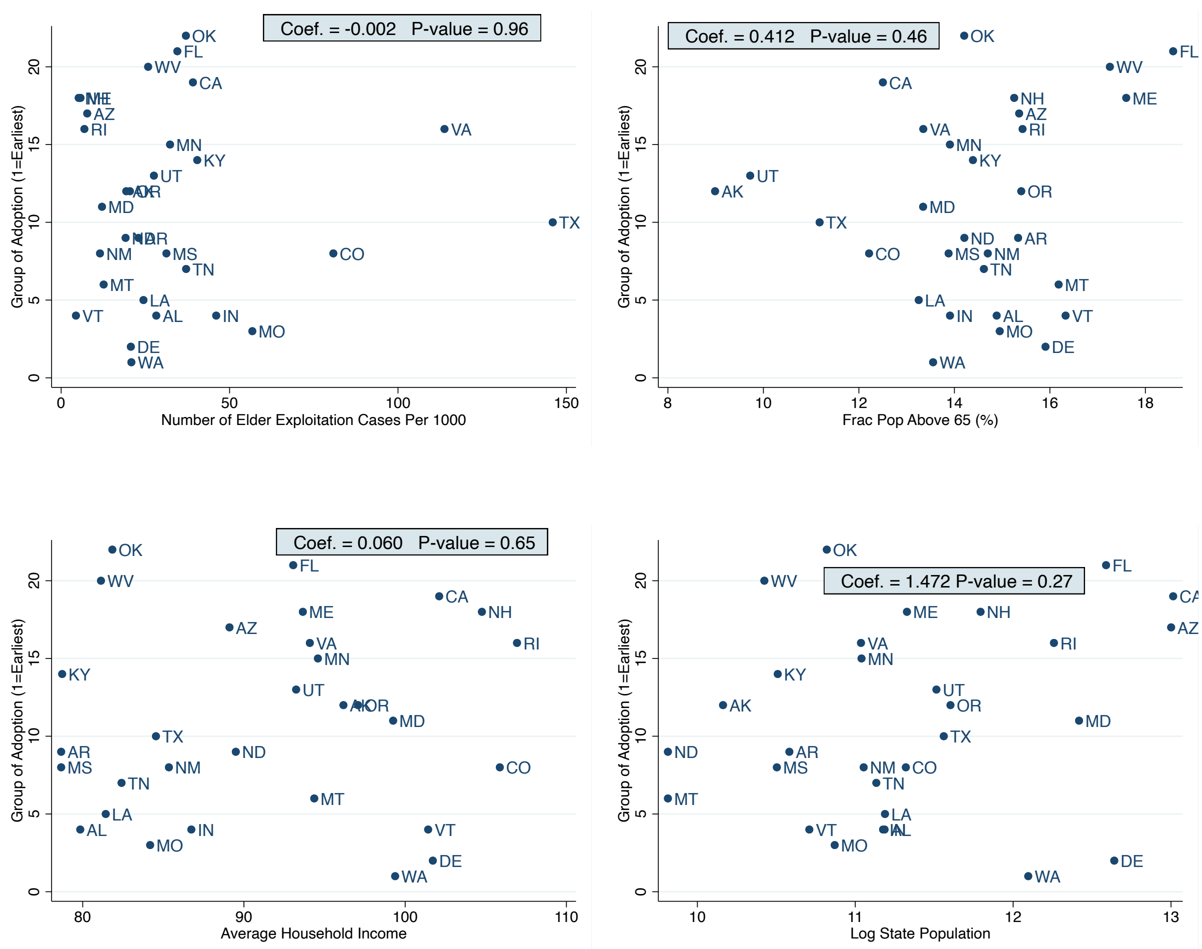
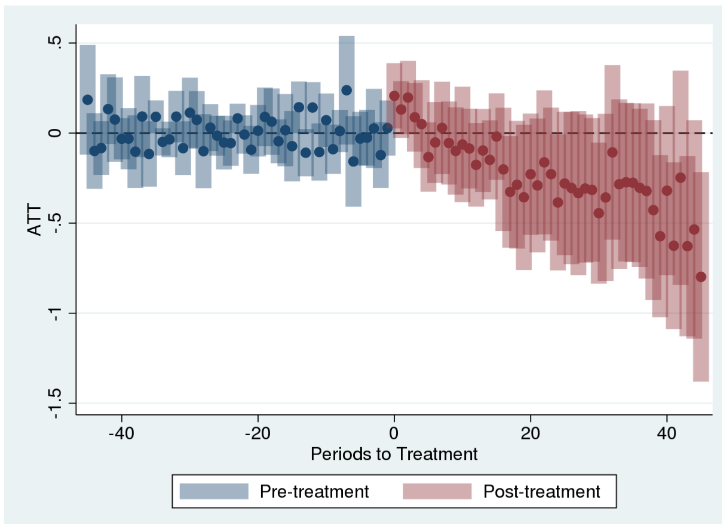
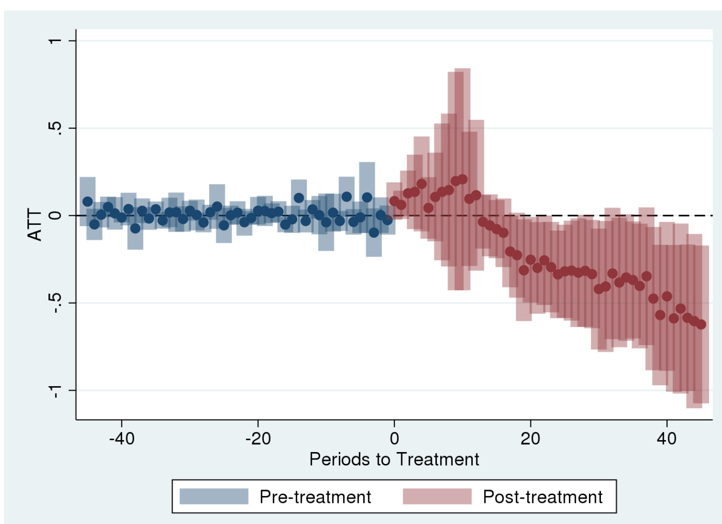


Figure 7. Estimating the Effect of Deputization using Only Never-Treated States as Controls

This figure estimates the monthly effect of deputizing financial professionals on elder financial exploitation around the date a state adopts the Model Act, using only never-treated states as controls per Callaway and Sant'Anna (2021). Specifically, the method estimates the DiD coefficient separately for all possible pairs of treated and never-treated states. The figure shows the time average treatment (ATT) effects, which is the average treatment effect at different lengths of exposure to the treatment. The outcome variable in (a) is the number of elder financial exploitation cases in a county-month; the outcome in (b) is the number of abuse cases involving funds transfers. The lighter (darker) bands are 95% (90%) confidence intervals based on standard errors clustered by state. Note that the Callaway and Sant'Anna (2021) approach discards data and thus has lower efficiency (Wooldridge, 2021).



(a) # Abuse Cases



(b) # Abuse Cases Involving Funds Transfers

TABLE 1. Comparison Between NASAA Model Act and FINRA Rules 2165 & 4512

This table presents a detailed comparison between the institutional features of the NASAA Model Act and FINRA Rules 2165 and 4512, along dimensions such as adoption status, applicable institutions, adults covered, temporary holds, the granting of immunity, reporting requirement to APS, record sharing, and training. A more detailed discussion can be found in Section 3.

	NASAA Model Act	**FINRA Rules 2165 & 4512**
Adoption status	Staggered adoption by state	Nationwide adoption on Feb 5, 2018
Applies to Whom	Agents, broker-dealers, and investment advisers	FINRA-registered broker-dealers
Adults Covered	A person 65 years of age or older or a person subject to a state APS statute	A person 65 years of age or older or a person 18 years of age or older with mental or physical impairment
Third-Party Notification	Expressly permitted with respect to any third-party previously designated by the eligible adult.	FINRA member firms are required to make reasonable efforts to obtain the name and contact information for a trusted contact person when opening or updating a retail account. The trusted contact person is intended to be a resource for the FINRA member firm in administering the customer's account, protecting assets, and responding to possible financial exploitation.
Holds Applicability	Disbursements of funds	Disbursements of funds or securities
Holds Period	The sooner of (a) a determination that the disbursement will not result in financial exploitation of the eligible adult; or (b) 15 business days after the date on which disbursement of the funds was delayed, unless APS or the Commissioner of Securities requests an extension of the delay, in which it shall expire no more than 25 business days after the date on which the disbursement was first delayed.	15 business days unless (1) otherwise terminated or extended by a state regulator, or agency of competent jurisdiction, or a court of competent jurisdiction; or (2) extended by the member firm for no longer than 10 business days.
Immunity	Agents, Broker-Dealers, and Investment Advisers	N/A
Reporting to APS	Mandatory	Voluntary
Record Sharing	Mandatory with APS and law enforcement	Mandatory upon FINRA request
Training	N/A	Pursuant to Supplementary Material .02 (Training), a FINRA member firm relying on Rule 2165 must develop and document training policies or programs reasonably designed to ensure that associated persons comply with the requirements of Rule 2165.

TABLE 2. Staggered Adoption of NASAA Model Act

This table shows the staggered adoption of the NASAA Model Act across U.S. states through 2020. We identify state-level acts, laws, statutes, and regulations that are based on the Model Act or contain similar provisions to those in the Model Act. For each state, we obtain the passage date, the effective date, and the applicable institutions from state's legislature website. If there is more than one effective date for a state, we use the earlier date.

State	**Passage Date**	**Effective Date**	**Applies to Whom**
AL	4/15/16	7/1/16	Broker-dealers and investment advisers
AK	4/17/17	1/1/18	Broker-dealers and investment advisers
AZ	5/13/19	8/27/19	Broker-dealers and investment advisers
AR	3/27/17	8/7/17	Broker-dealers and investment advisers
CA	9/6/19	1/1/20	Broker-dealers and investment advisers
CO	6/2/17	7/1/17	Broker-dealers and investment advisers
DE	9/30/14	9/30/14	Financial Institutions*
DE	8/29/18	11/27/18	Broker-dealers and investment advisers
FL	6/30/20	7/1/20	Broker-dealers and investment advisers
IN	3/21/16	7/1/16	Broker-dealers
IN	4/24/17	7/1/17	Investment advisers
KY	4/10/18	7/14/18	Financial Institutions*
LA	6/17/16	1/1/17	Broker-dealers and investment advisers
ME	4/2/19	9/19/19	Broker-dealers and investment advisers
MD	5/27/17	10/1/17	Broker-dealers and investment advisers
MN	5/19/18	8/1/18	Broker-dealers and investment advisers
MO	6/12/15	8/28/15	Broker-dealers
MS	3/27/17	7/1/17	Broker-dealers and investment advisers
MT	3/22/17	3/22/17	Broker-dealers and investment advisers
NH	7/10/19	9/8/19	Broker-dealers and investment advisers
NM	4/6/17	7/1/17	Broker-dealers and investment advisers
ND	4/10/17	8/1/17	Broker-dealers and investment advisers
OK		11/1/20	Broker-dealers and investment advisers
OR	6/29/17	1/1/18	Broker-dealers and investment advisers
RI	7/15/19	7/15/19	Broker-dealers
TN	5/18/17	5/18/17	Broker-dealers and investment advisers
TX	6/1/17	9/1/17	Financial Institutions*
UT	3/16/18	5/8/18	Broker-dealers and investment advisers
VT		7/1/16	Broker-dealers and investment advisers
VA	3/18/19	7/1/19	Financial Institutions*
WV	3/7/20	6/5/20	Broker-dealers and investment advisers
WA	3/19/10	6/10/10	Financial Institutions*

TABLE 3. Summary Statistics

The sample period is January 2014 to December 2020. Panel A reports county-level summary statistics for variables related to elder financial exploitation, the presence of investment advisers and brokers, and demographic and economic characteristics. The unit of observation is a county-month. *Elder Financial Exploitation Cases* is the county-month count of financial exploitation of elderly persons reported to the Department of Treasury. *Elder Financial Exploitation Cases Per 100,000 Adults 65+* is the rate of abuse cases per 100,000 elderly adults 65 years of age or older. *Elder Financial Exploitation Probability* is an indicator variable that equals to one hundred if there is at least one report of elder financial exploitation in a county-month. *Advisers Per 1,000* (*Brokers Per 1,000*) is the number of investment advisers (brokers) in a county divided by the total number of persons that are 16 years of age or older, multiplied by 1,000. *Population Above 65* is the number of persons 65 years of age or older. *Fraction of Population Above 65* is the proportion of a county's population that is 65 years of age or older. *Vantage Score (65+)* is the average credit score of adults 65 years of age or older in a county-month, based on a 2% representative sample of credit bureau records. *Subprime (65+)* is the percentage of elderly residents with a credit score below 660, based on credit records. *Low Income (65+)* is the percentage of elderly residents with incomes below the national median, based on credit records. *Average Age (65+)* is the average age of elderly residents in a county. *Male (65+)* is the percentage of elderly residents that are male. *Married (65+)* is the percentage of elderly residents that are married. *Household Income (65+)* is the average household income for elderly residents of a county. *Household Debt-to-Income Ratio (65+)* is the average household debt-to-income ratio for elderly residents of a county. *Average Retirement Income (65+)* is the average personal retirement income for retirees in a county. *Bachelor or Higher* is the percentage of county adults with at least a bachelor degree. *Religious Adherents Per 1000* is the number of individuals with and without an affiliation to a congregation per 1,000 individuals. *Religious Congregation per 1000* is the number of religious congregations per 1,000 individuals. Panel B reports characteristics of the abuse reports submitted to the U.S. Treasury's FinCEN database. Specifically, for the sample of county-months with at least one abuse case, the table shows the average county-month fraction of reports of elder financial exploitation classified by the instrument and product involved, overseeing regulator, and industry of the reporting institution. Panel C reports characteristics of the state-month panel of financial crimes submitted by local law enforcement agencies to NIBRS. The sample is limited to crimes involving a monetary loss above zero. We show the number of financial crimes for two age groups: persons above 65 years of age and those 50-64 years of age. We also show the number of financial crimes involving monetary losses above the sample median (exceeding approximately $700) by age group and the number of crimes below the sample median by age group.

Panel A: County-Month Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Mean	SD	p10	p50	p90	N
Elder Financial Exploitation Cases	1.3	4.1	0.0	0.0	3.0	263,676
Elder Financial Exploitation Cases Per 100,000 Adults 65+	6.4	31.7	0.0	0.0	16.9	263,676
Elder Financial Exploitation Probability (%)	20.3	40.2	0.0	0.0	100.0	263,676
Adviser Per 1,000	0.5	1.0	0.0	0.2	1.1	263,676
Brokers Per 1,000	0.8	2.0	0.0	0.5	1.8	263,676
Population Above 65 (000s)	15.1	43.3	1.0	4.5	31.1	263,676
% Fraction of Population Above 65	17.9	4.6	12.4	17.6	23.7	263,676
Vantage Score (65+)	724.6	53.9	696.2	730.1	755.5	263,676
% Subprime (65+)	19.0	10.4	7.5	17.5	33.3	263,676
% Low Income (65+)	52.0	12.6	37.5	51.8	66.7	263,676
Average Age (65+)	76.8	5.2	74.9	77.2	79.3	263,676
% Male (65+)	47.6	9.6	38.5	47.3	57.9	263,676
% Married (65+)	54.3	11.6	42.0	54.1	66.7	263,676
Household Income (65+) (000s)	90.1	16.3	72.6	88.7	110.2	263,676
% Household Debt-to-Income Ratio (65+)	6.5	2.3	3.6	6.5	9.2	263,676
Average Retirement Income (000s)	22.0	5.3	16.3	21.0	29.0	263,676
% Bachelor or Higher	21.2	9.3	12.0	18.9	33.5	263,676
Religious Adherent Per 1000	514.1	181.7	295.4	497.2	753.5	263,676
Religious Congregation Per 1000	2.4	1.4	0.9	2.2	4.2	263,676

TABLE 4. Summary Statistics (continued)

Panel B: The Composition of FinCEN Elder Financial Exploitation Cases by County-Month

Instrument Involved		Product Involved	
U.S. Currency	42.2%	Debit Card	34.7%
Funds Transfer	23.9%	Deposit Account	30.0%
Personal/Business Check	20.0%	Credit Card	9.5%
Bank/Cashier's Check	6.5%	Other	25.8%
Other	7.4%		
Regulator of Reporting Firm		**Industry of Reporting Firm**	
OCC	33.7%	Depository Institution	71.8%
IRS	26.6%	Money Services Business	26.2%
FRB	19.6%	Securities/Futures	1.5%
FDIC	13.8%	Other	0.5%
Other	6.3%		

Panel C: State-Month NIBRS Crime Data

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Mean	SD	p10	p50	p90	N
Elder Financial Exploitation Cases (Ages 65+)	51	60	5	29	144	4086
Elder Financial Exploitation Cases (Ages 50-65)	61	68	6	36	174	4086
Elder Financial Exploitation Cases (Ages 65+ & High Value)	30	36	3	17	84	4086
Elder Financial Exploitation Cases (Ages 50-65 & High Value)	29	34	3	17	81	4086
Elder Financial Exploitation Cases (Ages 65+ & Low Value)	21	27	2	11	58	4086
Elder Financial Exploitation Cases (Ages 50-65 & Low Value)	32	37	3	19	89	4086

TABLE 5. Effects of Deputization on Elder Financial Exploitation

This table presents difference-in-differences estimates of the effect of deputizing financial professionals on elder financial exploitation reported by financial professionals. The outcome in columns (1) to (3) is the number of elder financial exploitation cases in a county-month. Column (3) estimates a Poisson model. The outcome in column (4) is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. The outcome in column (5) is the number of cases per 100,000 persons 65 years of age or older. A similar setup exists in columns (6) to (10), but the outcome is only based on the number of abuse cases involving fund transfers. *Post* is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-month periods before and after the month financial professionals are deputized. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. The control variables, defined in Table 3, include *Vantage Score (65+)*, *% Subprime (65+)*, *% Low Income (65+)*, *Average Age (65+)*, *% Male (65+)*, *% Married (65+)*, *Household Income (65+)*, *% Household Debt-to-Income Ratio (65+)*, *Population Above 65*, and *Bachelor or Higher*. Specifications include county and year-month fixed effects as well as a county-linear trend in elder financial abuse cases, estimated using data prior to July 2016 (Goodman-Bacon, 2021). The sample size drops in columns (3) and (8) because a Poisson regression with county fixed effects removes counties without any variation in elder financial exploitation. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Y = Elder Financial Exploitation Cases					Z = Elder Exploitation Involving Fund Transfers				
	Y			Ln(1+Y)	Y/Pop. 65+	Z			Ln(1+Z)	Z/Pop. 65+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post	-0.186**					-0.050*				
	(0.092)					(0.026)				
Pre 8		-0.016	-0.034	0.008	-0.044		-0.029	0.082	-0.005	0.003
		(0.206)	(0.086)	(0.034)	(0.534)		(0.096)	(0.130)	(0.037)	(0.156)
Pre 7		0.030	-0.070	0.011	-0.020		-0.006	-0.123	-0.002	-0.021
		(0.134)	(0.107)	(0.025)	(0.360)		(0.060)	(0.177)	(0.025)	(0.107)
Pre 6		-0.024	-0.124	-0.005	-0.207		-0.000	-0.129	0.001	-0.020
		(0.129)	(0.089)	(0.024)	(0.354)		(0.053)	(0.140)	(0.022)	(0.102)
Pre 5		-0.025	-0.069	0.002	0.054		-0.005	-0.033	0.001	0.005
		(0.131)	(0.063)	(0.021)	(0.299)		(0.048)	(0.093)	(0.019)	(0.082)
Pre 4		-0.054	0.011	-0.009	-0.010		-0.017	0.047	-0.006	-0.040
		(0.102)	(0.057)	(0.017)	(0.256)		(0.039)	(0.097)	(0.016)	(0.073)
Pre 3		0.013	-0.002	0.007	0.154		-0.000	0.042	0.002	0.009
		(0.063)	(0.059)	(0.013)	(0.204)		(0.025)	(0.099)	(0.010)	(0.059)
Pre 2		0.049	-0.036	0.009	0.178		0.014	-0.046	0.003	0.002
		(0.044)	(0.050)	(0.009)	(0.156)		(0.015)	(0.070)	(0.006)	(0.045)
Pre 1		.	.	.	.		.	.	.	.
Post 0		-0.016	-0.009	0.002	0.177		0.001	0.012	0.001	0.025
		(0.054)	(0.039)	(0.011)	(0.179)		(0.018)	(0.050)	(0.007)	(0.042)
Post 1		-0.115	0.009	-0.005	0.028		-0.027	0.065	-0.007	-0.007
		(0.087)	(0.084)	(0.017)	(0.254)		(0.028)	(0.111)	(0.011)	(0.057)
Post 2		-0.208*	-0.097	-0.034*	-0.393		-0.062*	-0.126	-0.023*	-0.061
		(0.111)	(0.099)	(0.018)	(0.287)		(0.032)	(0.099)	(0.013)	(0.063)
Post 3		-0.296**	-0.151	-0.046*	-0.436		-0.100**	-0.319*	-0.038**	-0.102
		(0.134)	(0.117)	(0.023)	(0.339)		(0.040)	(0.163)	(0.016)	(0.079)
Post 4		-0.386**	-0.192	-0.065**	-0.702*		-0.125**	-0.424*	-0.052**	-0.198**
		(0.152)	(0.141)	(0.028)	(0.406)		(0.052)	(0.221)	(0.020)	(0.094)
Post 5		-0.388**	-0.198	-0.068**	-0.766*		-0.124**	-0.429**	-0.050**	-0.190*
		(0.165)	(0.124)	(0.029)	(0.420)		(0.056)	(0.179)	(0.021)	(0.098)
Post 6		-0.489**	-0.245*	-0.088**	-1.023**		-0.184***	-0.527***	-0.074***	-0.286**
		(0.187)	(0.144)	(0.034)	(0.423)		(0.067)	(0.203)	(0.025)	(0.111)
Post 7		-0.565**	-0.263*	-0.100*	-1.128*		-0.207***	-0.488***	-0.077***	-0.283*
		(0.253)	(0.142)	(0.053)	(0.625)		(0.073)	(0.158)	(0.028)	(0.148)
Specification	OLS	OLS	Poisson	OLS	OLS	OLS	OLS	Poisson	OLS	OLS
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.67	0.67	.	0.62	0.22	0.63	0.59	.	0.58	0.23
# Counties	3139	3139	2677	3139	3139	3139	3139	2342	3139	3139
Observations	245169	245169	210072	245169	245169	245169	245169	183755	245169	245169

TABLE 6. Effects of Deputization on Elder Exploitation, Using Crime Data from NIBRS

This table presents difference-in-differences estimates of the effect of deputizing financial professionals on financial crimes against the elderly. The crime data are from the FBI's National Incident-Based Reporting System (NIBRS). NIBRS data are incident-level data for each crime that is reported to the police agency. We know the state in which the crime occurred. Because we have a victim's age, we form two age groups: elderly (persons 65 years of age or older) and non-elderly (persons 50 to 64 years of age). *Elderly 65+* is an indicator variable that equals to one when a state-month observation of crimes is for persons 65 years of age or older. The data is for the years 2010 to 2020. We construct a state-month by age group panel. In column (1), the outcome is the number of crimes involving a positive amount of money for each age group in a state-month. In column (2), the outcome is the natural log of the number of crimes involving a positive amount of money for each age group in a state-month. In column (3), the outcome is the number of crimes involving an above-median amount of money (>$692). In column (4), the outcome is the number of crimes involving a below-median amount of money. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-month periods before and after the month financial professionals are deputized and empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. For example, *Post 0* is the average effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. Note that if a state does not adopt the Model Act by 2020, then the event time indicators are all zero. State-by-month fixed effects are included to capture overall differences in trends in crime incidents across states. Identification comes from comparing the treated elderly in a state to the non-elderly in the same state in the same month. We control for fixed differences in the amount of crimes against the elderly and non-elderly in a state. We also control for national trends in crimes against the elderly and non-elderly. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Y=# Elder Financial Crimes in NIBRS			
	Y	Ln(Y)	Y	Y
Value of Crime	All	All	High	Low
	(1)	(2)	(3)	(4)
Pre 8 × Elderly 65+	0.076	-0.009	-2.324	2.399
	(3.324)	(0.055)	(2.548)	(1.779)
Pre 7 × Elderly 65+	1.644	0.025	-1.055	2.700*
	(3.025)	(0.076)	(2.097)	(1.562)
Pre 6 × Elderly 65+	-0.406	0.009	-0.555	0.148
	(4.306)	(0.053)	(2.198)	(2.823)
Pre 5 × Elderly 65+	1.571	0.015	-0.601	2.171
	(2.495)	(0.061)	(1.978)	(1.481)
Pre 4 × Elderly 65+	-1.943	0.006	-2.330	0.387
	(2.915)	(0.047)	(2.422)	(1.694)
Pre 3 × Elderly 65+	0.518	-0.006	-0.668	1.186
	(1.905)	(0.061)	(1.537)	(1.146)
Pre 2 × Elderly 65+	-0.528	-0.005	-0.828	0.300
	(2.340)	(0.042)	(1.550)	(1.316)
Pre 1 × Elderly 65+	-1.504	-0.032	-2.128	0.624
	(2.366)	(0.045)	(1.588)	(1.299)
Post 0 × Elderly 65+	.	.	.	.
Post 1 × Elderly 65+	-1.965	0.000	-0.593	-1.372
	(2.520)	(0.035)	(1.395)	(1.485)
Post 2 × Elderly 65+	-0.830	-0.017	-0.240	-0.590
	(3.276)	(0.046)	(1.722)	(2.035)
Post 3 × Elderly 65+	-3.675	-0.090*	-1.931	-1.744
	(2.893)	(0.053)	(1.457)	(2.205)
Post 4 × Elderly 65+	-5.171**	-0.026	-3.256*	-1.915
	(2.531)	(0.053)	(1.873)	(1.857)
Post 5 × Elderly 65+	-5.821*	-0.027	-2.922	-2.899
	(2.979)	(0.062)	(1.773)	(2.418)
Post 6 × Elderly 65+	-9.867*	-0.139**	-6.260**	-3.606
	(5.093)	(0.062)	(2.757)	(2.869)
Post 7 × Elderly 65+	-11.456***	-0.125*	-6.986***	-4.470
	(3.925)	(0.068)	(2.088)	(3.014)
State-Month FE	Yes	Yes	Yes	Yes
State-Age Group FE	Yes	Yes	Yes	Yes
Age Group-Month FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.97	0.94	0.96	0.93
Observations (4086 Elderly, 4086 non-Elderly)	8172	8172	8172	8172

TABLE 7. Goodman-Bacon Decomposition

This table shows the Goodman-Bacon (2021) decomposition of our staggered difference-in-difference regression coefficient estimate in Table 5 column (1) of -0.186. The preferred source of variation in the presence of a gradual treatment response is *Treated vs Never Treated*, which estimates the effect using only the non-treated counties as controls. The most problematic source of variation in the presence of a gradual treatment responses is *Later Treated vs Earlier Control*, which estimates the effect using the counties treated earlier as controls for the counties treated later. *Earlier Treated vs Later Control* estimates the effect using the counties treated later as controls for the counties treated earlier. *Treated vs Already Treated* estimates the effect using counties that are always treated during the sample period as controls for counties treated during the sample period.

Variation	**Beta**	**Weight**
Treated vs Never Treated	-0.246	0.744
Earlier Treated vs Later Control	-0.024	0.164
Later Treated vs Earlier Control	0.049	0.091
Treated vs Already Treated	-0.055	0.001

TABLE 8. Effects of Deputization on Elder Exploitation: Matched Sample Analyses

This table shows the difference-in-difference analysis in Table 5 using a sample of matched counties. We implement the following minimum distance matching procedure: for each county, we calculate its geometric distance to all other counties based on a vector of covariates. The covariates are the controls in Table 5, which Table 3 defines, and include *Vantage Score (65+)*, *% Subprime (65+)*, *% Low Income (65+)*, *Average Age (65+)*, *% Male (65+)*, *% Married (65+)*, *Household Income (65+)*, *% Household Debt-to-Income Ratio (65+)*, *Population Above 65*, and *% Bachelor or Higher*. Geometric distance is calculated as the square root of the sum of the squares of the differences in covariates between two counties. Mathematically, it is expressed as $d_{ij} = \sqrt{(x_{1i} - x_{1j})^2 + (x_{2i} - x_{2j})^2 + \ldots + (x_{Ni} - x_{Nj})^2}$, where x_1, x_2, ..., x_N are standardized covariates, and i and j denote counties. All covariates are standardized to have a mean of zero and a standard deviation of one to receive equal weights. Next, for each county, we select a pair county that has the smallest geometric distance to the county, locates in a different state, and receives the treatment at a different point in time. Then, to ensure we use only high-quality matches, we keep the county pairs that have a geometric distance below the 25^{th} percentile of the distance distribution. Last, we use the subsamples of matched county pairs to perform difference-in-difference regressions, while including a set of matched-pair fixed effects. The outcome in column (1) is the number of elder financial exploitation cases in a county-month. The outcome in column (2) is the number of cases involving fund transfers. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month a state deputizes financial professionals by adoption the Model Act provisions. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. We also present the covariate balance test on the matched sample of counties in Panel B, where *Treat* is an indicator variable that equals to one if a county is in the State deputizing professionals first within a pair.

	Elder Financial Exploitation Cases	Elder Exploitation Involving Fund Transfer Cases
	(1)	(2)
	25^{th} Percentile	25^{th} Percentile
Pre 8	-0.058	0.004
	(0.422)	(0.168)
Pre 7	-0.017	-0.006
	(0.318)	(0.127)
Pre 6	-0.187	-0.019
	(0.304)	(0.104)
Pre 5	-0.073	-0.055
	(0.304)	(0.101)
Pre 4	0.012	-0.046
	(0.179)	(0.073)
Pre 3	0.057	0.003
	(0.111)	(0.048)
Pre 2	0.075	0.043
	(0.124)	(0.057)
Pre 1	.	.
Post 0	0.039	0.020
	(0.131)	(0.042)
Post 1	-0.287	-0.082
	(0.180)	(0.057)
Post 2	-0.405*	-0.147*
	(0.213)	(0.076)
Post 3	-0.167	-0.119
	(0.260)	(0.090)
Post 4	-0.562*	-0.241*
	(0.296)	(0.123)
Post 5	-0.487*	-0.228**
	(0.289)	(0.108)
Post 6	-0.677**	-0.301*
	(0.336)	(0.154)
Post 7	-0.667	-0.322*
	(0.441)	(0.167)
Pair FE	Yes	Yes
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.66	0.67
# Counties	698	698
Observations	78689	78689

Panel B: Covariate Balance: 25^{th} Percentile Threshold

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Vantage Score (65+)	0.04	(0.58)	0.05	(0.61)	(0.75)	0.01
Fraction of Subprime (65+)	-0.04	(0.53)	-0.05	(0.57)	(0.61)	-0.02
Fraction of Low Income (65+)	-0.15	(0.60)	-0.14	(0.60)	(0.84)	0.01
Average Age (65+)	0.05	(0.53)	0.06	(0.55)	(0.77)	0.01
Fraction of Male (65+)	-0.07	(0.36)	-0.08	(0.37)	(0.81)	-0.01
Fraction of Married (65+)	-0.12	(0.49)	-0.11	(0.56)	(0.87)	0.01
Household Income (65+)	0.10	(0.71)	0.10	(0.73)	(0.85)	-0.01
Household Debt-to-Income Ratio (65+)	0.19	(0.52)	0.18	(0.55)	(0.58)	-0.02
Pop 65+	0.82	(0.85)	0.81	(0.85)	(0.87)	-0.01
Bachelor or Higher	0.30	(0.99)	0.29	(1.00)	(0.89)	-0.01

TABLE 9. Effects of Deputization on Elder Exploitation Involving Fund Transfers Controlling for Less-Affected Types of Elder Financial Exploitation

This table presents difference-in-differences estimates of the effect of deputizing financial professionals on elder financial exploitation (EFE) reports involving fund transfers, controlling for other types of EFE. Column (1) controls for the county-month number of EFE reports from money services businesses, which do not employ the financial professionals deputized. Column (2) controls for the county-month number of EFE reports involving credit card abuse, which is less likely to be intermediated by an investment adviser or broker—the primary deputies. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized and empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. The control variables, defined in Table 3, include *Vantage Score (65+)*, *% Subprime (65+)*, *% Low Income (65+)*, *Average Age (65+)*, *% Male (65+)*, *% Married (65+)*, *Household Income (65+)*, *% Household Debt-to-Income Ratio (65+)*, *Population Above 65*, and *Bachelor or Higher*. Specifications include county and year-month fixed effects as well as a county-linear trend in elder financial abuse cases, estimated using data prior to July 2016 (Goodman-Bacon, 2021). Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Exploitation Reports Involving Fund Transfers	
	(1)	(2)
Pre 8	-0.036	-0.022
	(0.092)	(0.083)
Pre 7	-0.014	-0.001
	(0.059)	(0.053)
Pre 6	-0.004	0.001
	(0.055)	(0.048)
Pre 5	-0.008	-0.008
	(0.048)	(0.045)
Pre 4	-0.019	-0.020
	(0.040)	(0.036)
Pre 3	-0.006	-0.001
	(0.025)	(0.023)
Pre 2	0.011	0.015
	(0.014)	(0.015)
Pre 1	.	.
Post 0	-0.003	-0.001
	(0.018)	(0.017)
Post 1	-0.036	-0.020
	(0.027)	(0.027)
Post 2	-0.071**	-0.059*
	(0.033)	(0.030)
Post 3	-0.110***	-0.089**
	(0.041)	(0.038)
Post 4	-0.139**	-0.115**
	(0.052)	(0.048)
Post 5	-0.140**	-0.113**
	(0.058)	(0.052)
Post 6	-0.205***	-0.179***
	(0.067)	(0.063)
Post 7	-0.238***	-0.220***
	(0.075)	(0.074)
EFE Reports - Money Services Business	0.140***	
	(0.032)	
EFE Reports - Credit Card Abuse		0.131**
		(0.053)
Year-Month FE	Yes	Yes
County FE	Yes	Yes
County-Linear Trend	Yes	Yes
Controls	Yes	Yes
Adjusted R^2	0.61	0.61
# Counties	3139	3139
Observations	245169	245169

TABLE 10. Effects of Deputization and the Presence of Deputies

 # Elder Financial Exploitation Cases is the number of elder financial exploitation cases in a county-month. *Post* is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. *Per Capita Investment Advisers (Brokers)* is a county's per capita number of investment advisers (brokers). *Pure Brokers per Capita* is a county's per capita number of brokers that are not dual registered as investment advisers. All regressions include the time-varying county control variables in Table 5. All regressions include county and year-month fixed effects. Each control is interacted with *Post* (Yzerbyt et al., 2004). Additionally, each variable of interest interacted with *Post* is interacted with the year-month fixed effects to allow for different aggregate trends in areas with few and many deputies. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases			
	(1)	(2)	(3)	(4)
Post	-0.130	-0.114	-0.139	-0.132
	(0.089)	(0.094)	(0.090)	(0.090)
Post × Investment Advisers per Capita	-0.888***		-0.578**	-0.750***
	(0.140)		(0.242)	(0.155)
Post × Brokers per Capita		-0.841***	-0.337	
		(0.150)	(0.251)	
Post × Pure Brokers per Capita				-0.183
				(0.153)
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.69	0.68	0.69	0.69
# Counties	3139	3139	3139	3139
Observations	245169	245169	245169	245169

TABLE 11. Effects of Deputization by Client Wealth and Compensation Arrangements

This table studies whether the effect of deputization on elder financial exploitation varies with client wealth and how advisers charge clients for services. Characteristics of registered investment adviser firms are matched to individual adviser representatives and then averaged over individuals working in a specific county. *# Elder Financial Exploitation Cases* is the number of elder financial exploitation cases in a county-month. *Post* is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. *Investment Advisers per Capita* is a county's per capita number of investment advisers. *AUM-Per-Client* is the average AUM per client in a county, where AUM per client is determined at the firm level. *Hourly* is the proportion of advisers associated with firms that charge an hourly fee for services. *Commissions* is the proportion of advisers associated with firms that charge commissions. *Fixed Fees* is the proportion of advisers associated with firms that charge fixed fees. All regressions include county and year-month fixed effects. All regressions include the controls in Table 5. Each control is interacted with *Post* (Yzerbyt et al., 2004). Additionally, each variable of interest interacted with *Post* is interacted with the year-month fixed effects to allow for different aggregate trends in areas with few and many deputies or with low and high AUM-per-Client. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases				
	(1)	(2)	(3)	(4)	(5)
Post	-0.842***	-0.689***	-0.379***	-0.372***	-0.493***
	(0.220)	(0.234)	(0.122)	(0.121)	(0.109)
Post × Investment Advisers per Capita	-1.274	-2.115**	-0.770***	-0.749***	-0.319*
	(0.958)	(1.008)	(0.189)	(0.192)	(0.188)
Post × AUM-per-Client	-1.452***				-0.901***
	(0.387)				(0.139)
Post × Hourly		0.161			0.049
		(0.144)			(0.093)
Post × Commission			-0.123**		0.002
			(0.050)		(0.079)
Post × Fixed Fees				-0.149**	-0.125
				(0.072)	(0.127)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.56	0.55	0.63	0.63	0.64
# Counties	2198	2198	2198	2198	2198
Observations	178331	178720	178720	178720	178331

TABLE 12. Social Incentives

This table studies whether deputization is less effective in counties with more social connectedness and religiosity. *# Elder Financial Exploitation Cases* is the number of elder financial exploitation cases in a county-month. *Post* is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. *Investment Advisers per Capita* is a county's per capita number of investment advisers. *Social Connectedness Index* is a county's Social Connectedness Index measured using Facebook friendship connections. *Adherents (Congregations) Per 1000* is a county's number of religious adherents (congregations) per thousand population. *Social Capital Index* is a measure of a county's social capital developed by the Social Capital Project from the U.S. Joint Economic Committee. All regressions include county and year-month fixed effects. All regressions include the controls in Table 5. Each control is interacted with *Post* (Yzerbyt et al., 2004). Additionally, each variable of interest interacted with *Post* is interacted with the year-month fixed effects to allow for different aggregate trends in areas with few and many deputies or with low and high AUM-per-Client. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases				
	(1)	(2)	(3)	(4)	(5)
Post	-0.106	-0.092	-0.074	-0.206**	-0.198**
	(0.106)	(0.102)	(0.113)	(0.091)	(0.090)
Post × Investment Advisers per Capita	-0.890***	-0.791***	-0.982***	-0.995***	-0.796***
	(0.152)	(0.156)	(0.172)	(0.159)	(0.139)
Post × Social Connectedness Index	1.031***				
	(0.185)				
Post × Congregations Per 1000		0.975***			1.303***
		(0.153)			(0.186)
Post × Adherents Per 1000			0.223**		-0.297**
			(0.087)		(0.129)
Post × Social Capital Index				0.512***	0.391***
				(0.117)	(0.115)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.67	0.67	0.67	0.68	0.68
# Counties	3135	3139	3139	2990	2987
Observations	244887	245169	245169	232985	232787

Internet Appendix to Carlin, Umar, and Yi (2022)

Deputizing Financial Institutions to Fight Elder Abuse

This Internet Appendix contains supplementary analyses. These include the following:

Figures

1. Figure A1 shows the number of financial crimes against the elderly reported by law enforcement to the FBI's NIBRS database
2. Figure A2 shows Figure 3 without removing the state-specific linear trends.
3. Figure A3 is a monthly event time plot.
4. Figure A4 further decomposes the Goodman-Bacon (2021) decomposition in Table 7.
5. Figure A5 shows the main effect dropping each state.

Tables

1. Table A1 provides a correlation table.
2. Table A2 repeats Table 5 without the time-varying county controls to examine if a bad controls problem exists.
3. Table A3 examines the relation between state characteristics and the timing of adoption of the Model Act and whether a state adopts the Model Act.
4. Table A4 examines whether the effect varies before and after the national adoption of FINRA's Rules 2165 and 4512.
5. Table A5 shows the effect at the state-month level.
6. Table A6 Growth in Reporting from 2012 to 2016 and Timing of Model Act Adoption.
7. Table A7 shows main effect starting the sample in different years.
8. Table A8 shows main effect ending the sample in different years.
9. Table A9 shows the dynamics of the results in Table 10.
10. Table A10 shows no effect using placebo outcomes.

11. Table A11 shows no effect for money services business, which do not employ advisers and brokers.
12. Table A12 shows how a elder financial exploitation varies with a county's per-capita number of investment advisers and brokers.
13. Table A13 shows the main effect in counties with no deputies.
14. Table A14 examines whether regulatory actions changed with the policy.
15. Table A15 provides details for the Factiva news searches.

Appendix A. Robustness

Figure A1. Aggregate Financial Crimes Against Elderly Reported to the FBI's NIBRS database

This figure shows the natural logarithm of the nationwide number of financial crimes against the elderly reported by law enforcement agencies to the FBI's NIBRS database. The sample includes all state-months from 2010 to 2020.

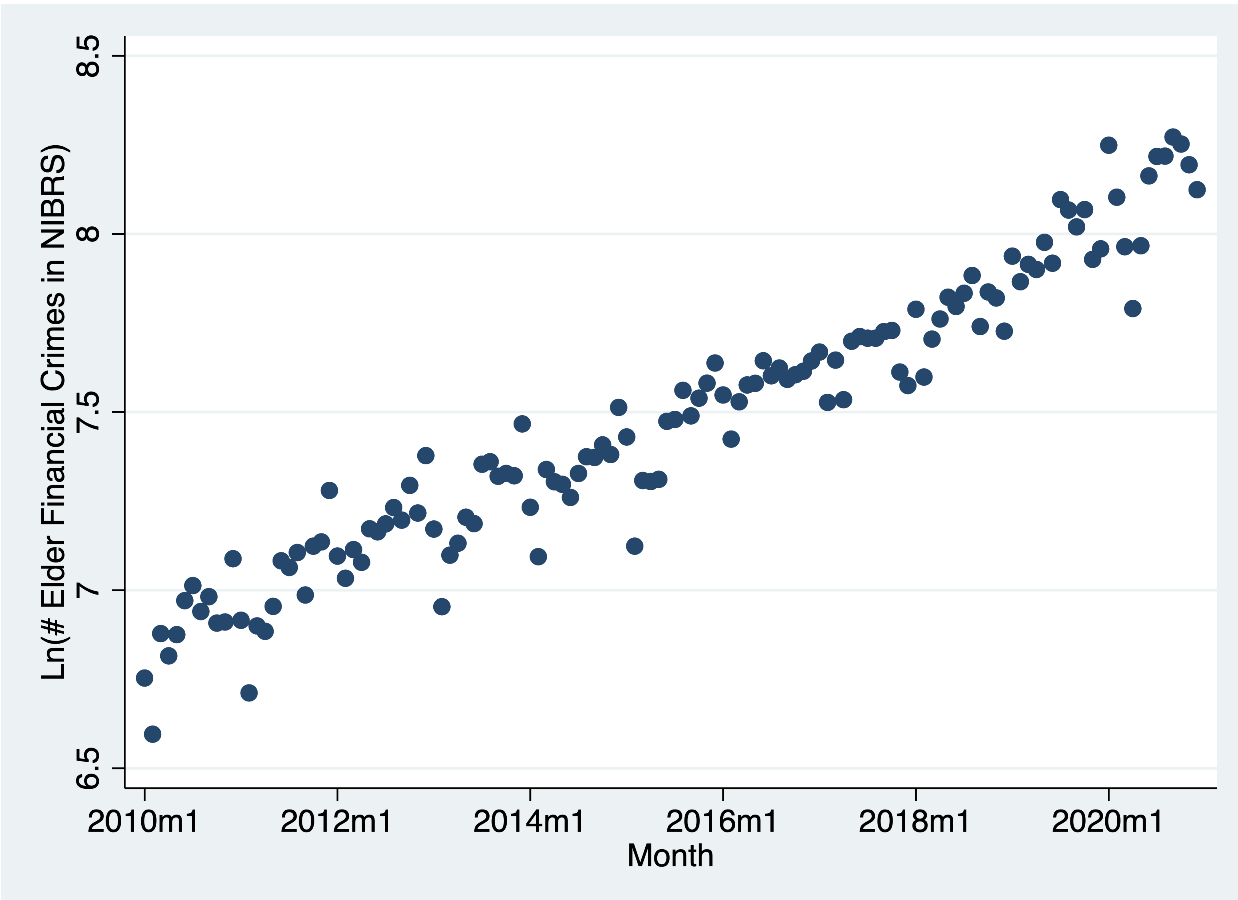


Figure A2. Removing Aggregate Trend in Elder Financial Abuse

This figure complements Figure 3. It shows the trends in the state-level number of elder financial exploitation reports *only* removing the aggregate monthly trend in elder financial exploitation reports using year-month fixed effects. The sample for this figure begins in January 2014 and ends in June 2016, which is before the NASAA Model Act is recommended for adoption.

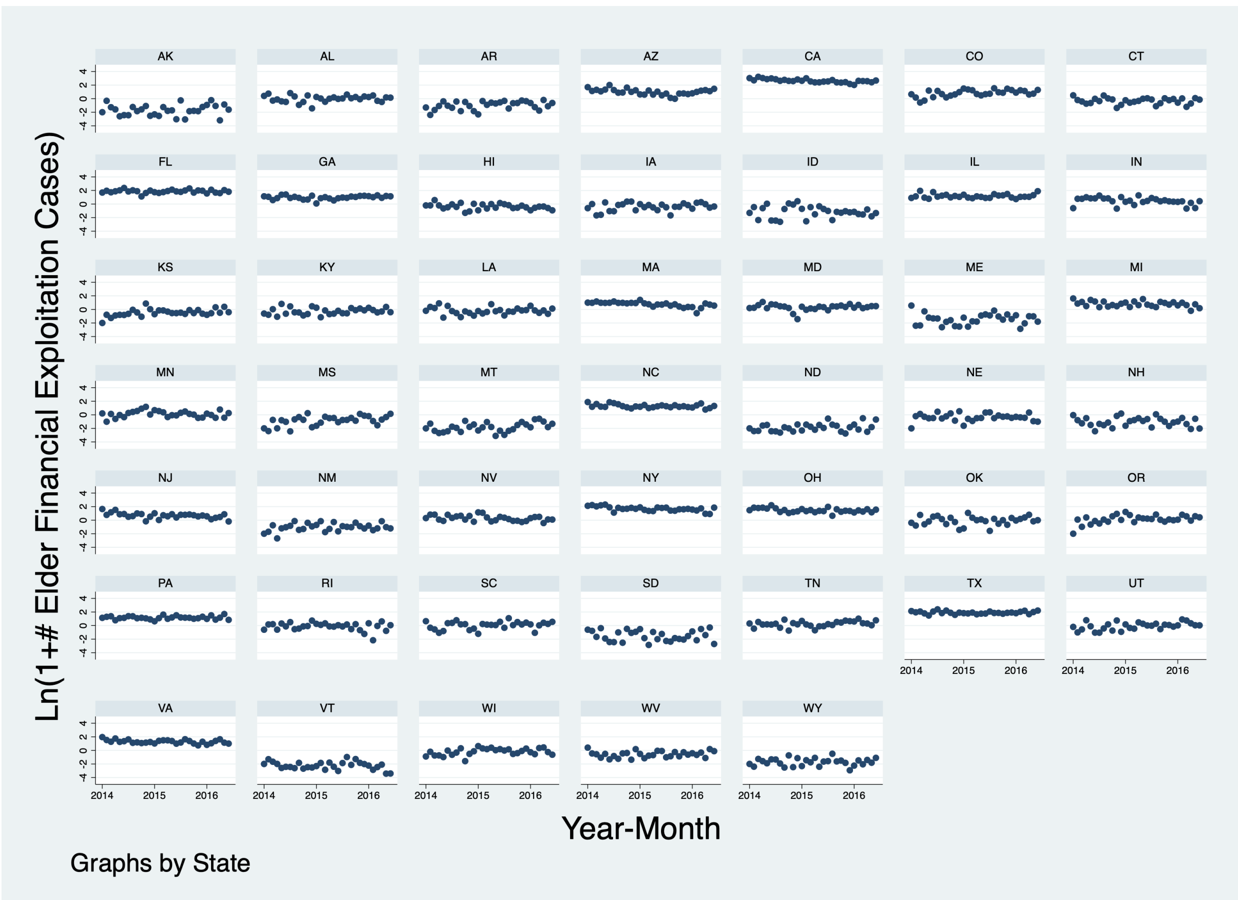


Figure A3. Dynamic Monthly Difference-in-Differences Estimates

This figure estimates the effect of deputizing financial professionals on elder financial exploitation around the date a state adopts the Model Act. The red vertical line at month zero indicates the month of treatment. The outcome variable is *# Elder Financial Exploitation Cases*, the number of elder financial exploitation cases in a county-month. The coefficients plotted are those on indicator variables indicating the event time. If a state does not adopt the Model Act by 2020, then the event time indicators are all zero. Year-month and county fixed effects are included. We show 90% confidence intervals based on standard errors clustered by state. We omit the month six months before the month of treatment.

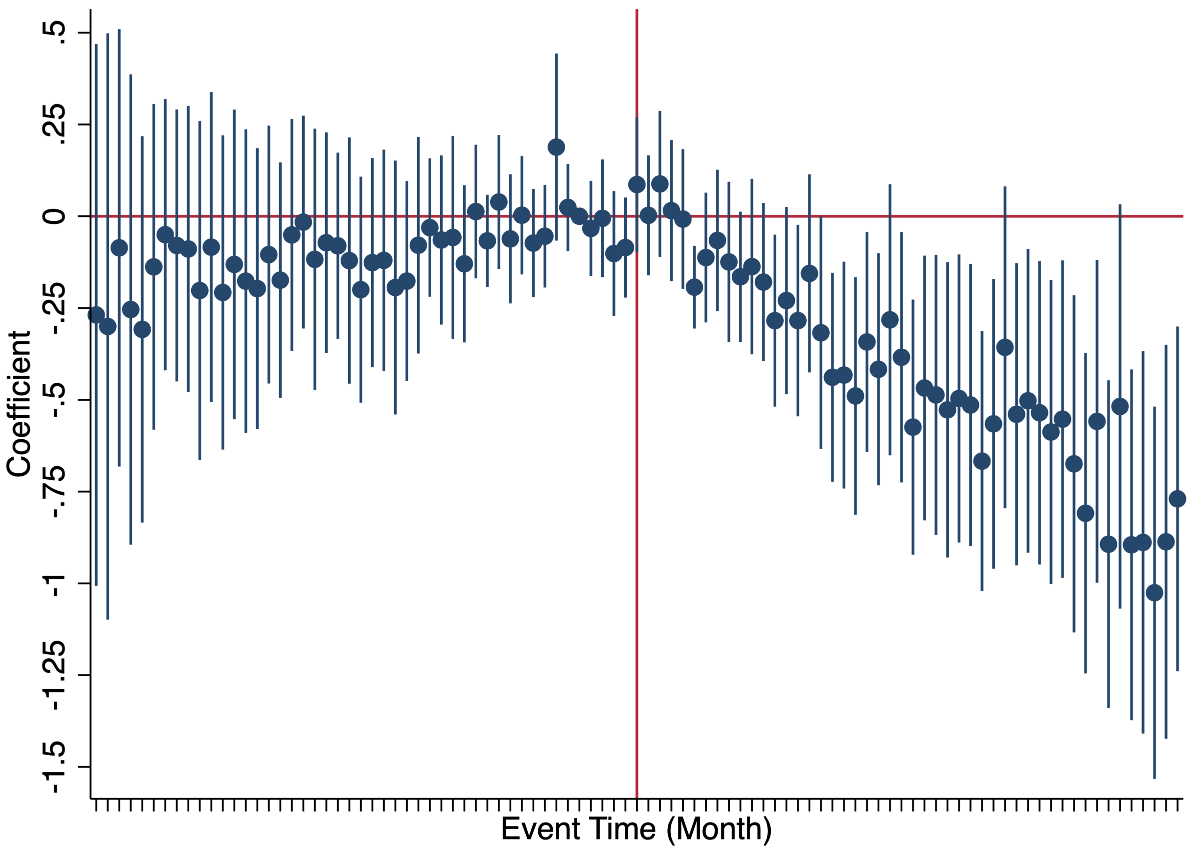


Figure A4. Goodman-Bacon Decomposition

This figure shows graphically the Goodman-Bacon decomposition of staggered difference-in-difference regression coefficient estimate (Goodman-Bacon, 2021). "Earlier Group Treatment vs. Later Group Comparison" is the effect measured using states treated later as controls for the states treated earlier. "Later Group Treatment vs. Earlier Group Comparison" is the effect measured using states treated earlier as controls for the states treated later. "Treatment vs. Never Treated" is the effect measured using states that are never treated as control firms for states that are treated. "Treatment vs. Already Treated" is the effect measured using states that are always treated during the sample period as controls for states treated during the sample period. The average treatment effects for the different comparison groups are shown in Table 7.

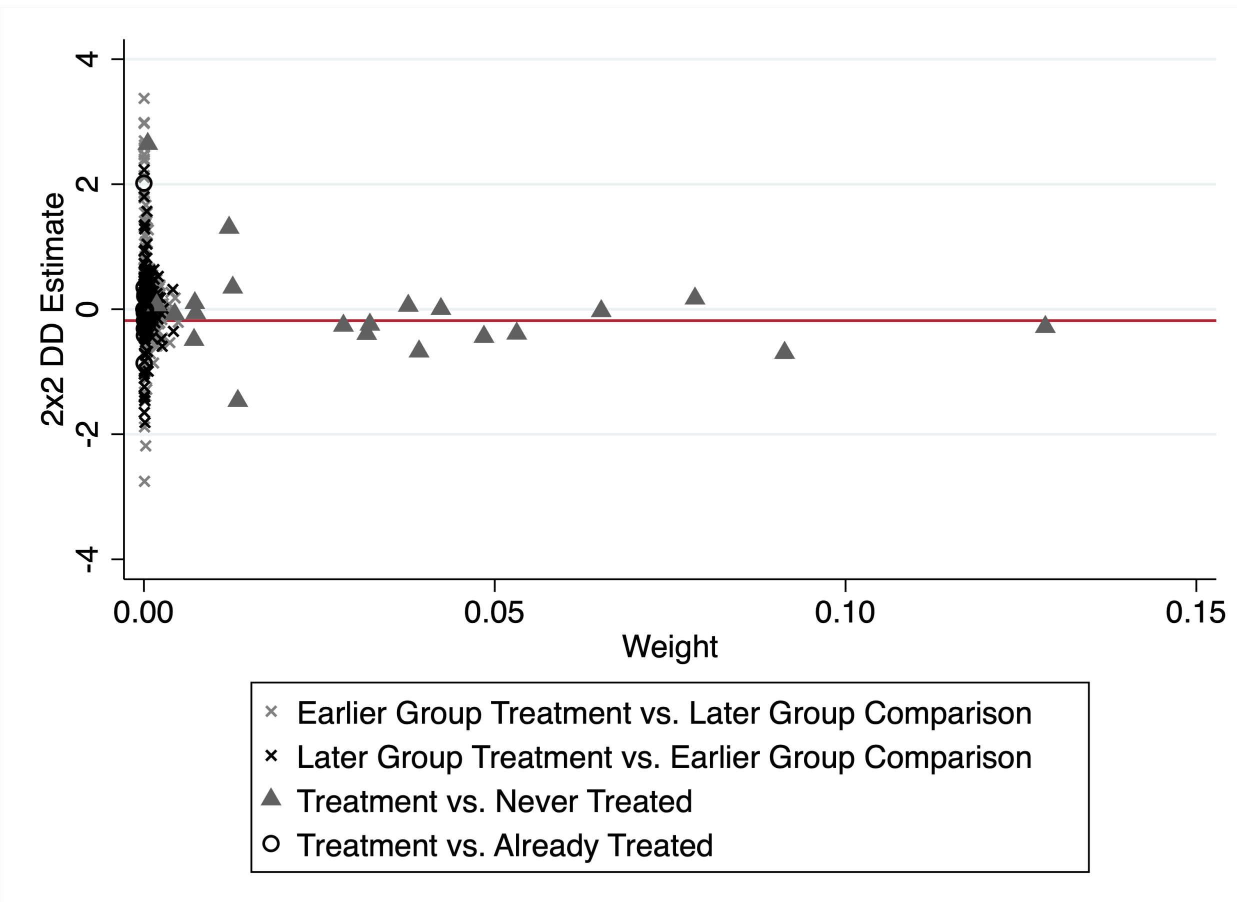
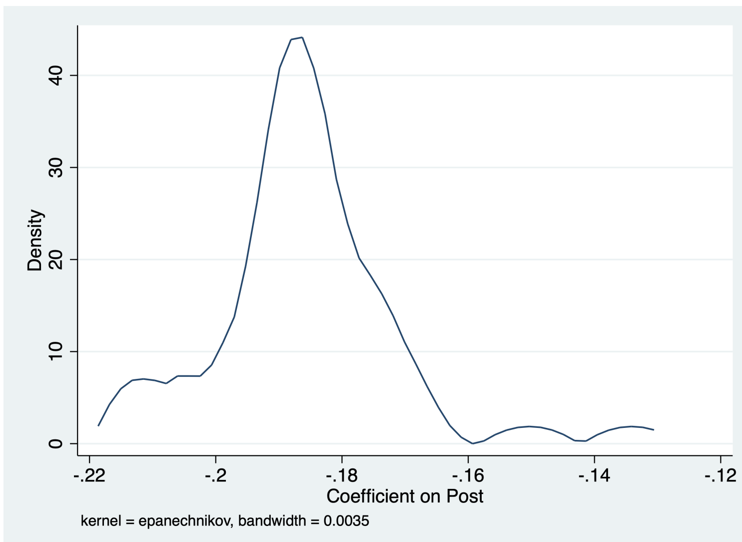


Figure A5. Main Effect Dropping Each State

This figure shows the distribution of the estimated policy effect in Table 5 Column (1) when dropping one state at a time. The y-axis is the fraction of the sample that has a coefficient that falls within a specific bin's range. The figure shows that the result is not driven by any one state. The bottom figure shows the distribution of t-statistics for the estimated effect dropping one state at a time.



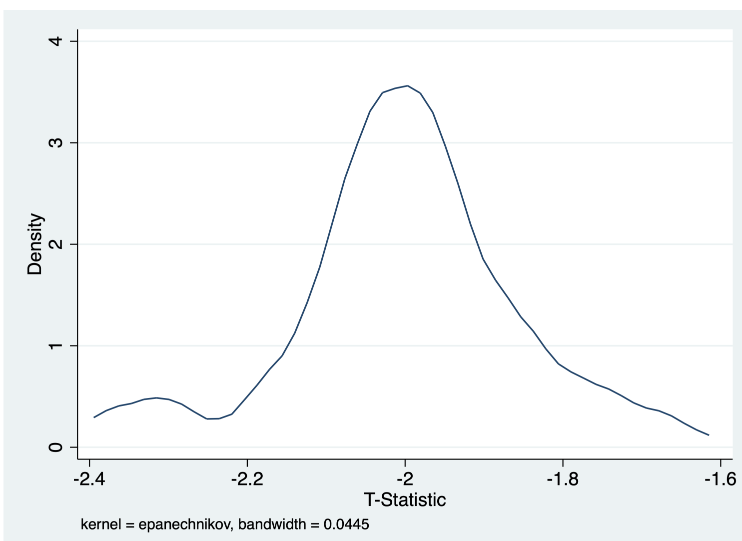


TABLE A1. Correlations

Ln(1+Elder Financial Exploitation Cases)	1.0																					
Log Population Above 65	0.5	1.0																				
Vantage Score	0.1	0.1	1.0																			
Fraction of Subprime	-0.1	-0.1	-1.0	1.0																		
Fraction of Low Income	-0.1	-0.2	-0.8	0.8	1.0																	
Average Age	-0.1	-0.2	0.3	-0.3	-0.1	1.0																
Fraction of Male	-0.1	-0.1	0.2	-0.2	-0.1	0.1	1.0															
Married	-0.2	-0.4	0.4	-0.3	-0.4	0.1	0.2	1.0														
Household Income	0.3	0.3	0.8	-0.8	-0.8	0.2	0.1	0.3	1.0													
Household Debt-to-Income Ratio	0.1	0.2	-0.1	0.1	-0.2	-0.4	0.0	0.2	0.1	1.0												
Bachelor or Higher	0.3	0.5	0.5	-0.5	-0.7	-0.2	-0.0	-0.0	0.8	0.2	1.0											
Income Larger 200k	0.3	0.5	0.4	-0.4	-0.6	-0.2	-0.0	0.0	0.7	0.2	0.8	1.0										
Mean Retirement Income	0.3	0.4	0.2	-0.2	-0.4	-0.1	-0.0	-0.1	0.5	0.2	0.6	0.6	1.0									
Vantage Score	0.1	0.1	1.0	-1.0	-0.8	0.3	0.2	0.4	0.8	-0.1	0.5	0.4	0.2	1.0								
Married	-0.2	-0.4	0.4	-0.3	-0.4	0.1	0.2	1.0	0.3	0.2	-0.0	0.0	-0.1	0.4	1.0							
Female	0.2	0.3	-0.3	0.3	0.3	-0.2	-0.2	-0.5	-0.2	0.0	0.0	0.0	-0.1	-0.3	-0.5	1.0						
Pop Above 85	0.0	-0.0	0.4	-0.4	-0.1	0.1	0.0	-0.0	0.2	-0.2	0.2	0.1	-0.2	0.4	-0.0	0.4	1.0					
Bachelor or Higher	0.3	0.5	0.5	-0.5	-0.7	-0.2	-0.0	-0.0	0.8	0.2	1.0	0.8	0.6	0.5	-0.0	0.0	0.2	1.0				
Pop White	-0.2	-0.1	0.6	-0.5	-0.4	0.3	0.3	0.4	0.3	-0.1	0.0	-0.0	-0.1	0.6	0.4	-0.3	0.2	0.0	1.0			
Asian	0.4	0.5	0.1	-0.1	-0.2	-0.3	-0.1	-0.2	0.4	0.2	0.5	0.6	0.4	0.1	-0.2	0.1	-0.0	0.5	-0.3	1.0		
Black	0.1	0.1	-0.6	0.5	0.4	-0.2	-0.3	-0.5	-0.3	0.1	-0.1	-0.1	0.0	-0.6	-0.5	0.4	-0.2	-0.1	-0.9	0.1	1.0	
Hispanic	0.1	0.1	-0.2	0.2	0.1	-0.2	0.0	0.0	-0.1	0.2	-0.0	0.1	0.1	-0.2	0.0	-0.0	-0.0	-0.0	0.0	0.2	-0.1	1.0

TABLE A2. Effects of Deputization on Elder Financial Exploitation (Excluding time-varying controls to examine if a bad controls problem)

This table presents difference-in-differences estimates of the effect of deputizing financial professionals on elder financial exploitation reported by financial professionals. The outcome in columns (1) to (3) is the number of elder financial exploitation cases in a county-month. Column (3) estimates a Poisson model. The outcome in column (4) is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. The outcome in column (5) is the number of cases per 100,000 persons 65 years of age or older. A similar setup exists in columns (6) to (10), but the outcome is only based on the number of abuse cases involving fund transfers. *Post* is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. We exclude the time varying control variables in Table 5 to examine if a bad controls problem exists. Specifications include county and year-month fixed effects as well as a county-linear trend in elder financial abuse cases, estimated using data prior to July 2016 (Goodman-Bacon, 2021). The sample size drops in columns (3) and (8) because a Poisson regression with county fixed effects removes counties without any variation in elder financial exploitation. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Y = Elder Financial Exploitation Cases					Z = Elder Exploitation Involving Fund Transfers				
	Y			Ln(1+Y)	Y/Pop. 65+	Z			Ln(1+Z)	Z/Pop. 65+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post	-0.208*					-0.050*				
	(0.112)					(0.027)				
Pre 8		-0.047	-0.033	0.002	-0.157		-0.047	0.078	-0.012	-0.032
		(0.225)	(0.090)	(0.038)	(0.617)		(0.106)	(0.149)	(0.042)	(0.180)
Pre 7		0.026	-0.070	0.009	-0.055		-0.010	-0.130	-0.004	-0.033
		(0.148)	(0.106)	(0.027)	(0.421)		(0.067)	(0.193)	(0.028)	(0.123)
Pre 6		-0.030	-0.129	-0.006	-0.243		-0.004	-0.146	-0.001	-0.031
		(0.139)	(0.089)	(0.026)	(0.394)		(0.059)	(0.154)	(0.024)	(0.113)
Pre 5		-0.030	-0.074	0.001	0.030		-0.007	-0.056	-0.001	-0.002
		(0.136)	(0.063)	(0.022)	(0.330)		(0.052)	(0.089)	(0.020)	(0.091)
Pre 4		-0.053	0.007	-0.010	-0.017		-0.017	0.038	-0.006	-0.043
		(0.105)	(0.058)	(0.018)	(0.267)		(0.041)	(0.092)	(0.017)	(0.077)
Pre 3		0.011	-0.004	0.006	0.146		-0.001	0.031	0.002	0.007
		(0.066)	(0.060)	(0.013)	(0.216)		(0.027)	(0.093)	(0.011)	(0.063)
Pre 2		0.055	-0.036	0.009	0.191		0.016	-0.041	0.004	0.006
		(0.045)	(0.051)	(0.009)	(0.158)		(0.016)	(0.071)	(0.007)	(0.045)
Post 0		-0.014	-0.011	0.002	0.188		0.002	0.001	0.002	0.028
		(0.055)	(0.041)	(0.012)	(0.181)		(0.019)	(0.052)	(0.007)	(0.043)
Post 1		-0.109	0.007	-0.004	0.044		-0.025	0.052	-0.006	-0.002
		(0.088)	(0.087)	(0.017)	(0.262)		(0.029)	(0.118)	(0.012)	(0.059)
Post 2		-0.199*	-0.097	-0.033*	-0.378		-0.060	-0.145	-0.022	-0.055
		(0.115)	(0.102)	(0.019)	(0.304)		(0.036)	(0.104)	(0.014)	(0.069)
Post 3		-0.300**	-0.147	-0.046*	-0.458		-0.104**	-0.338**	-0.039**	-0.107
		(0.137)	(0.121)	(0.024)	(0.363)		(0.044)	(0.167)	(0.017)	(0.086)
Post 4		-0.391**	-0.190	-0.066**	-0.728*		-0.130**	-0.449**	-0.054**	-0.203*
		(0.156)	(0.146)	(0.029)	(0.428)		(0.056)	(0.227)	(0.021)	(0.102)
Post 5		-0.396**	-0.201	-0.069**	-0.798*		-0.129**	-0.464**	-0.052**	-0.197*
		(0.175)	(0.130)	(0.030)	(0.462)		(0.063)	(0.188)	(0.024)	(0.112)
Post 6		-0.506**	-0.249*	-0.091**	-1.088**		-0.195**	-0.565***	-0.078***	-0.302**
		(0.195)	(0.151)	(0.035)	(0.460)		(0.074)	(0.213)	(0.028)	(0.124)
Post 7		-0.581**	-0.273*	-0.103*	-1.194*		-0.219***	-0.534***	-0.081**	-0.298*
		(0.271)	(0.152)	(0.056)	(0.676)		(0.079)	(0.183)	(0.031)	(0.162)
Specification	OLS	OLS	Poisson	OLS	OLS	OLS	OLS	Poisson	OLS	OLS
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No	No	No	No
Adjusted R^2	0.67	0.67	.	0.62	0.22	0.63	0.58	.	0.58	0.23
# Counties	3139	3139	2677	3139	3139	3139	3139	2342	3139	3139
Observations	245169	245169	210072	245169	245169	245169	245169	183755	245169	245169

TABLE A3. Timing of Adoption of the Model Act and State Characteristics

In this table, we model when and whether states adopt the Model Act. In Panel A, we limit the analysis to the 30 states that have adopted the Model Act by 2020, and examine whether the timing of adoption is related to state characteristics. The outcome variable, *Group of Adoption*, is equal to 1 for the earliest adopting state(s), 2 for the second earliest adopting state(s), and so on. If multiple states adopt the Model Act in the same month, then those states receive the same group number. In Panel B, we examine all 50 states to test whether the extensive margin of adoption (i.e. *whether* a state adopts the Model Act by 2020) is related to state characteristics. The outcome variable, *Adoption Dummy*, is an indicator variable that takes a value of one if a state adopts the Model Act by 2020. In both panels, the following characteristics are measured at the state level as of December 2015, before the Model Act was finalized. *Number of Elder Exploitation Cases Per 1000* measures the number of elder exploitation cases per 1,000 population that are age 65 and above. *Fraction of Population 65+* measures the fraction of the population that is 65 years of age or older. *Log State Population* is the natural logarithm of state population. *Average Credit Score* measures the average credit score of the elderly in a state. *Subprime 65+* is the proportion of elderly who are subprime in a state. *Low Income 65+* is the proportion of elderly who are low income in a state. *Age 65+* is the average age of the elderly in a state. *Male 65+* is the proportion of the elderly that are male in a state. *Married 65+* is the proportion of the elderly that are married in a state. *Average Household Income* is the average household income of the elderly in a state. *Debt-to-Income 65+* is the average debt-to-income ratio for the elderly in a state. *Bachelor or Higher* is the proportion of elderly who have at least a bachelors degree.

Panel A: Group of Adoption (1 = Earliest)				
	(1)	(2)	(3)	(4)
Number of Elder Exploitation Cases Per 1000	-10.067			-4.110
	(6.835)			(12.084)
Fraction of Population 65+		0.412		0.760
		(0.551)		(0.996)
Log State Population			0.984	-0.155
			(1.090)	(1.845)
Average Credit Score 65+				-0.331
				(1.047)
Subprime 65+				-46.301
				(223.770)
Low Income 65+				37.592
				(126.308)
Age 65+				2.706
				(3.342)
Male 65+				1.075
				(2.232)
Married 65+				0.133
				(0.700)
Average Household Income 65+				0.533
				(0.604)
Debt-to-Income 65+				0.556
				(4.696)
Bachelor or Higher 65+				-18.217
				(74.895)
R^2	0.07	0.02	0.03	0.27
# States	30	30	30	30

Panel B: Adoption Dummy (1=Adopted Model Act, 0=Not Adopted)				
	(1)	(2)	(3)	(4)
Number of Elder Exploitation Cases Per 1000	0.595			0.262
	(0.554)			(0.732)
Fraction of Population 65+		0.001		0.021
		(0.041)		(0.064)
Log State Population			-0.033	0.030
			(0.068)	(0.092)
Average Household Income 65+				-0.035
				(0.028)
Average Credit Score 65+				-0.042
				(0.057)
Subprime 65+				-10.592
				(12.972)
Low Income 65+				-5.272
				(6.445)
Age 65+				-0.150
				(0.210)
Male 65+				-0.036
				(0.135)
Married 65+				-0.003
				(0.035)
Debt-to-Income 65+				0.050
				(0.240)
Bachelor or Higher 65+				0.331
				(3.427)
R^2	0.02	0.00	0.00	0.16
# States	51	51	51	51

TABLE A4. Effect of NASAA's Model Act vs. FINRA's Rules 2165 and 4512

Post is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. *FINRA Passed* is an indicator variable that equals to one after February 2018, which is when FINRA rules 2165 and 4512 granting the same two authorities exclusively to brokers becomes effective nationwide. All regressions include the time-varying county control variables in Table 5. All regressions include county and year-month fixed effects. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Y = Elder Financial Exploitation Cases	
	(1)	(2)
Post	-0.186**	-0.205*
	(0.092)	(0.108)
Post × FINRA Passed		0.070
		(0.193)
Year-Month FE	Yes	Yes
County FE	Yes	Yes
County-Linear Trend	Yes	Yes
Controls	Yes	Yes
Adjusted R^2	0.67	0.67
# Counties	3139	3139
Observations	245169	245169

TABLE A5. Effects of Deputization on Elder Financial Exploitation at State-Month Level

This table presents difference-in-differences estimates of the effect of deputizing financial professionals on elder financial exploitation. The outcome variables are listed at the top of each columns. *Post* is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Y = Elder Financial Exploitation Cases				
	Y		Ln(1+# Elder Abuse Cases	Y/Pop. 65+	Y
	(1)	(2)	(3)	(4)	(5)
Post	-36.962*				
	(21.903)				
Pre 8		10.873	-0.059	0.220	-0.136
		(39.572)	(0.144)	(0.893)	(0.137)
Pre 7		11.836	-0.188	-0.126	-0.148
		(33.077)	(0.124)	(0.819)	(0.140)
Pre 6		8.838	-0.171	-0.481	-0.147
		(29.993)	(0.110)	(0.775)	(0.091)
Pre 5		4.726	-0.019	0.127	-0.092
		(26.768)	(0.105)	(0.723)	(0.079)
Pre 4		2.445	-0.012	0.304	-0.014
		(19.119)	(0.077)	(0.508)	(0.066)
Pre 3		4.937	-0.057	-0.180	-0.011
		(13.177)	(0.079)	(0.409)	(0.063)
Pre 2		2.763	0.025	0.254	-0.010
		(9.563)	(0.079)	(0.371)	(0.050)
Pre 1		.	.	.	.
Post 0		-8.912	-0.048	-0.364	-0.039
		(8.290)	(0.065)	(0.389)	(0.053)
Post 1		-34.302**	-0.137	-0.893*	-0.040
		(13.565)	(0.089)	(0.479)	(0.080)
Post 2		-28.738	-0.175*	-1.312*	-0.131
		(20.127)	(0.098)	(0.777)	(0.117)
Post 3		-48.384	-0.128	-0.609	-0.209
		(29.246)	(0.104)	(0.766)	(0.135)
Post 4		-63.755*	-0.189	-1.353	-0.242
		(34.491)	(0.131)	(0.859)	(0.152)
Post 5		-75.966*	-0.203*	-2.053**	-0.251*
		(40.550)	(0.114)	(0.877)	(0.133)
Post 6		-95.481**	-0.226*	-1.773*	-0.296**
		(45.470)	(0.134)	(1.015)	(0.147)
Post 7		-128.121***	-0.104	-1.991*	-0.291**
		(47.538)	(0.140)	(1.046)	(0.130)
Specification	OLS	OLS	OLS	OLS	Poisson
Year-Month FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
State-Linear Trend	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.81	0.82	0.89	0.75	.
Observations	3913	3913	3913	3913	3913

TABLE A6. Growth in Reporting from 2014 to 2016 and Timing of Model Act Adoption

This table examines whether the change in reporting of elder abuse cases at the state level is related to the timing of adoption of the Model Act. *% Δ Elder Financial Exploitation Cases (2014 to 2016)* is the growth in elder abuse cases in a state from 2014 to 2016. In Column (1), if a state has not adopted the Model Act by the end of the sample (December 2020), then we assume the state adopted the Model Act in December 2020. In Column (2), only states that adopted the Model Act in the sample period are included. Robust standard errors reported. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Months until State Adopts Model Act	
	(1)	(2)
% Δ Elder Financial Exploitation Cases (2012 to 2016)	-3.352	3.194
	(10.217)	(7.712)
Adjusted R^2	-0.02	-0.03
Observations	50	30

TABLE A7. Effects of Deputization on Elder Financial Exploitation for Different Sample Start Years

For different start years, this table presents difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. The outcome variable is the number of elder financial exploitation cases in a county-month. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. The controls are those in Table 5. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases		
	(1)	(2)	(3)
Pre 8	-0.016	-0.179	-0.319
	(0.206)	(0.327)	(0.513)
Pre 7	0.030	0.010	-0.124
	(0.134)	(0.203)	(0.295)
Pre 6	-0.024	-0.115	-0.255
	(0.129)	(0.174)	(0.269)
Pre 5	-0.025	-0.037	-0.106
	(0.131)	(0.158)	(0.272)
Pre 4	-0.054	-0.059	-0.149
	(0.102)	(0.118)	(0.173)
Pre 3	0.013	0.000	0.022
	(0.063)	(0.070)	(0.087)
Pre 2	0.049	0.034	0.068
	(0.044)	(0.047)	(0.059)
Post 0	-0.016	-0.018	0.005
	(0.054)	(0.056)	(0.060)
Post 1	-0.115	-0.115	-0.089
	(0.087)	(0.091)	(0.098)
Post 2	-0.208*	-0.208*	-0.177
	(0.111)	(0.111)	(0.117)
Post 3	-0.296**	-0.293**	-0.249*
	(0.134)	(0.134)	(0.140)
Post 4	-0.386**	-0.382**	-0.333**
	(0.152)	(0.153)	(0.161)
Post 5	-0.388**	-0.384**	-0.336*
	(0.165)	(0.166)	(0.177)
Post 6	-0.489**	-0.484**	-0.430**
	(0.187)	(0.188)	(0.200)
Post 7	-0.565**	-0.564**	-0.523*
	(0.253)	(0.253)	(0.266)
Specification	≥ 2014	≥ 2015	≥ 2016
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adjusted R^2	0.67	0.68	0.69
# Counties	3139	3100	3100
Observations	245169	214451	181476

TABLE A8. Effects of Deputization on Elder Financial Exploitation for Different End Years

For different end years, this table presents difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. The outcome variable is the number of elder financial exploitation cases in a county-month. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. The controls are those in Table 5. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases			
	(1)	(2)	(3)	(4)
Pre 8	-0.016	0.022	0.139	0.095
	(0.206)	(0.169)	(0.105)	(0.099)
Pre 7	0.030	0.047	0.152*	0.116
	(0.134)	(0.114)	(0.086)	(0.073)
Pre 6	-0.024	-0.014	0.087	0.053
	(0.129)	(0.111)	(0.084)	(0.070)
Pre 5	-0.025	-0.017	0.087	0.119*
	(0.131)	(0.105)	(0.086)	(0.068)
Pre 4	-0.054	-0.051	0.068	0.072
	(0.102)	(0.095)	(0.066)	(0.054)
Pre 3	0.013	0.007	0.073	0.055
	(0.063)	(0.076)	(0.051)	(0.040)
Pre 2	0.049	0.049	0.036	0.047
	(0.044)	(0.060)	(0.045)	(0.033)
Post 0	-0.016	-0.104	-0.082	-0.033
	(0.054)	(0.070)	(0.050)	(0.059)
Post 1	-0.115	-0.220**	-0.091	-0.036
	(0.087)	(0.095)	(0.056)	(0.088)
Post 2	-0.208*	-0.264**	-0.171**	-0.056
	(0.111)	(0.110)	(0.080)	(0.106)
Post 3	-0.296**	-0.319**	-0.214*	-0.388***
	(0.134)	(0.136)	(0.126)	(0.076)
Post 4	-0.386**	-0.462***	-0.257	
	(0.152)	(0.153)	(0.172)	
Post 5	-0.388**	-0.390**		
	(0.165)	(0.160)		
Post 6	-0.489**			
	(0.187)			
Post 7	-0.565**			
	(0.253)			
Specification	≤ 2020	≤ 2019	≤ 2018	≤ 2017
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.67	0.67	0.68	0.69
# Counties	3139	3100	3100	3100
Observations	245169	207774	172320	135828

TABLE A9. Effects of Deputization by Type of Financial Professional

The outcome variable is the number of elder financial exploitation cases in a county-month. In Column (1), we examine how the effect varies with the number of advisers per capita. In Columns (2) and (3), we vary the number of brokers and pure brokers (which are not dual-registered as advisers). The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. All regressions include the time-varying county control variables in Table 5. All regressions include county and year-month fixed effects. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases		
Deputy =	Investment Advisers	Brokers	Pure Brokers
	(1)	(2)	(3)
Pre 8	-0.273	-0.385	-0.399
	(0.285)	(0.311)	(0.328)
Pre 8 × Deputy	0.221	0.118	0.070
	(0.320)	(0.351)	(0.339)
Pre 7	-0.194	-0.299	-0.309
	(0.191)	(0.209)	(0.220)
Pre 7 × Deputy	0.190	0.070	0.018
	(0.250)	(0.261)	(0.242)
Pre 6	-0.224	-0.316*	-0.321
	(0.164)	(0.182)	(0.193)
Pre 6 × Deputy	0.102	0.004	-0.032
	(0.230)	(0.243)	(0.228)
Pre 5	-0.136	-0.208	-0.212
	(0.160)	(0.177)	(0.187)
Pre 5 × Deputy	0.111	0.040	0.022
	(0.213)	(0.221)	(0.198)
Pre 4	-0.109	-0.161	-0.172
	(0.117)	(0.128)	(0.135)
Pre 4 × Deputy	0.197	0.146	0.109
	(0.155)	(0.154)	(0.135)
Pre 3	-0.031	-0.069	-0.078
	(0.078)	(0.082)	(0.082)
Pre 3 × Deputy	0.156	0.123	0.087
	(0.159)	(0.143)	(0.115)
Pre 2	0.029	0.011	0.006
	(0.052)	(0.054)	(0.052)
Pre 2 × Deputy	0.106	0.090	0.061
	(0.123)	(0.117)	(0.101)
Post 0	-0.034	-0.050	-0.048
	(0.069)	(0.071)	(0.075)
Post 0 × Deputy	-0.660***	-0.627***	-0.555***
	(0.101)	(0.105)	(0.102)
Post 1	-0.139	-0.150	-0.142
	(0.100)	(0.104)	(0.108)
Post 1 × Deputy	-0.897***	-0.830***	-0.713***
	(0.143)	(0.150)	(0.143)
Post 2	-0.168	-0.161	-0.159
	(0.132)	(0.140)	(0.144)
Post 2 × Deputy	-0.862***	-0.781***	-0.669***
	(0.132)	(0.141)	(0.141)
Post 3	-0.129	-0.096	-0.106
	(0.154)	(0.165)	(0.170)
Post 3 × Deputy	-0.724***	-0.610***	-0.504***
	(0.170)	(0.182)	(0.174)
Post 4	-0.169	-0.113	-0.127
	(0.181)	(0.195)	(0.201)
Post 4 × Deputy	-0.678***	-0.510**	-0.383*
	(0.186)	(0.198)	(0.192)
Post 5	-0.081	0.007	-0.022
	(0.189)	(0.206)	(0.216)
Post 5 × Deputy	-0.604***	-0.399*	-0.285
	(0.225)	(0.237)	(0.232)
Post 6	-0.201	-0.104	-0.134
	(0.208)	(0.224)	(0.236)
Post 6 × Deputy	-0.677***	-0.467*	-0.344
	(0.252)	(0.262)	(0.259)
Post 7	-0.372*	-0.260	-0.277
	(0.214)	(0.227)	(0.240)
Post 7 × Deputy	-0.623*	-0.336	-0.161
	(0.315)	(0.298)	(0.287)
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes
Adjusted R^2	0.67	0.67	0.66
# Counties	3139	3139	3139
Observations	245169	245169	245169

TABLE A10. Placebo

This table presents difference-in-differences estimates of the effect of the deputizing financial professionals on placebo outcomes. In column (1), the placebo outcome is "Ln(1+Insider Trading)", which is the number of FinCEN suspicious activity reports related to insider trading in a county-month. In column (2), the placebo outcome is "Ln(1+Terrorism Financing)", which is the number of FinCEN suspicious activity reports related to terrorism. *Post* is an indicator variable that equals to one after the Model Act becomes effective in a state. The controls are listed in Table 5. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Insider Trading)	Ln(1+Terrorism Financing)
	(1)	(2)
Post	-0.002	0.000
	(0.004)	(0.001)
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.36	0.56
# Counties	3139	3139
Observations	225333	225333

TABLE A11. Effects of Deputization on Elder Exploitation by Industry of Reporting Firm

This table presents the dynamic DiD estimates of the effect of the deputizing financial professionals on elder financial exploitation. The outcome in Column (1) is the number of cases in a county-month reported by depository institutions; the outcome in Column (2) is the number of cases reported by money services business; and the outcome in Column (3) is the number of cases reported by pure broker-dealers. Note that depository institutions include bank holding companies that may contain divisions providing investment advisery and broker-dealer services. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized and thereby empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Depository Institution	# Money Services Business	# Securities
	(1)	(2)	(3)
Pre 8	-0.260	0.049	-0.031
	(0.381)	(0.099)	(0.030)
Pre 7	-0.152	0.051	-0.022
	(0.257)	(0.094)	(0.022)
Pre 6	-0.133	0.013	-0.025
	(0.229)	(0.086)	(0.028)
Pre 5	-0.089	0.004	-0.025
	(0.184)	(0.037)	(0.019)
Pre 4	-0.070	-0.008	-0.022
	(0.138)	(0.037)	(0.019)
Pre 3	-0.030	0.022	-0.024
	(0.077)	(0.030)	(0.017)
Pre 2	0.019	0.003	-0.021
	(0.039)	(0.024)	(0.016)
Pre 2	0.019	0.003	-0.021
	(0.039)	(0.024)	(0.016)
Pre 1	.	.	.
Post 1	-0.163	0.059	0.023
	(0.111)	(0.039)	(0.022)
Post 2	-0.330**	0.052	-0.006
	(0.144)	(0.039)	(0.021)
Post 3	-0.401**	0.052	-0.035**
	(0.181)	(0.051)	(0.016)
Post 4	-0.534**	0.070	-0.034
	(0.211)	(0.046)	(0.021)
Post 5	-0.511**	0.065	-0.055**
	(0.231)	(0.046)	(0.024)
Post 6	-0.655**	0.078*	-0.059
	(0.251)	(0.046)	(0.037)
Post 7	-0.810***	0.081*	-0.050
	(0.288)	(0.046)	(0.049)
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adjusted R^2	0.58	0.36	0.37
# Counties	3139	3139	3139
Observations	245169	245169	245169

TABLE A12. Elder Financial Exploitation by Per Capita Investment Advisers

The outcome variable is the number of elder financial exploitation cases in a county-month. *Per Capita Investment Advisers (Brokers)* is a county's per capita number of investment advisers (brokers). This sample is a cross-section of our main sample taken in December 2015. The control variables are listed in Table 5. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases		
	(1)	(2)	(3)
Per Capita Investment Advisers	0.369**		-0.377**
	(0.149)		(0.158)
Per Capita Brokers		0.514***	0.815***
		(0.158)	(0.202)
Constant	1.049***	1.044***	1.048***
	(0.086)	(0.084)	(0.083)
Year-Month FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adjusted R^2	0.34	0.35	0.35
# Counties	3139	3139	3139

TABLE A13. Effects of Deputization on Elder Financial Exploitation in Counties with No Advisers and No Brokers

This table presents difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. The outcome variable is the number of elder financial exploitation cases in a county-month. *Post* is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Elder Financial Exploitation Cases	
	(1)	(2)
Post	0.071	
	(0.046)	
Pre 8		-0.007
		(0.048)
Pre 7		0.029
		(0.044)
Pre 6		0.025
		(0.048)
Pre 5		0.042
		(0.051)
Pre 4		0.032
		(0.046)
Pre 3		0.052
		(0.047)
Pre 2		0.096
		(0.067)
Pre 1		.
		.
Post 0		0.087
		(0.089)
Post 1		0.096
		(0.061)
Post 2		0.072
		(0.068)
Post 3		0.118
		(0.075)
Post 4		0.101
		(0.061)
Post 5		0.112
		(0.085)
Post 6		0.039
		(0.072)
Post 7		-0.008
		(0.120)
Year-Month FE	Yes	Yes
County FE	Yes	Yes
County-Linear Trend	Yes	Yes
Controls	Yes	Yes
Adjusted R^2	0.78	0.78
# Counties	2997	2997
Observations	59245	59245

TABLE A14. Was there a coinciding increase in monitoring from regulatory authorities?

This table studies whether empowerment of financial professionals to halt suspicious disbursements coincides with increases in monitoring by regulatory authorities of investment advisers and brokers. More specifically, we test whether there are coinciding increases in regulatory actions, customer complaints, and criminal charges filed against advisers and brokers. *I(Regulatory Actions>0)* is an indicator variable that equals to one if there are any regulatory actions taken against advisers and brokers in a county-month. A regulatory action is a sanction taken by the regulator against an adviser or broker, for example, permanently barring him or her from registering with a state's security division. *Post* is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. All regressions include county and year-month fixed effects. All regressions include the controls in Table 5. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	I(Regulatory Actions)	
Post	0.00019	
	(0.00044)	
Pre 8		-0.00035
		(0.00103)
Pre 7		-0.00014
		(0.00089)
Pre 6		0.00021
		(0.00114)
Pre 5		-0.00070
		(0.00081)
Pre 4		-0.00009
		(0.00080)
Pre 3		0.00137**
		(0.00068)
Pre 2		0.00151
		(0.00093)
Post 0		0.00051
		(0.00047)
Post 1		0.00103
		(0.00079)
Post 2		0.00047
		(0.00054)
Post 3		0.00123
		(0.00090)
Post 4		0.00068
		(0.00082)
Post 5		0.00032
		(0.00097)
Post 6		0.00148
		(0.00139)
Post 7		0.00048
		(0.00104)
Constant	-0.00063	-0.00074
	(0.00351)	(0.00346)
Controls	Yes	Yes
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.04	0.04
# Counties	2812	2812
Observations	183796	183796

TABLE A15. Details Regarding Factiva Searches

In this table, we present the text, date, region, timestamp, and other details of the searches that we conduct on Factiva's global news search engine. "And" and "Or" are operational words.

Panel A	
Text	(adviser Or advisor) And (halt Or delay) And (financial abuse Or financial exploitation)
Date	In the last 5 years
Source	All pictures Or All publications Or All web news Or All multimedia Or All blogs
Author	All authors
Company	All companies
Industry	All Industries
Region	United States
Language	English
Results Found	67
Timestamp	19 April 2020 1:58 GMT
Panel B	
Text	(adviser Or advisor) And (suspicious transaction) And (financial abuse Or financial exploitation)
Date	In the last 5 years
Source	All pictures Or All publications Or All web news Or All multimedia Or All blogs
Author	All authors
Company	All companies
Industry	All Industries
Region	United States
Language	English
Results Found	2
Timestamp	16 April 2020 23:16 GMT
Panel C	
Text	(adviser Or advisor) And (elder financial exploitation Or elder financial abuse Or elder financial fraud)
Date	In the last 5 years
Source	All pictures Or All publications Or All web news Or All multimedia Or All blogs
Author	All authors
Company	All companies
Industry	All Industries
Region	United States
Language	English
Results Found	209
Timestamp	16 April 2020 23:08 GMT