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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 where the elderly are more isolated. Our results highlight the role financial professionals play in combating social problems and the impact of permissive policies.

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).

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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 et al., 2022). Our identifying assumption is that states' timing of adoption is independent of factors that might otherwise affect elder financial abuse. 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. We also find parallel pre-trends.

Using two measures of elder financial exploitation, we find that this permissive policy appears to be effective at reducing the 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. The effect is stronger in counties with more deputies, and where more deputies work for bank holding companies. This is consistent with the fact that financial exploitation typically involves a checking or savings account (wire transfer, check, or debit card).[1] 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 is likely due to a few reasons. The new authorities allow financial professionals to stop abuse faster and earlier, reducing the number of cases reaching the $5000 mandatory reporting threshold to the Department of Treasury. Additionally, family members and other perpetrators likely 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. 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.

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 $5000 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 et al., 2018; Charoenwong et al., 2019; Egan et al., 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 au-

[1] The county-level presence of bank branches per capita is associated with abuse reports. We control for the presence of banks, either through branches or deposits, and show that our findings regarding the presence of deputies remain robust.

thorities to abuse the elderly, as there is no evidence of an increase in regulatory actions against advisers. In general, 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 (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 1051 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 disproportionately victimized, whereas DeLiema et al. (2020) do not find a 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. 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. 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-

[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.

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 Sections 2.3.1 and 2.3.2.

	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.

dealer as any "company engaged in the business of buying and selling securities on behalf of its clients, for its own account (as a dealer), or both." 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.

2.2.3. Institutions and oversight

RIAs and broker-dealers may be standalone 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). In our sample, slightly more than half of advisors and brokers work for subsidiaries of bank holding companies. Internet Appendix Tables A1 and A2 show that the Top 50 registered advisor or broker-dealer firms employ about two-thirds of advisers and brokers. Among these advisers and brokers, slightly more than 50% of them work for depository institutions (i.e., the parent company is a bank holding company). In the full sample of investment adviser (broker-dealer) firms, 56.5% (40.6%) of investment advisers (brokers) work for bank holding companies.

When a financial professional fills out a Suspicious Activity Report (SAR) to report elder financial exploitation to the U.S. Department of Treasury, they must provide information about the parent company that owns their firm. For example, if an adviser works at Merrill Lynch, they indicate that Bank of America is their parent company. The SAR asks advisors to indicate what type of firm the parent company is, and in particular whether it is a depository institution or a securities firm (see Internet Appendix Figs. A1 and A2). We leverage this feature of the data in our later analyses.

2.3. Legislation targeting elder financial exploitation

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 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.

[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.

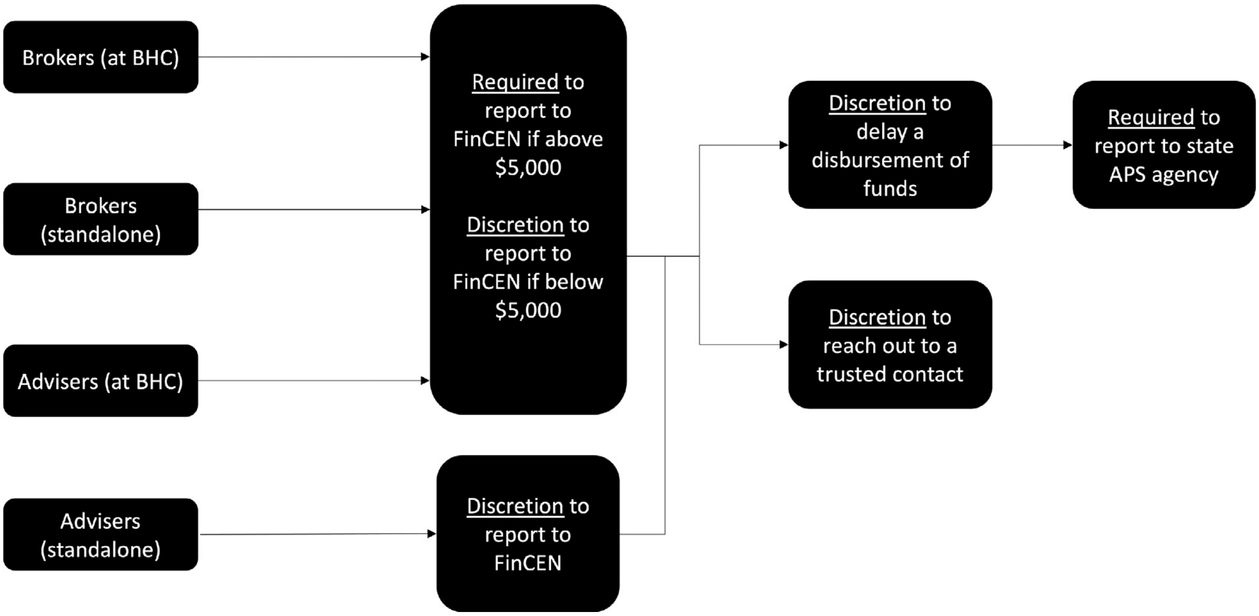

Fig. 1. Reporting elder abuse.
Advisers refers to investment advisers, which have a fiduciary duty to clients when providing financial planning advice. *Brokers* assist clients with transactions and are not held to a fiduciary standard. *BHC* refers to bank holding company, which is a financial institution that contains a bank subsidiary. *FinCEN* refers to "The Financial Crimes Enforcement Network", which is a bureau of the United States Department of the Treasury. The figure shows that brokers at BHCs, advisers at BHCs, and standalone brokers must (may) report suspicious activity above (below) $5000 to FinCEN. Standalone investment advisers are not required to report suspicious activity to FinCEN. The figure also shows that in states that adopted the Model Act, brokers and investment advisers have the discretion to delay a disbursement of funds or reach out to a trusted contact. In the event that a disbursement is delayed, the financial professional must report the action to the state's adult protective services.

2.3.1. 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 the 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 the 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.

Figure 1 provides a flowchart to appreciate how the Model Act may have affected advisor and broker behavior. For advisors and brokers working at depository institutions (i.e., where the parent company of their organization is a bank holding company), they are required to report suspicious activity involving more than $5000, but have discre-

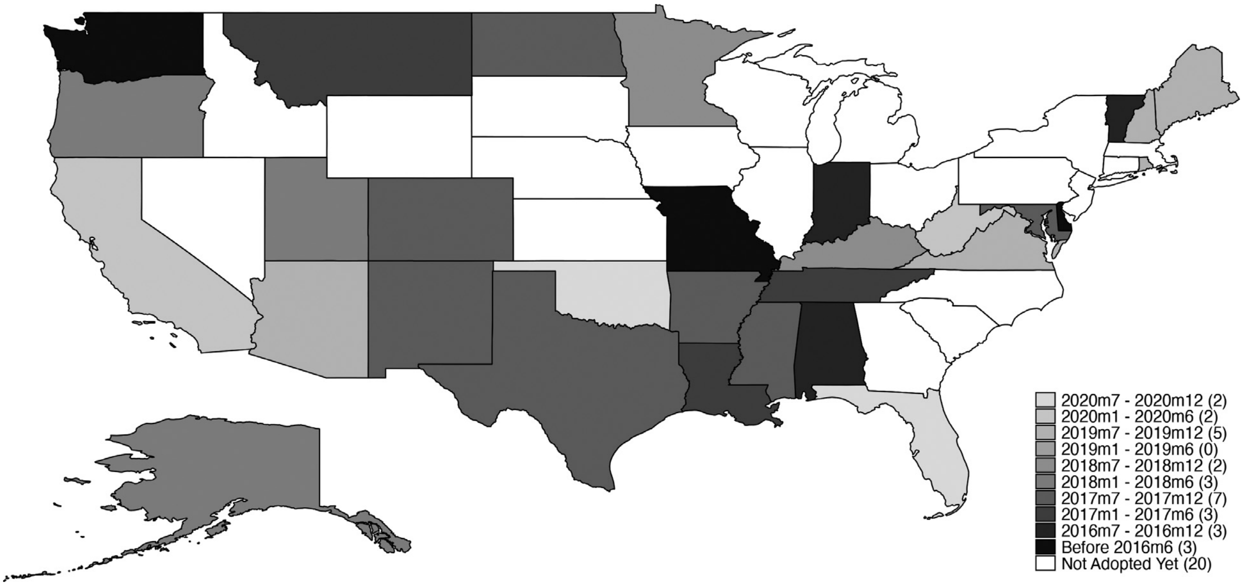

Fig. 2. Staggered adoption of the model act across states.
The map shows the staggered adoption of the Model Act across states through December 2020 as listed in Table 1. In the legend, the number in parentheses is the number of states in that group.

tion over reporting smaller amounts. Brokers at independent entities faced similar requirements. 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. The flowchart makes clear that advisors at independent entities had no reporting requirements to FinCEN at any dollar amount. With the Model Act Provisions, advisors and brokers of all types could halt disbursements and reach out to a trusted contact.

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 2 shows graphically the staggered adoption of the Model Act or similar provisions across U.S. states.

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.

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).

2.3.2. 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.

Because the essence of FINRA Rules 2165 and 4512 is similar to that of the Model Act, the national passage of these FINRA regulations may confound our analysis of the staggered adoption of the Model Act across states. We examine this in Internet Appendix Table A3 and find that the effect of the Model Act on elder financial abuse is not significantly different before and after the implementation of the FINRA rules. There are a few reasons why we might expect this. First, the FINRA rules only apply to brokers as opposed to a broader range of financial professionals. Second, the Model Act grants immunity to deputies that disrupt abuse from some forms of client backlash (i.e., lawsuits) but not others (i.e., client terminates relationship with deputy). By contrast, FINRA as a self regu-

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 the state legislature's 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*

latory agency cannot grant immunity. Finally, is the fact that states continued to dedicate legislative time to adopting the Model Act provisions years after the passage of the FINRA rules.[4]

3. Data and sample

3.1. 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 professionals 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

[4] In Internet Appendix B.1, we also discuss the *Senior Safe Act*. Briefly, it was a national rule change that provides immunity to financial institutions for reporting potential exploitation but does not provide any tools to advisers and brokers.

Table 3
Summary statistics.
Panel A: County-month summary statistics
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 sample period is January 2014 to December 2020. 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 Capita* 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 Capita* (*Brokers Per Capita*) is the number of investment advisers (brokers) in a county divided by the total county population, multiplied by 1000. *Population 65+* is the number of persons 65 years of age or older. *% Population 65+* is the percentage of the total population in a county that is 65 years of age or older. *Credit 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 in thousands 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. *% Bachelor or Higher* is the percentage of county adults with at least a bachelor's degree. *Religious Adherents Per Capita* is the number of individuals with and without an affiliation to a congregation per 1000 individuals. *Religious Congregation Per Capita* is the number of religious congregations per 1000 individuals.

Variables	(1) Mean	(2) SD	(3) *p*10	(4) *p*50	(5) *p*90	(6) *N*
Elder Financial Exploitation Cases	1.3	4.1	0.0	0.0	3.0	263,676
Elder Financial Exploitation Cases Per Capita	3.8	9.2	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 Capita	0.4	0.9	0.0	0.2	1.0	263,676
Brokers Per Capita	0.7	1.7	0.0	0.4	1.5	263,676
Population 65+ (×1000)	15.1	43.3	1.0	4.5	31.1	263,676
% Population 65+	17.9	4.6	12.4	17.6	23.7	263,676
Credit Score (65+)	727.8	24.1	697.0	730.1	755.5	263,676
% Subprime (65+)	19.1	10.4	7.7	17.6	33.3	263,676
% Low Income (65+)	52.2	12.2	37.9	51.8	66.7	263,676
Average Age (65+)	77.2	1.9	74.9	77.2	79.3	263,676
% Male (65+)	47.8	9.1	38.6	47.4	57.9	263,676
% Married (65+)	54.5	11.1	42.3	54.1	66.7	263,676
Household Income (65+)	90.5	15.1	72.9	88.8	110.2	263,676
% Household Debt-to-Income Ratio (65+)	6.5	2.3	3.8	6.5	9.2	263,676
% Bachelor or Higher	21.2	9.3	12.0	18.9	33.5	263,676
Religious Adherent Per Capita	514.1	181.7	295.4	497.2	753.5	263,676
Religious Congregation Per Capita	2.4	1.4	0.9	2.2	4.2	263,676

Panel B: The composition of FinCEN elder financial exploitation cases by county-month
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 and industry of the reporting institution.

Instrument involved		Product involved		Industry of reporting firm	
U.S. Currency	42.2%	Debit Card	32.4%	Depository Institution	70.0%
Funds Transfer	23.9%	Deposit Account	28.7%	Money Services Business	26.2%
Personal/Business Check	20.0%	Credit Card	6.0%	Securities/Futures	1.5%
Bank/Cashier's Check	6.5%	Other	32.9%	Other	2.3%
Other	7.4%				

Panel C: State-month NIBRS crime data
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.

Variables	(1) Mean	(2) SD	(3) *p*10	(4) *p*50	(5) *p*90	(6) *N*
Elder Financial Exploitation Cases (Ages 65+)	53	61	5	33	147	3536
Elder Financial Exploitation Cases (Ages 50–65)	63	68	7	41	172	3536

product involved (e.g., fund transfer). Reports are tied to the county in which the victim resides.[5]

Figure 3 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). While reports of abuse continue to increase since 2014, in Internet Appendix Fig. A3, we show that after removing the national, aggregate reporting trend using year-month fixed effects, the number of residual reports of abuse in a state is steady over time prior to the Model Act.

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

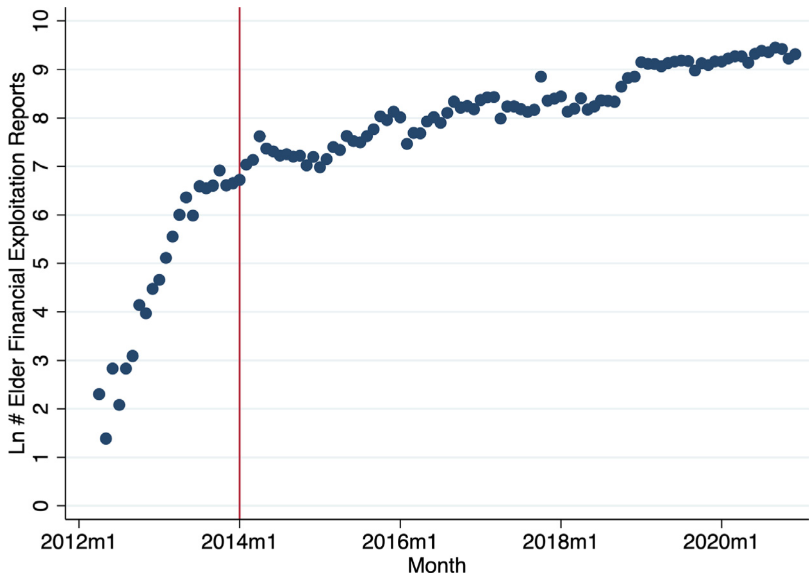

Fig. 3. Elder financial exploitation by month.
This figure depicts, for each month ("m"), the natural logarithm of the total number of suspicious activity reports submitted to FinCEN that are flagged as related to elder financial exploitation in the United States. The category for suspicious activity 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Reports would fall if abuse is interrupted earlier, before reaching the $5000 mandatory reporting threshold to the U.S. Department of Treasury. Family members could also 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.

3.2. 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 6328 participating law enforcement agencies in the US and the agencies cover about one-third 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 Fig. A4 shows the nationwide trend in financial crimes against the elderly. Consistent with financial exploitation of the elderly becoming a growing problem, there is a general increase in financial crimes against the elderly in the NIBRS database.

3.3. 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 representatives, we

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

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.

In our analysis, we also determine whether an adviser or broker works for a bank holding company. To do so for brokers, we find the detailed report for the firm in the CRD database managed by FINRA and used by the SEC. There is a question asking whether a registered investment adviser is controlled directly or indirectly by a bank holding company. (See caption of Fig. A2.) To do so for investment advisers, we look at Item 7 on the employing registered investment adviser's annual Form ADV filing with the SEC. Item 7 asks about the firm's lines of business and those of any related or commonly controlled entity. Additionally, we reference a list of all registered banks. We find that 56.5% (40.6%) of investment advisers (brokers) work for bank holding companies.

Because many advisers and brokers work for depository institutions, we collect data on the presence of banks from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposit (SOD) database. It details the physical location of bank branch offices in the US and deposits at each branch from 2014 to 2020. We aggregate the deposits and number of branches at the county and year level.

3.4. Social connectedness measures

3.4.1. 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.

3.4.2. 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.

3.4.3. 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, nonprofit 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]

3.5. 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 educational attainment and average household income for individuals 65 years of age or older.

We also use data from a major credit bureau that tracts a random sample of 1% of adults. For individuals in a county who are 65 years of age or older, we average their credit score, fraction subprime, fraction low income, age, fraction married, and household debt-to-income ratio at the county level, and we standardize these variables.

3.6. Summary statistics

Our sample includes monthly observations for 3139 counties from January 2014 to December 2020, resulting in 263,676 total county-month observations.

Table 3 presents summary statistics for the counties in our sample. Panel A shows that the average number of

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

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 3.1 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 3.8 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 1st and 99th percentile in all OLS specifications to reduce skewness and alleviate the influence of outliers.

In terms of access to financial professionals, the average number of investment advisers (brokers) per 1000 individuals is 0.4 (0.7). There is a large distribution in access to financial professionals as the standard deviations of these variables are more than twice as large as their means.

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. The average credit score is about 728. 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%. We present a correlation table in Internet Appendix Table A4. In Table A5, we show a positive correlation between the number of elder financial exploitation reports and the number of advisers and brokers per capita.

Table 3 Panel B breaks out the county-month abuse cases by the product or instrument involved 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 70% 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 53 cases on average against persons above 65 years of age in a state-month. The standard deviation in case counts is 61 cases per state-month. Counts range at the 10th percentile from 5 cases per state-month to the 90th percentile being 147 cases per state-month.

4. Results

4.1. 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 Fig. 2 show variations in the treatment dates across states.

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

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

Here, we index county by c, state by s, and month by t. In Eq. (2), $POST_{st}$ is an indicator variable that equals to one in the month the Model Act goes into effect in a state. 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 include county fixed effects, denoted by η_c, to absorb any unobserved persistent county characteristics. We also 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 Fig. 3 and the related discussion in Section 3.1). For additional robustness, we also estimate and control for state-level and county-level linear trends in elder abuse, estimated during the pretreatment period

[8] In Appendix B.4.1, we show our main result holds 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

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

1. "Log Pop Above 65", captures the size of the elderly population.
2. "Credit Score", captures the general financial health. A higher score may suggest a wealthier base of elderly to exploit.
3. "% Married (65+)", captures the extent to which the elderly are socially isolated.
4. "% Subprime (65+)", indicates the amount of assets available to exploit.
5. "% Low Income (65+)", 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 (65+)", DeLiema et al. (2020) finds females more subject.
8. "Household income (65+)", may indicate the amount of financial resources available to exploit.
9. "Household Debt-to-Income (65+)", 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.

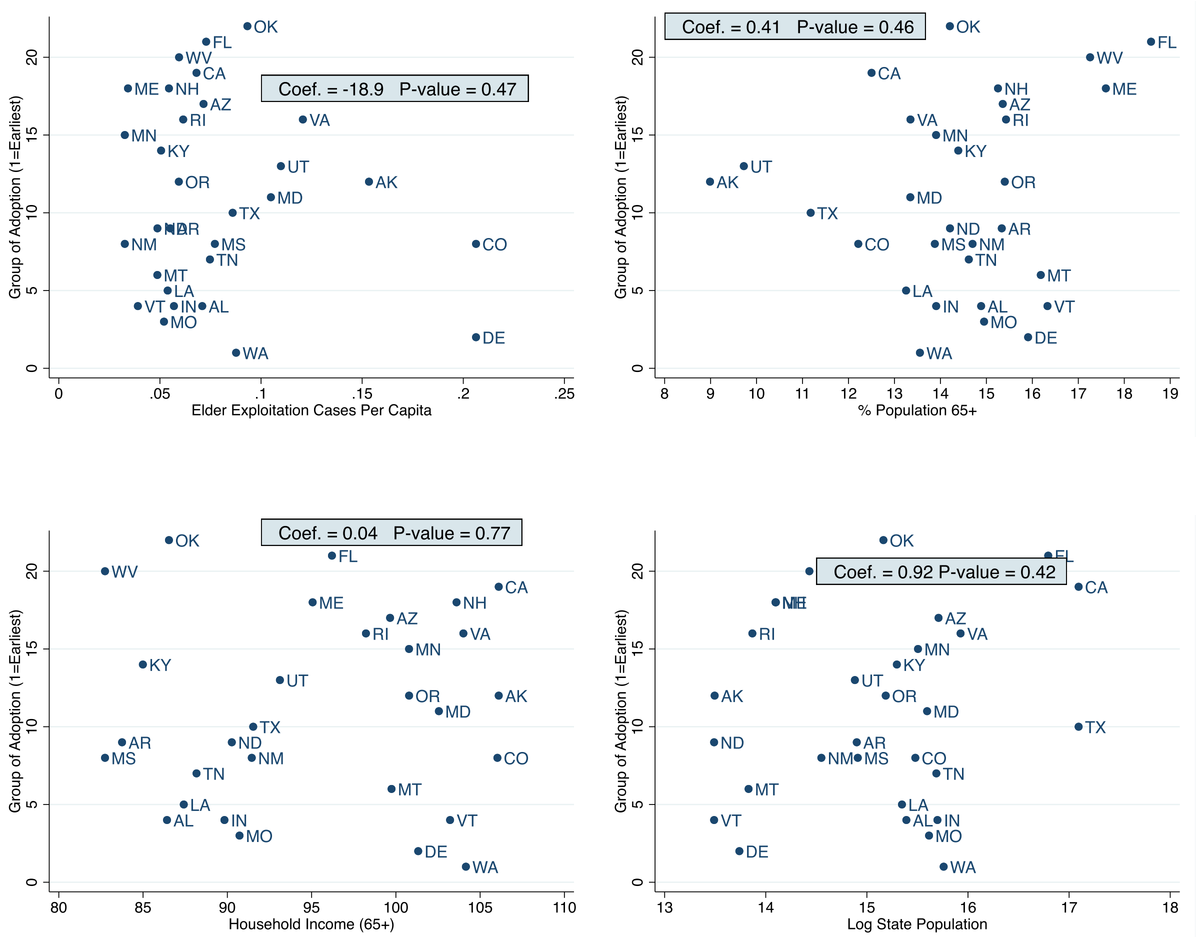

Fig. 4. Do state characteristics predict the timing of adoption?
This figure shows scatter plots of the timing of states' adoption of the Model Act against states' characteristics, for the 30 states that adopted the Model Act by December 2020. The variable plotted on the y-axis, *Group of Adoption*, 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. We show several state characteristics on the x-axis. *Elder Exploitation Per Capita* measures the rate of elder financial exploitation cases per 1000 people in a state that are age 65 and above. *% Population 65+* measures the fraction of the population in a state that is age 65 and above. *Household Income* measures the average household income of the elderly in a state. *Log State Population* is the natural logarithm of the population in a state. All variables on the x-axis are measured as of 2015, the year before the Model Act was finalized. The coefficients and p-values of the slopes are reported in each figure. The corresponding regression results are reported in panel A of Internet Appendix Table A6, which also examines additional covariates using a multivariate regression specification.

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 Eq. (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." The parameter h corresponds to 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. As in Callaway and Sant'Anna (2021), we omit the indicator immediately before a state adopts the Model Act. We present our estimates of Eq. (3) graphically and provide the corresponding tables in the Internet Appendix.[11]

4.2. Identification assumptions

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.

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 Fig. 4,

[11] We discuss the Model Act's interaction with FINRA Rules 2165 and 4512 in Section 2.3.2.

Table 4
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 Column (1) is the total number of elder financial exploitation cases in a county-month. The outcomes in Columns (2), (3), and (4) are the number cases of elder financial exploitation reported by depository institutions, money services businesses, and securities firms, respectively. *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 control variables, defined in Table 3, include *Credit 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 linear state and county trends 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 financial exploitation cases reported by			
	All institutions (1)	Depository institutions (2)	Money service businesses *(Placebo)* (3)	Securities firms (4)
Post	−0.196**	−0.209**	0.030	0.011
	(0.096)	(0.093)	(0.019)	(0.018)
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Linear Trends	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.67	0.62	0.34	0.38
# Counties	3139	3139	3139	3139
Observations	263,676	263,676	263,676	263,676

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. Regression analysis shows similar results across a wider range of covariates (Internet Appendix Table A6 Panel A). The extensive margin—whether to adopt the policies at all by 2020—is also unrelated to the aforementioned state characteristics (Table A6 Panel B). We also find no evidence that state-level growth in elder financial exploitation cases between 2012 and 2016 is correlated with when states adopt the Model Act provisions (Table A7). Overall, there is no strong relation between a variety of state characteristics and *when* and *whether* a state adopts the Model Act.

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)

Equation (3) allows us to estimate dynamic DiD regressions and examine whether the trends in treated and control counties diverge prior to the implementation of new regulations. In Section 4.3, we discuss Fig. 5, which shows no unusual changes in elder financial exploitation in treated counties relative to the control counties prior to the rule change, and a noticeable drop only following the rule change. This pattern is robust to four different specifications and transformations of the outcome variables, as shown in Fig. 5.

4.3. Main effects

We find that deputizing financial professionals appears to be effective at deterring financial exploitation of the elderly. Table 4 shows the results. In Column (1), the outcome variable is the total count of elder financial exploitation in a county-month. The estimated effect is a 0.196 drop in the number of abuse cases per county-month, which represents 4.8% (0.196/4.1) of a standard deviation in abuse and 15.1% (0.196/1.3) of the mean. These magnitudes speak to effects within the set of abuse that goes through the hands of financial professionals, rather than the entire universe of elder financial abuse. Internet Appendix Table A8 shows that the estimate in Column (1) is stable to layering in the controls and fixed effects.

In Columns (2) to (4) of Table 4, we decompose the main effect by the type of reporting institution. Unconditionally, 70.0%, 26.2%, and 1.5% of reports come from depository institutions, money services businesses, and securities firms, respectively (Table 3 Panel B). Because money services businesses do not employ investment advisers and brokers, they act as a placebo group and we would not expect to see a drop in their reports of elder financial exploitation. Consistent with this reasoning, Column (3) shows no drop in reports of abuse from money services businesses after states' adoptions of the Model Act. In subsequent tables, we exclude reports of abuse by money services businesses from the construction of the outcome variable. By contrast, Column (2) shows a significant drop in reports by depository institutions. This is expected, because as we noted above, more than 50% of advisers and more than 40% of brokers work for bank holding companies. Lastly, Column (4) shows no drop in reports by securities firms, which include standalone broker-dealer firms, but these firms do not generally seem to be active re-

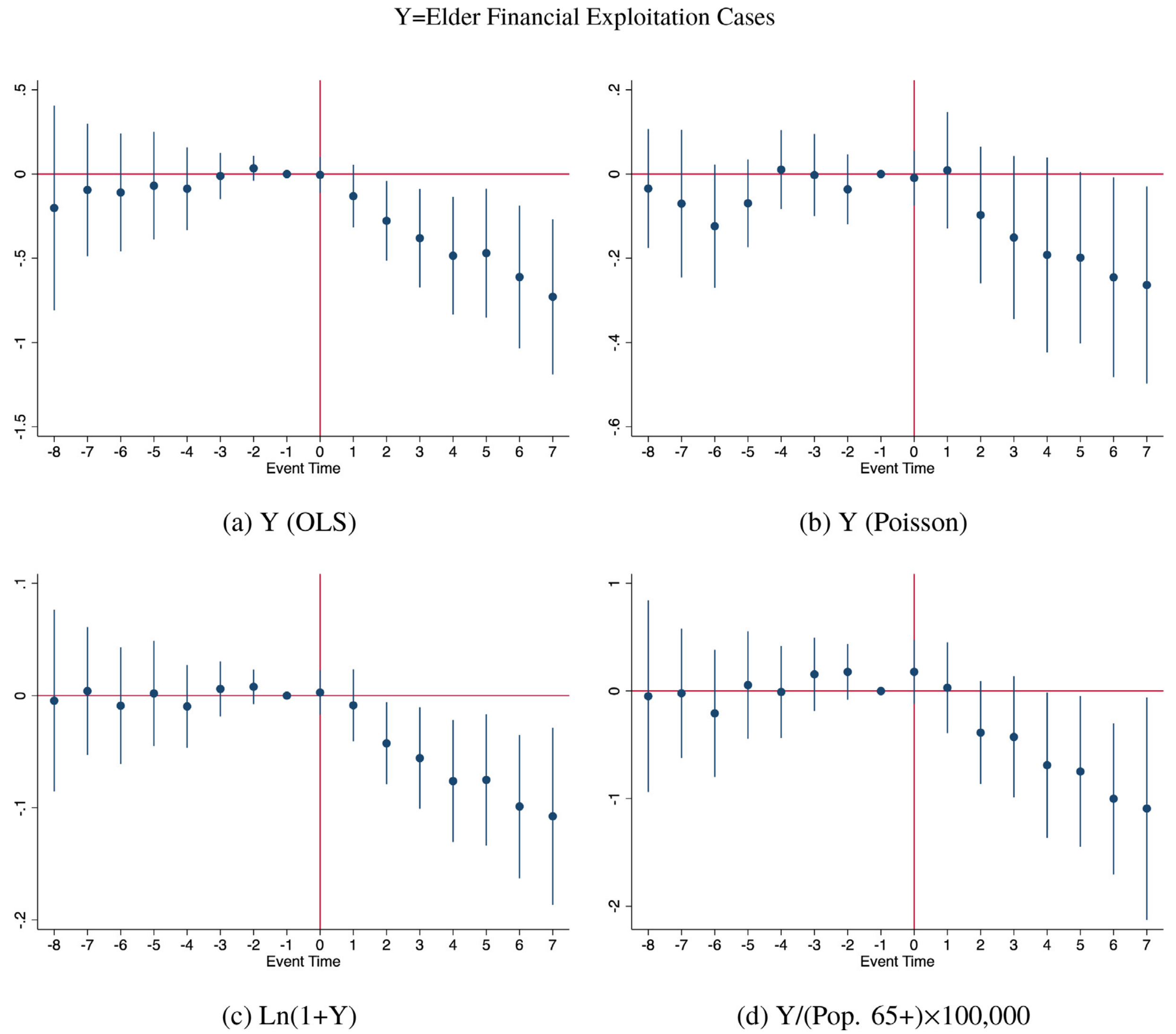

Fig. 5. Effect of deputization on elder financial exploitation.
The event-time figure shows the dynamic effect of deputizing financial professionals on elder financial exploitation around the month a state adopts the Model Act. We plot the coefficients on the event-time indicators from the dynamic difference-in-differences regression in Eq. (3). We estimate the dynamic effects using monthly data for six-month intervals up to four years before and after the month of adoption. For example, 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. Note that if a state does not adopt the Model Act by 2020, then the event time indicators are equal to zero. Year-month and county fixed effects are included. The time-varying county controls listed in Table 4 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 (baseline). In Internet Appendix Fig. A6, we repeat Fig. 5(a) at the monthly frequency. In Table A9, we report the regression estimates of these dynamic effects in a table. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

porters of elder financial exploitation prior to the Model Act as only 1.5% of total reports of abuse come from securities firms according to the summary statistics table (Table 3 Panel B).

To examine the dynamics of the main effect in Table 4 Column (1), we plot the coefficients of the dynamic specifications (Eq. (3)) in Fig. 5(a). There is no evidence that treated and control counties have different trends in abuse prior to treatment. After the adoption of the Model Act, the effects are increasing over time. 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.[12]

[12] A tabular version of the coefficients are presented in the Internet Appendix Table A9. Internet Appendix Table A10 shows results from the dynamic specifications for Table 4 Columns (2) to (4). Also, Table A11 finds no evidence that the drop in elder financial exploitation is stronger in states that deputized all types of financial professionals. This finding is consistent with investment advisers having close relations with clients that allow them to spot and thwart abuse.

The effect may be increasing in magnitude over time 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 to inform financial professionals 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 at front-line financial professionals who have regular contact with clients. Likewise, Michigan's Corporations, Securities and Commercial Licensing Bureau also held two outreach seminars in 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.

The second reason behind the increasing effects over time could be the deterrence effect. It may take time to become known among the perpetrators that financial professionals are reaching out to trusted contacts and to halting transactions, thus deterring criminals from exploiting the elderly in the first place. The increasing effects over time are also inconsistent 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.

Because we use count data as our outcome variable of interest, Fig. 5(b) also examines whether the results hold using a Poisson specification as advised in Cohn et al. (2022). We see a similar decline in elder abuse over time. Furthermore, in Fig. 5(c) and (d), we use different variations to the outcome variable and find a similar decline. In Fig. 5(c) we take the natural logarithm of one plus the number of abuse cases to reduce skewness in the count data. In Fig. 5(d) we examine the per capita number of elder financial exploitation cases (per 100,000 persons 65 years of age or older). 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.

The Internet Appendix describes a battery of robustness and placebo tests we perform. We rule out salient alternative explanations such as changes in reporting or confounding regulations. In Appendix B.2, we analyze and discuss different sources of variation used in our DiD design following the procedure developed by Goodman-Bacon (2021) and Callaway and Sant'Anna (2021). Appendix B.3 shows similar results using a minimum-distance matching procedure. Appendix B.4 shows that the main effect is robust to sub-sampling tests. For instance, the results are robust to leaving out any state, varying the sample start year or sample end year, and aggregating the county level data to the state level. Table A12 shows no effect for several placebo categories of suspicious activity reports that are not related to elder financial exploitation.

4.4. 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:

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

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 6 shows a drop in monetary crimes against the elderly, and this effect builds up over time as in Fig. 5. 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. By the first (second) year following treatment, the decline in crimes 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 are 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 there is no reporting threshold requirement. Internet Appendix Table A13 tabulates the dynamics plotted in Fig. 6. Internet Appendix Fig. A5 excludes state-by-month fixed effects to show that financial crimes against the non-elderly (ages 50 to 64) do not change with adoption of the Model Act, while financial crimes against the elderly drop with adoption of the Model Act.

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.

4.5. The types of deputies and products at risk

Next, we consider how effective the law is based on the types of financial professionals and financial products involved. First, we explore how the drop in abuse because of the Model Act varies across counties with differing presence of financial professionals in the community. Table 5 presents the results. Column (1) is a placebo test where

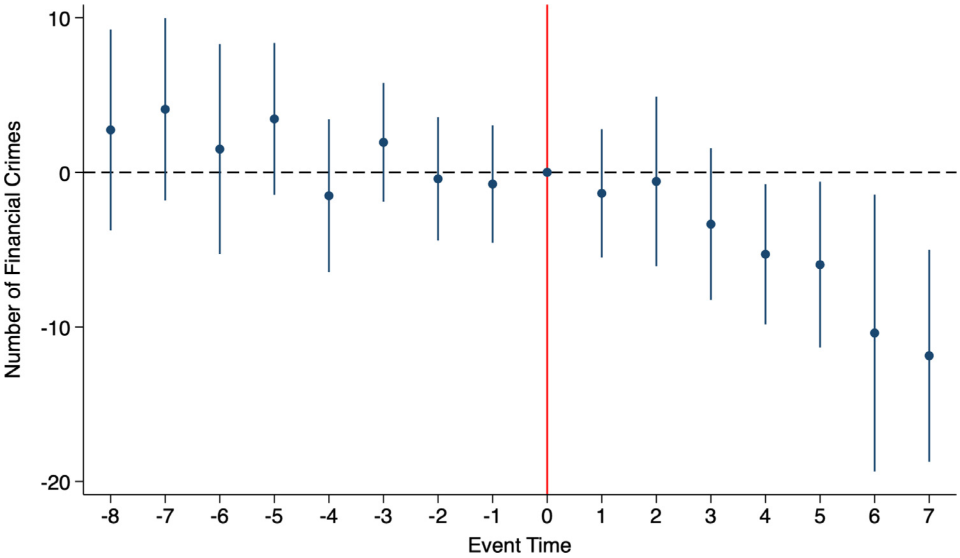

Fig. 6. Effect of deputization on elder financial exploitation, using incident-level crime data from NIBRS.
This figure uses data from the FBI's National Incident-Based Reporting System (NIBRS) for the years 2010 to 2020. NIBRS data are incident-level data for each crime that is reported to the police 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. For example, 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5
Drop in elder abuse by type of advisers in a county.
This table presents difference-in-differences estimates of the effect of deputizing financial professionals on elder financial exploitation reported by financial professionals. We present these effects for subsets of counties based on the types of advisers present in a county. The outcome is the number of elder financial exploitation cases in a county-month, excluding reports by money services businesses. *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. In Column (1), we limit the sample to counties with no registered investment adviser. There are 532 such counties. In Column (2), we limit the sample to counties with above zero advisers but no advisers who work for bank holding companies. There are 971 such counties. In Column (3), we limit the sample to counties with at least one adviser working for a bank holding company. There are 1636 such counties. In Column (4), using the full sample of counties, we interact *Post* with the standardized number of investment advisers working at bank holding companies per capita in December 2015. The control variables are listed in the caption for Table 4. Specifications include county and year-month fixed effects as well as state and county linear trends in elder financial abuse cases, estimated using data prior to July 2016 (Goodman-Bacon, 2021). In Column (4), we interact each control with *Post* (Yzerbyt et al., 2004). Additionally, we interact the variable of interest with year-month fixed effects to allow for different aggregate trends in areas with differing numbers of per capita advisers working for bank holding companies. 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			
Subsample: counties with	No adviser (*Placebo*) (1)	No bank adviser (2)	Bank adviser > 0 (3)	All counties (4)
Post	0.019	0.001	−0.278**	−0.201*
	(0.017)	(0.019)	(0.128)	(0.101)
Post × Advisers at BHCs per Capita				−0.907***
				(0.110)
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Linear Trends	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.12	0.06	0.63	0.65
# Counties	532	210	2397	3139
Observations	44,688	17,640	201,348	263,676

Table 6
Effect by product and instrument. This table presents difference-in-differences estimates of the effect of deputizing financial professionals on the number of elder financial exploitation cases in a county-month, calculated separately for the different types of financial products and instruments involved. For each product and instrument, we exclude any reports by money services businesses, if any. *Post* is an indicator variable that equals to one after the Model Act becomes effective in a state. All regressions include county and year-month fixed effects as well as linear state and county trends in elder financial abuse cases, estimated using data prior to July 2016 (Goodman-Bacon, 2021). All regressions include the controls listed in the caption of Table 4. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: By product

	# Elder financial exploitation cases of type X						
X=	Debit card (1)	Credit card (2)	Deposit account (3)	HELOC (4)	Insurance (5)	Mutual fund (6)	Prepaid access (7)
Post	−0.091**	−0.019***	−0.160	0.000	0.001	−0.002	−0.002
	(0.041)	(0.006)	(0.100)	(0.001)	(0.001)	(0.003)	(0.002)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.50	0.31	0.34	0.02	0.12	0.10	0.08
# Counties	3139	3139	3139	3139	3139	3139	3139
Observations	263,676	263,676	263,676	263,676	263,676	263,676	263,676

Panel B: By instrument

	# Elder financial exploitation cases of type X					
X=	Fund transfer (1)	Bank cashier check (2)	Personal check (3)	U.S. currency (4)	Money orders (5)	Foreign currency (6)
Post	−0.080**	−0.015	−0.058*	−0.156*	−0.005	−0.003**
	(0.039)	(0.027)	(0.031)	(0.079)	(0.011)	(0.001)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear Trends	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.54	0.42	0.51	0.51	0.27	0.03
# Counties	3139	3139	3139	3139	3139	3139
Observations	263,676	263,676	263,676	263,676	263,676	263,676

we study the effect of the law in the 532 counties with zero registered investment advisers. Column (2) is another placebo test, where we analyze the 210 counties that have at least one investment adviser, but zero that are employed by bank holding companies (depository institutions). We do not find a significant drop in reports of elder financial exploitation in these counties: The magnitudes in Columns (1) and (2) are small and statistically insignificant.

By contrast, Table 5 Column (3) shows a large and significant drop in abuse in the counties that employ at least one investment adviser that works for a bank holding company. Column (4) also shows, using a Triple DiD design and the full sample of counties, that the drop in elder abuse is significantly larger in counties with more advisers working for bank holding companies (measured in per capita terms).[13] As noted above, we find that 56.5% (40.6%) of advisers (brokers) at investment advisory (brokerage) firms work for bank holding companies (Tables A1 and A2). The results in Columns (3) and (4) are consistent with the fact that our reports mainly capture abuse reported by banks.

Relatedly, we find significant drops in bank-related products and instruments. Table 6 shows a significant drop in abuse involving debit cards, credit cards, fund transfers, and personal checks. By contrast, we see less of a drop when the product has more safeguards in place or occur mostly outside of banking institutions. For example, Panel A shows no evidence of a drop in abuse involving home equity lines of credit (HELOCs), likely because getting a HELOC involves a long and arduous process, including a closing process with loan documents that evaluate other liens on the property. Panel A also shows no evidence of an effect for abuse involving insurance claims, which also require documentation and perhaps visits from an agent as well as tend to originate outside of banks. Panel B shows no significant effect for bank cashier checks and money orders, which generally require documentation and proof of identity.

Now that we have shown that the drop in abuse is stronger when investment advisers work for bank holding companies and for banking-related products, one may wonder if there is simply something about banking institutions that are driving our results or if it is the deputization itself. Indeed, advisors may not handle credit cards and checks directly. To investigate this, we present results in Table 7 where we control for the time-varying presence of depository institutions, either through the number of bank branches or deposits at the county level. Our main effect regarding the presence of advisors remains largely unchanged.

In addition to variation in the effect of deputization across types of financial professionals and products, we also observe differences within the set of investment ad-

[13] When interacting $Post_{st}$ with the per capita number of advisers, we also control for the interaction of $Post_{st}$ with the control variables. 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 (Yzerbyt et al., 2004).

Table 7
Main effect controlling for bank presence.
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 (5) 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. In each column, we separately control for the natural logarithm of the county-level bank deposits, number of branches, bank deposits per capita, and number of branches per capital. The additional control variables are listed in the caption of Table 4. Specifications include county and year-month fixed effects as well as state and county linear trends 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 financial exploitation cases				
	(1)	(2)	(3)	(4)	(5)
Post	−0.196**	−0.200**	−0.195**	−0.194**	−0.194**
	(0.096)	(0.095)	(0.095)	(0.096)	(0.095)
Log Deposit		1.789***			
		(0.378)			
Log Deposit Per Capita			0.576***		
			(0.155)		
Log Branches				−0.265	
				(0.230)	
Log Branches Per Capita					−0.319***
					(0.090)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Linear Trends	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.67	0.67	0.67	0.67	0.67
# Counties	3139	3139	3139	3139	3139
Observations	263,676	263,676	263,676	263,676	263,676

visers related to assets under management (AUM) and compensation structure. Table 8 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 $5000 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.[14]

Given the growing literature that documents that some financial professionals engage in frequent misconduct and even prey on the elderly themselves (e.g. Dimmock and Gerken, 2012; Dimmock et al., 2018; Charoenwong et al., 2019; Egan et al., 2019), it is reasonable to suspect that the deputies may use their new authorities to abuse the elderly. We examine this in Internet Appendix Table A14. Fortunately, we find no evidence of an increase in regulatory actions against individual investment advisers and firms. Instead, our paper documents the ability of financial professionals to prevent financial fraud, which represents an important contribution of finance to society.

4.6. Heterogeneous effects by social connectedness

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 9 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 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).[15] A larger number of congregations can

[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.

[15] 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).

Table 8
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, excluding reports by money services businesses. *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. *Advisers at BHCs per Capita* is a county's standardized per capita number of investment advisers working for bank holding companies in December 2015. *AUM-Per-Client* is the standardized average AUM per client in a county, where AUM per client is determined at the firm level. *Hourly* is the standardized proportion of advisers associated with firms that charge an hourly fee for services. *Commissions* is the standardized proportion of advisers associated with firms that charge commissions. *Fixed Fees* is the standardized proportion of advisers associated with firms that charge fixed fees. All regressions include county and year-month fixed effects as well as linear state and county trends in elder financial abuse cases, estimated using data prior to July 2016 (Goodman-Bacon, 2021). All regressions include the controls listed in the caption of Table 4. 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 higher or lower values of that variable. 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	−0.675***	−0.529***	−0.536***	−0.527***	−0.670***
	(0.113)	(0.124)	(0.120)	(0.119)	(0.107)
Post × Advisers at BHCs per Capita	−0.325***	−0.772***	−0.757***	−0.723***	−0.292***
	(0.108)	(0.110)	(0.107)	(0.108)	(0.107)
Post × AUM-per-Client	−1.093***				−1.060***
	(0.136)				(0.135)
Post × Hourly		−0.144***			0.059
		(0.048)			(0.096)
Post × Commission			−0.193***		0.018
			(0.054)		(0.078)
Post × Fixed Fees				−0.305***	−0.245*
				(0.072)	(0.133)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Linear Trends	Yes	Yes	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.65	0.63	0.63	0.63	0.65
# Counties	2441	2441	2441	2441	2441
Observations	205,044	205,548	205,548	205,548	205,044

foster intimate relationships through frequent interactions and may indicate a higher desire by people in a community to seek meaningful connections.[16] 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.) 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.

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 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, holding fixed measures of social connectedness (including the Social Capital Index and religious congregations per capita).

[16] 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).

Table 9
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, excluding reports by money services businesses. *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. *Advisers at BHCs per Capita* is a county's per capita number of investment advisers working for bank holding companies in December 2015. *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 as well as linear state and county trends in elder financial abuse cases, estimated using data prior to July 2016 (Goodman-Bacon, 2021). All regressions include the controls in Table 4. 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	−0.191*	−0.175*	−0.173	−0.297***	−0.279***
	(0.102)	(0.096)	(0.108)	(0.105)	(0.096)
Post × Advisers at BHCs per Capita	−0.837***	−0.747***	−0.996***	−0.993***	−0.714***
	(0.100)	(0.099)	(0.113)	(0.110)	(0.104)
Post × Social Connectedness Index	1.108***				
	(0.197)				
Post × Congregations Per 1000		1.090***			1.481***
		(0.168)			(0.203)
Post × Adherents Per 1000			0.259***		−0.315**
			(0.091)		(0.133)
Post × Social Capital Index				0.449***	0.313***
				(0.124)	(0.112)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Linear Trends	Yes	Yes	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.64	0.64	0.63	0.64	0.65
# Counties	3135	3139	3139	2990	2987
Observations	263,340	263,676	263,676	251,160	250,908

5. 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.

Declaration of Competing Interest

Authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2023.06.004.

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