Elder Financial Fraud: The Economic and Ethical Case for Instituting Mandatory Reporting Laws in Financial Institutions

Lauren Tse

Professor Kate Bundorf, Faculty Advisor
Professor Michelle Connolly, Faculty Advisor

Honors Thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University.

Duke University
Durham, North Carolina
2024

Acknowledgments

I am deeply grateful to Professor Michelle Connolly for her invaluable guidance and mentorship over the past two semesters. Her thoughtful advice and unwavering support have been instrumental in both shaping this thesis and developing my interest in Economics research. I would like to extend my sincere gratitude to Professor Kate Bundorf for her invaluable insights in refining my research question and helping me grasp the broader implications of my findings from a health economics perspective. Her keen expertise has added a critical depth to my work.

I would also like to express my appreciation to the students in my honors thesis class for their constructive feedback and thought-provoking discussions throughout this process. It has been wonderful becoming friends with you all. To my parents and close friends, thank you for your constant support and encouragement.

Finally, I am grateful for this enriching research opportunity, which has nurtured my intellectual curiosity and a deep admiration for research in the field of Economics.

Abstract

This study examines the effectiveness of the 2016 NASAA Model Act, specifically if states that implemented its provisions see greater levels of elder fraud reporting. This legal reform introduces reporting requirements for broker-dealers and investment advisers to report suspected elder fraud to government authorities, granting explicit immunity to those who comply. To analyze both the immediate and longer-term effects of the Model Act's staggered passage across states, I use a dynamic Difference-in-Difference model to analyze institutionally reported elder fraud cases from the U.S. Department of Treasury's Financial Crimes Enforcement Network. Regression findings suggest that the Model Act has a positive enabling effect, increasing the number of elder fraud reports filed by financial professionals. Further, I quantify the monetary losses associated with these fraud cases using self-reported data from the Federal Trade Commission's Consumer Sentinel Network. In line with this 'placebo' dataset, I find that the passage of the Model Act — targeted at financial professionals — has inconclusive impacts on the number of self-reported elder fraud and no effect on the financial losses incurred.

JEL classification: G28; K42; J14

Keywords: Elder Financial Fraud; NASAA Model Act; Mandatory Reporting Requirements

Contents

1. Introduction

1.1 Elder Financial Abuse

Elder financial abuse can be broadly defined as the "illegal or improper use of an older adult's funds, property, or assets." (U.S. Government Accountability Office, 2011).[1] Examples of financial exploitation can range from improper withdrawals of cash from the elderly victim's bank account to writing checks without their consent. It can also manifest in more nebulous forms, such as the misuse of the power of attorney, identity theft or the transfer of property deeds. These financial abuse cases span a wide range of categories, including fraudulent sweepstakes prizes and romance scams.[2] In 2023, the primary categories involving senior victims were internet and social media scams as well as digital assets (NASAA, 2024). [3]

The National Elder Mistreatment Study, which has been tracking older adults since 2008, found financial abuse to be the most prevalent form of elder abuse (Acierno et al., 2010).[4] Experts have labeled this phenomenon a "burgeoning public health crisis" and an "epidemic" (Peterson et al., 2014). Between 2016 and 2020, 8.7% of older Americans reported experiencing some form of financial fraud within the 5-year window (DeLiema et al., 2020). Several surveys report that as many as 1 in 5 elderly people are victims of financial fraud (Investor Protection Trust, 2016).

---

[1] Federal institutions such as the US Social Security Administration and National Institutes of Health define being elderly as "65 years and older" — however, this number varies depending on different states and statutory boards. For instance, the Federal Trade Commission and the U.S. Treasury Department define elders as those aged 60 years and above, while the FBI records the elderly as 65 years and above. States themselves have individual age cutoffs (see Table A1).

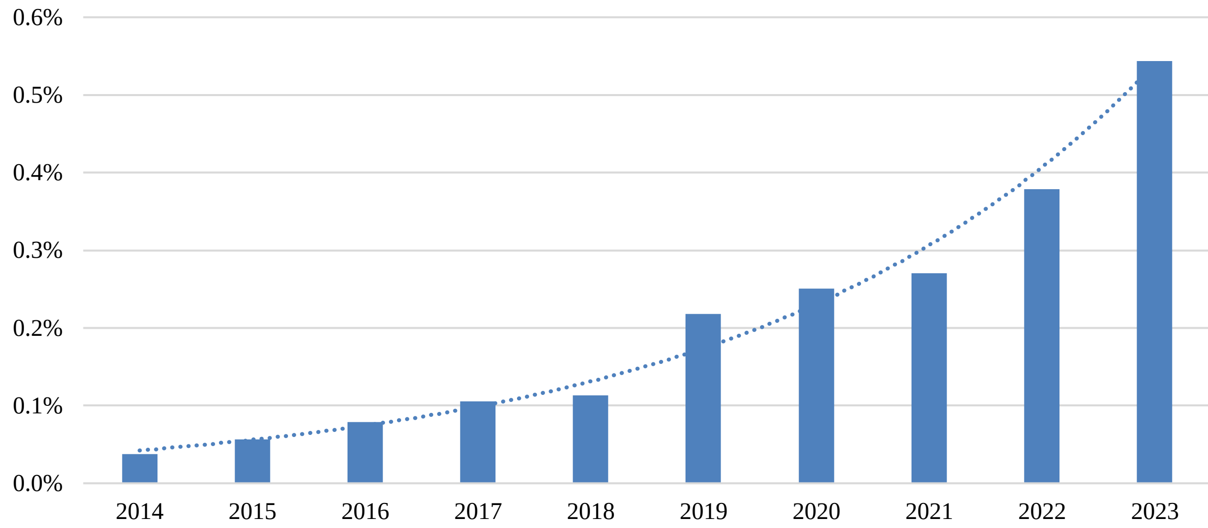
[2] Miscellaneous investments, romance scams, business imposters and government imposters make up approximately 76% of self-reported elder fraud. See Table A10 Panel B in the appendix for the full list.

[3] Digital assets exclude non-fungible tokens (NFTs) and staking.

[4] Financial abuse is one of five broad categories of elder abuse — others include physical abuse, neglect, sexual abuse, and psychological abuse.

Figure 1 shows the sizeable increase in total reported elder fraud cases over the last 10 years, accounting for changes in the elderly population.

Figure 1: Fraud Count Per Elder (%) from 2014 to 2023
(Institutionally Reported, from FinCEN)



The monetary loss is highly significant as well. From 2022 to 2023 alone, suspicious transactions involving elder financial exploitation amounted to approximately $27 billion (FinCEN, 2024). A global financial crime report revealed that $77.7 billion (27%) of all reported global fraud was linked to elderly victims, labeling elder financial abuse a threat of 'greatest concern' (Nasdaq, 2024). In an especially alarming development, Mexican drug cartels have recently been revealed as the perpetrators of large-scale timeshare scams targeted at American elderly, resulting in over $40 million in losses (Department of the Treasury, 2024). Beyond strangers, family members also constitute a sizeable proportion of perpetrators — stealing an average of 28% of the elderly victims' net worth (FinCEN, 2019).[5] Moreover, the FBI estimates that these reported figures likely underestimate the true prevalence of elder fraud as "only about half" of the fraud reports disclose the victim's age. More importantly, many elder fraud cases go unreported (FBI, 2023).

[5] This calculation excludes the elderly victims' home equity. See Table A6 in Appendix for the full breakdown of suspected perpetrators and the respective median loss per elderly victim.

Why do the elderly constitute a sizeable proportion of financial fraud victims? Firstly, health and cognitive conditions such as dementia and Alzheimer's render them more susceptible to financial abuse (Pinsker et al., 2010). Secondly, as the elderly have accumulated wealth and retirement savings over time, they are often financially attractive targets. Finally, the US is facing an impending 'silver tsunami' — by 2040, about 1 in 5 Americans will be considered 'elderly' (U.S. Census Bureau, 2017). This aging trend exacerbates the previous two trends. As the elderly face a higher risk of being targeted and a diminished ability to protect their assets once targeted, they are an especially vulnerable demographic.

Given this backdrop, the government has sought to enhance protections for elderly investors. One primary strategy is the strengthening of fraud reporting mechanisms, which was introduced through the 2016 NASAA Model Act. This legal reform introduced reporting requirements for broker-dealers and investment advisers to report suspected elder fraud to government authorities, while providing immunity to those who comply. Unlike previous federal legislation, this law was adopted in a staggered fashion and according to the discretion of individual states. This paper focuses on the Model Act's marginal impact on elder fraud reporting activity. Specifically, it seeks to explore how states' adoption of the 2016 Model Act provisions has affected the levels of elder fraud reporting by financial professionals.

1.2 U.S. State Securities Laws and Fraud Reporting Landscape

The primary federal law surrounding financial fraud reporting is the Bank Secrecy Act (1970). Financial institutions in the U.S. such as banks, mutual funds, and money service businesses are mandated to disclose both suspected and confirmed, unlawful or unusual transactions to the

Department of Treasury's Financial Crimes Enforcement Network (FinCEN). These reports, officially filed as Suspicious Activity Reports (SARs), serve as the primary data source for this study. In 2002, a new federal ruling 31 CFR § 1023.320 expanded this requirement to include standalone broker-dealer firms.[6] These federal laws exist in parallel with more targeted regulations that apply to certain financial professionals. For instance, FINRA is a self-regulatory organization authorized by the U.S. government to govern broker-dealers only. FINRA Rule 4512 requires that brokers make 'reasonable efforts' to obtain a trusted contact when opening any customer's account, while FINRA Rule 2165 allows brokers to temporarily suspend suspicious transactions.[7] Alongside this overlapping and disparate regulatory landscape, the NASAA Act emerged with the intention of not only addressing elder financial fraud, but specifically empowering state securities regulators to enforce the reporting of such fraud at a state level.[8]

1.3 NASAA Model Act

Established in 1919, the North American Securities Administrators Association (NASAA) is the oldest international organization dedicated to investor protection, comprising state securities administrators across the U.S., Canada, and Mexico. The 2016 NASAA Model Act was borne out of the belief that state securities regulators were optimally positioned "to intercede on behalf of vulnerable seniors" (NASAA, 2019). It primarily aims to empower state regulators and financial

[6] Other federal guidance such as the Gramm-Leach-Bliley Act and Regulation S-P also broadly permit fraud reporting to government and regulatory authorities, but do not have a specific focus on the elderly.
[7] Both FINRA rules only apply to FINRA-registered brokers and were adopted nationwide on Feb 5, 2018. FINRA Rule 2165 applies to elderly and vulnerable persons. FINRA Rule 4512 applies to all customers, not just seniors.
[8] While the Securities and Exchange Commission (SEC)'s mandate is enforcing federal securities laws, state securities regulators are responsible for administering and enforcing state-level securities laws, known as 'Blue Sky Laws'. These laws are designed to protect investor, involving the licensing of broker-dealers and investment firms, as well as the enforcement of strict reporting standards.

institutions to better detect and prevent elder financial abuse. The Model Act, passed in 2016, strengthens existing federal reporting requirements in four main ways:

Firstly, its mandate focuses on protecting 'older investors'[9] and/or 'vulnerable persons'[10], unlike other reporting laws that apply to investors in general.[11] Secondly, it constitutes a state-level securities law, empowering state regulators to actively regulate reporting as opposed to relying on the SEC to enforce broader federal laws (see Footnote 7). Further, it applies to a wider range of financial professionals — broker-dealer agents, investment advisors, those in related compliance or legal roles, and independent contractors carrying out these functions. This differs from FINRA which only governs brokers (see Footnote 6). Finally, all reporters are explicitly guaranteed civil and administrative immunity which institutions like FINRA are unable to offer.[12]

Provisions of the Model Act were created to be adopted by states as part of their existing securities laws and consist of five main features, where financial professionals have:

(1) A mandatory/voluntary obligation to report potential financial exploitation to government authorities, such as state APS agencies and law enforcement
(2) A mandatory/voluntary obligation to notify select third parties of potential financial fraud with advance consent of the investor
(3) The authority to temporarily delay the disbursement of funds
(4) Immunity from civil and administrative liability for reporting, notifications, and delays

[9] NASAA's 2024 report explicitly declares its prioritization of "protecting older investors". In 2023, they opened 1,305 investigations and filed 131 enforcement actions involving 2,869 older investors.
[10] These individuals generally refer to individuals who have certain physical and/or mental disabilities. They are similarly protected under Adult Protective Services (APS) statutes.
[11] See Footnote 6.
[12] As a self-regulatory agency, FINRA cannot grant immunity to its brokers. Other federal and securities laws do not offer explicit immunity for its reporting requirements (SEC, 2018).

(5) An obligation to share all records with government authorities in cases of exploitation

Four states (California, Maryland, Nevada and Oregon) have also imposed civil penalties for failure to report suspected financial fraud within the given timeframe. For instance, the Securities Commissioner in Maryland has the authority to impose civil penalties of up to $5,000 as well as to enforce temporary/permanent injunctions and asset freezes (SB 951, 2017).

As of February 2024, 40 states have passed some version of the Model Act. Table A1 in the Appendix lists the staggered adoption dates of the Model Act for each state, along with the relevant institutions it applies to and the age cutoffs defining an 'elder'. The NASAA Model Act functions primarily as a framework for state-level legislation. States exercise their autonomy in determining the precise scope of the legislation, with many adopting statutes and regulations based on the Model Act or incorporating similar provisions. For instance, Vermont's regulation follows the Model Act entirely, while other states enacted only certain or revised provisions. Table A2 in the Appendix lists the provisions that each state adopted, and their respective rank based on the overall severity of law passed. Most states that adopted the Act enacted regulations applicable to only broker-dealers and investment advisers, while six states (Delaware, Kentucky, Michigan, Texas, Virginia, and Oregon) expanded the scope to include all financial institutions.[13] Four states

[13] The exact definition of 'financial institutions' varies by state but broadly refers to both national and state banks, bank holding companies, savings and loan associations and credit unions operating in those states. These institutions employ a wide range of financial professionals, including money managers, retirement planners, brokers, and investment advisers (Carlin et al., 2023). In this study, I include broker-dealers and investment advisors in this category.

Kentucky's law has an especially wide scope, defining 'financial institution' as "any person doing business under the laws of any state or commonwealth or the United States relating to banks, bank holding companies, savings banks, savings and loan associations, trust companies, or credit unions".

(Delaware, Nevada, Washington and Missouri) had similar reporting laws in place even before the Model Act was passed.

1.4 COVID-19 Pandemic Landscape

This study aims to examine elder abuse specifically within the context of COVID, which greatly exacerbated the incidence of elder financial abuse. The FBI has published reports detailing a 55% increase in reported elder fraud victims between 2019 and 2020 alone (FBI, 2020). Some possible mechanisms accounting for increased elder fraud include greater social isolation amongst the elderly given COVID restrictions and reduced access to medical care. Psychological vulnerability is not only strongly correlated with, but also a predictor of fraud among older adults (Acierno et al., 2010). Beyond elderly victims, COVID-19 also exacerbated perpetrator-centric risk factors. Higher stress levels, lower financial means and greater co-dependency are known risk factors for caregiver/familial financial abuse of older adults.

2. Literature Review

While most research surrounding elder financial abuse surrounds analyzing risk factors such as health and demographic characteristics, there is limited literature evaluating the reporting role of financial institutions. Financial professionals are uniquely positioned to detect and prevent suspected elder fraud, often identifying fraud before the victim's family and friends. However, they currently face limited incentives or regulatory mandates to fulfill this monitoring role effectively. Enhanced reporting mechanisms can encourage more frequent reporting. Fraud reports provide critical information that is shared between financial institutions and authorities like the state Adult Protective Services (APS) and law enforcement. They are essential not only for identifying and prosecuting current fraud cases but also for preventing future fraud. Elder financial abuse is a complex issue that requires cross-collaboration across various institutions to effectively address. Reporting is, therefore, an essential element of this collaborative approach and critical in advancing efforts against elder financial fraud.

This thesis focuses on financial institutions, specifically examining the effectiveness of mandatory reporting laws as a form of deputization. Presently, this concept of deputization — whereby individuals are empowered to carry out specific functions they would not normally would not be able to do — exists in various contexts. For instance, major social media companies have been encouraged to monitor and flag potential terrorist activities hosted on their platforms; FedEx employees flag suspicious packages to law enforcement. Various professionals are already required to report suspected financial abuse in many states, including in legal, social services, and mental health fields. For instance, Oregon mandated that all attorneys report suspected elder abuse in 2015 (HB 2205, 2015). In Arizona, lawyers, doctors and accountants face similar reporting laws (Title 46. § 46-454, 2010).[14] Thus, this study aims to explore the case for deputizing financial professionals, specifically if mandatory reporting requirements can effectively empower them to take on a policing and monitoring role.

There has been very limited literature assessing the effectiveness of the Model Act. Based on annual NASAA reports, the Model Act increased fraud reporting by 55% in states that

[14] These reporting requirements apply to all types of elder abuse, including physical abuse, neglect, financial exploitation, verbal abuse and sexual abuse.

implemented its provisions from 2019 to 2020.[15] However, critics highlight that the effectiveness of the Model Act varies significantly depending on its implementation and enforcement across states. For instance, legal attorneys involved in securities arbitration argue that the Model Act should encourage states to pass obligatory, not just permissive provisions. Currently, 14 states have only voluntary government reporting requirements. The Public Investors Arbitration Bar Association believes that the Model Act "does not go far enough" to protect senior investors, even recommending that the Act include penalties for failure to report (PIABA, 2015). Some research has also suggested that the Model Act serves a deterrent function. Specifically, a paper using a staggered difference-in-differences model found that the Model Act led to a 0.196 decrease in the number of elder fraud reports per county-month. They draw on data from the pre-pandemic period and at the time of the study, only 30 states had adopted provisions.[16] The paper concludes that the Model Act has some effectiveness in deterring actual fraud, measured using actual monetary crimes against the elderly reported by local law enforcement and suspected elder fraud reported to the Department of Treasury (Carlin et al, 2023).

My research seeks to contribute to this existing literature by primarily focusing on the reporting of elder fraud, not the incidence of actual elder fraud crimes. I also analyze a more recent and extended period (2014 to 2024), including the 13 states that implemented the Model Act between 2020 and 2023. Given the notable increase in fraud during and after the pandemic, I hope to specifically examine post-2020 data to assess the resilience of the Model Act provisions in

[15] These reports led to "245 investigations, 139 delayed disbursements, and 65 enforcement actions" (NASAA, 2021). In 2024 alone, state securities regulators meted out 1,1886 enforcement actions, collectively sentencing 461 years in prison and collecting $333 million in fines and restitution (NASAA, 2024).
[16] The paper also controlled for the number of registered investment advisors per county through SEC data which I was unable to access.

encouraging elder financial fraud reporting. Finally, my research aims to capture not only numerical changes in elder fraud reports, but also quantify the monetary losses incurred using a dataset from the Federal Trade Commission obtained through a FOIA request.

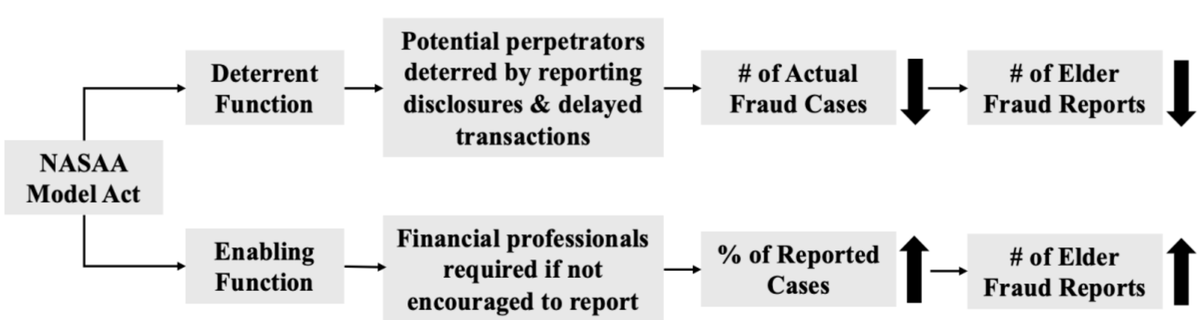
3. Theoretical Framework

The suspicious activity reports (SARs) received by FinCEN record both suspected and confirmed cases of elder fraud.[17] These reports reflect not only actual elder fraud occurrence but also how many are actually recognized and subsequently reported. This can be captured by the formula:

(1) **# of Elder Fraud Reports = # of Actual Elder Fraud Cases × % of Identified Cases × % of Identified Cases that are Reported**

I propose that the NASAA Model Act serves both a deterrent and enabling function, which may influence the number of elder fraud reports through separate and opposing mechanisms.

Figure 2: Deterrent and Enabling Functions of NASAA Model Act



[17] These reports are then investigated and ultimately prosecuted through fines and incarceration. Thus, the SARs are not a measure of actual fraud and simply reported fraud by institutions (see Footnote 14).

If potential fraudsters perceive that the new provisions empowering financial advisors to delay suspicious transactions make it more challenging for perpetrators to access their funds, the Act could deter attempts at financial fraud. This could potentially reduce the number of actual cases and overall reported incidents. However, the Model Act also explicitly mandates or encourages financial professionals to report such cases, supported by civil and administrative immunity. This requirement directly increases the % of cases that are reported, thereby contributing to a higher volume of overall fraud reports. These opposing effects highlight the importance of understanding the underlying mechanisms of the Model Act and adopting a nuanced interpretation of any changes observed in SAR reports received.

4. Empirical Specification

4.1 Static Difference-in-Differences Specification

The primary empirical objective of this thesis is to assess the impact of states' adoption of the 2016 NASAA Model Act on the incidence of elder financial fraud. As states passed these legal provisions in a staggered fashion, my empirical strategy consists of a difference-in-differences (DiD) approach with two-way fixed effects. This specification was chosen as it allows us to focus on the marginal impact of the treatment — in this case, the Model Act's passage — on elder fraud reporting activity, accounting for overall changes in fraud incidence and other external factors.

(2) $$\textbf{Reported Fraud Per Elder}_{cm} = \boldsymbol{\alpha}_0 + \boldsymbol{\beta}\ \textbf{Provision}_{sm} + \lambda\ \textbf{Control}_{cm} + \textbf{Fraud}_{y} + \mathbf{q} + \boldsymbol{\alpha}_c + \boldsymbol{\tau}_y + \boldsymbol{\varepsilon}_{cm}$$

Here, the dependent variable **Reported Fraud Per Elder**$_{cm}$ refers to the number of reported elder financial fraud cases in a given county *'c'* and month *'m'*, divided by its elderly population —

defined as individuals over 65. This variable analyzes the number of Suspicious Activity Reports filed per county-month from the U.S. Department of Treasury's Financial Crimes Enforcement Network (FinCEN). $\boldsymbol{\alpha_0}$ refers to the constant. $\mathbf{Provision}_{sm}$ is a dummy variable that equals one in the month that any one of the provisions of the Model Act goes into effect in a state, where *'s'* refers to the state. $\boldsymbol{\beta}$ measures the static effect of the Model Act provision — in other words, the marginal change in reported elder fraud for counties where a provision was passed relative to counties without. $\mathbf{Control}_{\mathbf{cm}}$ is a vector of five time-varying demographic traits from 2014 to 2024. The incidence of elder financial fraud is influenced by both victim-centric and perpetrator-centric risk factors.[18] These county-level averages aim to capture primary risk factors, including educational attainment, economic status, social isolation and mental health, for both victims and perpetrators.[19] The academic literature supporting the selection of these controls as well as their data sources can be found in the appendix (see Table A6).

(1) Post-Secondary Education *(American Community Survey, 5-Year Estimates)*

(2) Debt-to-Income Ratio *(Federal Reserve System)*

(3) Median Household Income *(American Community Survey, 5-Year Estimates)*

(4) Social Associations *(County Business Patterns)*

(5) Mental Health *(CDC Behavioral Risk Factor Surveillance System)*

[18] Perpetrator-centric variables identify common characteristics of offenders, such as higher rates of substance abuse, criminal history, and mental health issues (Conrad & Conrad, 2019). Victim-centric factors linked to higher abuse rates include lower financial status, limited familial and social support, as well as cognitive and/or physical decline (Storey, 2020). See Table A7 in the Appendix for more details.

[19] It is also important to consider the nature and locality of elder fraud. Based on an analysis from the Consumer Financial Protection Bureau (see Table A6), 51% of suspected perpetrators were strangers. This suggests that elder fraud may not be confined to local areas and could be conducted by organized robo-scammers or regional/global crime syndicates. Therefore, while considering county-level characteristics is important, it is also limited in scope.

q refers to quarters, specifically the second, third, and fourth quarters of each year to assess any potential seasonality in elder fraud reporting patterns. The first quarter is set as the reference category. $\boldsymbol{\alpha_c}$ refers to county fixed effects, which capture any persistent characteristics specific to each county. $\boldsymbol{\tau_y}$ captures year fixed effects, which controls for annual changes in the reports of elder financial fraud across all states, such as the significant increase in cases during COVID-19. As an additional robustness check, $\mathbf{Fraud_y}$ captures yearly changes in nationally reported fraud cases for individuals below 60 years old, accounting for the population changes amongst non-elders.[20] This variable serves as a time-trend aiming to capture the general movement of fraud as a whole. As the Model Act targets elder financial fraud reporting specifically, the regression controls for non-elder fraud to capture the law's marginal impact on reported elder fraud. $\boldsymbol{\varepsilon}_{cm}$ is the error term, with standard errors clustered at the county level to account for county-level similarities.

I also aim to decompose the main effect of the Model Act by the type of legal provision. The same regression was run for three key provisions, using the same control data and fixed effects. $\mathbf{Government}_{sm}$ is a dummy variable that equals one in the month that the mandatory government disclosure provision goes into effect in a state. $\mathbf{Third\ Party_{sm}}$ refers to the mandatory third-party notification provision, while $\mathbf{Penalties_{sm}}$ refers to any provision imposing civil penalties for failure to comply. This specification allows me to discern whether certain provisions had more significant effects on elder fraud reporting compared to the law as a whole, adding nuance to the analysis of the Model Act.

[20] Total count of non-elder fraud reports taken from CSN annual reports (2014 to 2023); population data of non-elders (citizens below 65 years old) taken from ACS community survey estimates (2014 to 2023). As the population data for 2020 was missing, it is taken as an average of 2019 and 2021; 2024 is imputed as a projection from past years' data.

(3) $$\textbf{Reported Fraud Per Elder}_{cm} = \alpha_0 + \beta\ \textbf{Government}_{sm} + \beta\ \textbf{Third Party}_{sm} + \beta\ \textbf{Penalties}_{sm} + \lambda\ \textbf{Control}_{cm} + \textbf{Fraud}_y + \textbf{q} + \alpha_c + \tau_y + \varepsilon_{cm}$$

Additionally, regression equation (4) seeks to analyze the effectiveness of the Model Act based on the severity of the overall law passed. As each state passed different combinations of provisions, they were classified into one of three main categories: mild, moderate and harsh (see Table 1). States with the rank 'none' (i.e. did not pass the Model Act) were used as the reference category.

Table 1: Categories of Law Severity by State

Law Severity	Criteria	Count
None	No Model Act Provision passed	10
Mild	Voluntary Reporting to Government Authorities	14
Moderate	Mandatory Reporting to Government Authorities	22
Harsh	Presence of Civil Penalties	4
Total		50

(4) $$\textbf{Reported Fraud Per Elder}_{cm} = \alpha_0 + \beta\ \textbf{Mild}_{sm} + \beta\ \textbf{Moderate}_{sm} + \beta\ \textbf{Harsh}_m + \lambda\ \textbf{Control}_{cm} + \textbf{Fraud}_y + \textbf{q} + \alpha_c + \tau_y + \varepsilon_{cm}$$

Regressions (2), (3) and (4) were also run with an additional dummy included, **COVID**, which equals one in the years during and post-pandemic — 2020 to 2024 (see sample in Equation 5).[21] To gain further insights on reporting activity during the pandemic, this regression analyzes if there is a significant interaction between the COVID time frame and elder fraud reporting.

(5) $$\textbf{Reported Fraud Per Elder}_{cm} = \alpha_0 + \beta\ \textbf{Provision}_{sm} + \lambda\ \textbf{Control}_{cm} + \textbf{Fraud}_y + \textbf{COVID} + \textbf{q} + \alpha_c + \varepsilon_{cm}$$

[21] Given the inclusion of the COVID dummy, year fixed effects were omitted for this regression specification.

Finally, the Model Act specifically encourages financial professionals, not elderly victims or their families, to report more actively. As an additional layer of analysis, I analyze a ‘control’ dataset in the form of self-reported elder fraud cases. The Federal Trade Commission’s Consumer Sentinel Network collects individual cases of elder fraud reported by victims and/or family members. It also records the monetary amount associated with each fraud case (see Figure A4). As the database is only accessible to law enforcement, this data was accessed through a Freedom of Information Act (FOIA) request. The same regression as Equation (2) was run on both self-reported elder fraud cases and the fraud amount lost per elder. I hypothesize that the passage of Model Act provisions should have no statistically significant effect on both the number of self-reported elder fraud cases and fraud losses incurred.

$$\textbf{Reported Fraud Per Elder}_{cm} = \boldsymbol{\alpha}_0 + \boldsymbol{\beta}\ \textbf{Provision}_{sm} + \lambda\ \textbf{Control}_{cm} + \textbf{Fraud}_y + \textbf{q} + \boldsymbol{\alpha}_c + \boldsymbol{\tau}_y + \boldsymbol{\varepsilon}_{cm} \tag{6}$$

$$\textbf{Reported Fraud Losses Per Elder}_{cm} = \boldsymbol{\alpha}_0 + \boldsymbol{\beta}\ \textbf{Provision}_{sm} + \lambda\ \textbf{Control}_{cm} + \textbf{Fraud}_y + \textbf{q} + \boldsymbol{\alpha}_c + \boldsymbol{\tau}_y + \boldsymbol{\varepsilon}_{cm} \tag{7}$$

4.2 Dynamic Difference-in-Differences Specification

I further employ a dynamic DiD model to chart the effect of the Model Act over time — both before and after its passage. This is crucial as there might be implementation lags in the passage of legislation, or significant immediate effects that fade out over time. The effects could also potentially be gradual as it takes time for information about the law to percolate throughout the state. A Poisson Pseudo-Maximum Likelihood (PPML) regression with high-dimensional fixed effects was chosen as it is specifically designed to analyze count data and is robust to heteroskedasticity, a common characteristic of such data. To measure these time-sensitive dynamics, my empirical strategy consists of estimating fraud effects in annual intervals, 6 years before and 6 years after the month the policy becomes effective in a state. The baseline in the regression is the year the state implemented the provision.

$$(8) \qquad \textbf{Reported Elder Fraud}_{\mathbf{cm}} = \boldsymbol{\beta}_{\mathbf{h}}\mathbf{1}\ \textbf{(t - Provision Date}_{\mathbf{s}}\textbf{ = d)} + \lambda\ \textbf{Control}_{\mathbf{cm}} + \boldsymbol{\alpha}_{\mathbf{c}} + \boldsymbol{\tau}_{\mathbf{y}} + \boldsymbol{\varepsilon}_{\mathbf{cm}}$$

Here, *‘d’* denotes the date the provision was implemented — *‘d’* is equal to 0 before the state adopts the provision and 1 after its effective date. I aim to measure the effect **Reported Elder Fraud**$_{\mathbf{cm}}$ in six yearly successive periods before and after the law was passed for each county. In my panel event-study design, the base period *‘Law’* is set as the year preceding the event. Periods *‘Pre-2’* to *‘Pre-6’* capture any pre-trends, while periods *‘Post-1’* to *‘Post-6’* allow us to evaluate the impact of the law’s passage. This dynamic DiD regression was run for the whole dataset (Figure 4) and for each state rank (see Figures 5 to 7). The same PPML regression was also run for self-reported elder fraud data and fraud losses incurred (Figures X and Y), with the only difference being that 6-month instead of annual intervals were used given the shorter time frame.[22]

5. Data Section

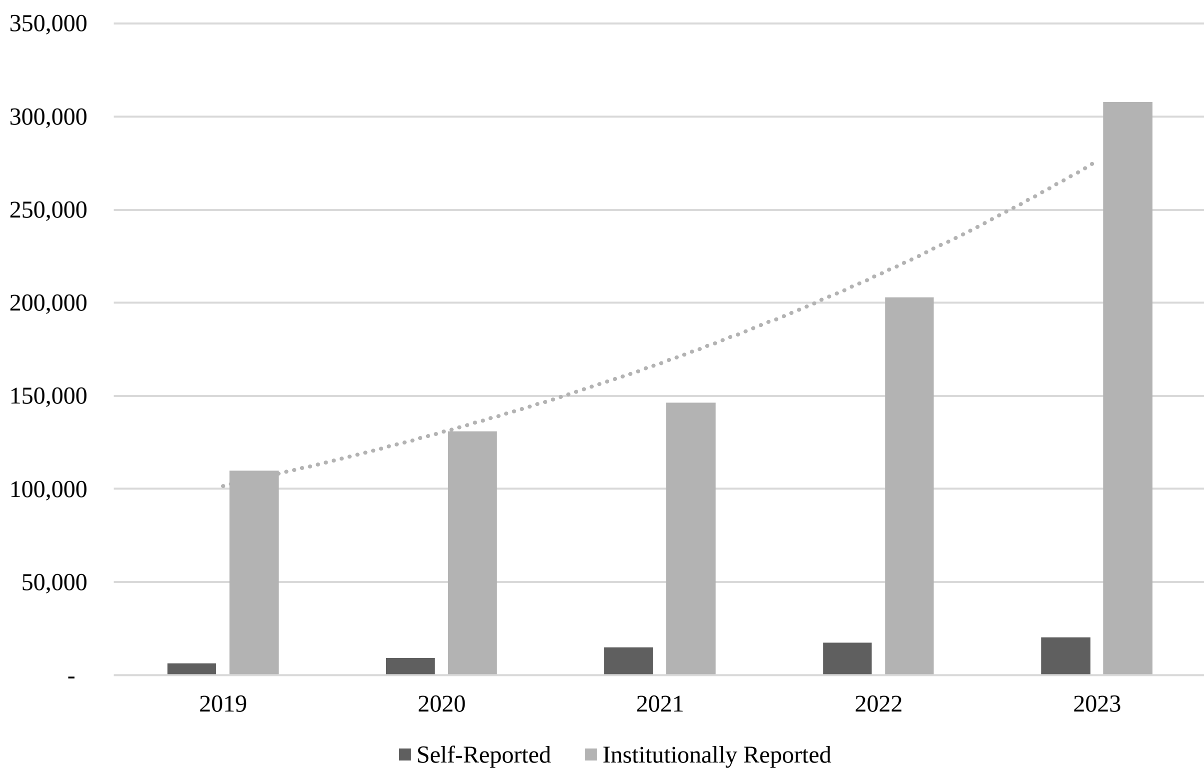
This paper draws on two main datasets — institutionally reported elder fraud and self-reported elder fraud. Their respective totals from 2019 to 2023 are graphed in Figure 3.

[22] See Table 2. Self-reported elder fraud data is only available for a 5-year period (2019 to 2023) due to the FTC’s 5-year data retention policy —– any reports preceding this window are deleted from the system biannually.

Table 2: Key Differences between Datasets

	FinCEN	**Consumer Sentinel Network**
Reporting Entities	Institutionally Reported (Financial Institutions)	Self-Reported (Victim and/or Family of the Victim)
Time Period	Jan 2014 to Feb 2024	Jan 2019 to Dec 2023
Unit of Observation	County-Month Count	Individual Fraud Reports, aggregated to: County-Month Count County-Month Fraud Amount
Definition of Elderly	60 Years and Above	60 Years and Above

Figure 3: Total Reported Elder Fraud Cases from 2019 to 2023 [23] [24]
(Comparing FinCEN and CSN Data for the overlapping 5-year Period)



[23] The total sample of self-reported elder fraud (68,241 individual cases) is much smaller than institutionally reported elder fraud (1,136,593 cases). This is because self-reported data is only available for a 5-year window (see Footnote 22), while the institutionally reported data spans a 10-year period.
[24] Additionally, the reporting frameworks and processes in financial institutions are much more rigorous compared to self-reporting, which is largely subject to victim/family discretion. Elderly victims may be deterred from self-reporting as discussed in the literature — e.g. perpetrator being a family member or elderly themselves being unaware of the abuse.

5.1 Institutionally Reported Elder Fraud

This dataset is maintained by the U.S. Department of Treasury's FinCEN, which serves as a central hub for collecting Suspicious Activity Reports (SARs) from financial institutions.[25] In response to the rising incidence of elder fraud, FinCEN established a specific reporting category, 'Elder Financial Exploitation' for victims aged 60 years and above in April 2012. The FinCEN sample includes a total of 356,972 county-month observations of elder financial fraud for 2,926 counties, from January 2014 to February 2024.[26] [27] The first variable *'Elder Fraud Cases'* refers to the county-month count of elder financial fraud cases reported to FinCEN (see Table 3).

Table 3: Select Descriptive Statistics for Institutionally Reported Fraud (FinCEN)
(County-Month Elder Fraud Reports)

Total *(Jan 2014 to Dec 2023)*

	(1) Mean	(2) Median	(3) SD	(4) Min	(5) Max	(6) N
Elder Fraud Cases (#)	3.2	0.0	25.8	0.0	2,622.0	357,826
Fraud per 100,000 elderly (#)	11.6	0.0	54.5	0.0	5,920.2	357,826
Probability of Elder Fraud (%)	27.1	0.0	44.5	0.0	100.0	357,826

Pre-COVID *(Jan 2014 to Dec 2019)*

	Mean	Median	SD	Min	Max	N
Elder Fraud Cases	1.4	0.0	7.2	0.0	555.0	211,176

Post-COVID *(Jan 2020 to Feb 2024)*

	Mean	Median	SD	Min	Max	N
Elder Fraud Cases	5.8	0.0	39.2	0.0	2,622.0	146,650

Across all observations, the average number of reports in a county-month is 3.2 cases, with a standard deviation of 25.8. Prior to the pandemic, the average elder fraud count per month was 1.4

[25] FinCEN analyzes this data to identify emerging patterns in financial crime and shares relevant information with law enforcement agencies for investigative purposes. This data set provides only county-month reports of elder fraud, with no information on victims or perpetrators at the individual level.
[26] The full summary statistics for FinCEN data are reported in Table A3 in the Appendix. This is solely county-level information.
[27] The sample excludes U.S. territories and the District of Columbia.

with a standard deviation of 7.2.[28] After the pandemic, this number rose significantly to 5.8 with a standard deviation of 39.2. There is an average of 11.6 cases of fraud per month for every 100,000 elders (0.0116%) and a 27.1% probability of at least one report of elder fraud in any given county-month. An estimated 72.9% of county-month observations reported zero fraud cases. The highest number of fraud reports in a single county-month within our sample is 2,622, constituting 1.75% of the elderly population in that county.[29]

These reports are segmented by state, industry, regulator, instrument and product for further analysis (see Table A8). The top three states with the highest total elder fraud reports are Alaska, Delaware and South Dakota for the period 2014 to 2024, after adjusting for each state's elderly populations. Both Alaska and Delaware passed Model Act provisions with mandatory government disclosures, while South Dakota did not pass the Model Act. As outlined in Equation (1), these state counts may reflect higher underlying elder fraud occurrences and/or greater reporting. Thus, state-level totals alone remain a limited indicator of the Model Act's effectiveness.

How has elder fraud as a proportion of total fraud changed over time? Based on data from the FTC, elder fraud constituted 5.6% of total reported fraud in 2015, rising to a peak of 9.1% in 2019 and stabilizing at around 7% over the last 3 years (see Figure A1, Panel B). This is notable given that non-elder fraud itself has increased significantly by an average annual growth rate (AAGR) of 7.9% over the same period (see Figure A1, Panel A). Figure A2 breaks down the fraud reports by its reporting entity. There has been a significant rise in elder fraud reports filed specifically by the 'Securities/Futures Industry' and 'Depository Institution Industry' which have grown at an AAGR

[28] The pandemic start date is set as January 20, 2020, when the CDC reported the first confirmed COVID case.
[29] This occurred in San Francisco County, California in October 2023, with a total elderly population of 149,666.

of 19% and 11% respectively from 2016 to 2023 (see Figure A2, Panels A and B). This coincides with the implementation of the 2016 Model Act, which explicitly targets broker-dealers and investment advisers employed within these sectors.

5.2 Self-Reported Elder Fraud

Since 1997, the Federal Trade Commission has collected consumer reports in an online database only accessible to law enforcement. In 2023 alone, this database known as the Consumer Sentinel Network recorded over 5.4 million consumer complaints, ranging from fraud to identity theft. This dataset was accessed through a Freedom of Information Act (FOIA) request. The CSN adheres to a five-year data retention policy – any reports preceding this window are deleted from the system biannually. My data sample thus consists of the most recent time frame from 2019 to 2023. Excluding all U.S. territories, D.C. and military addresses, I analyze 68,241 individual cases of self-reported elder fraud complaints after removals.[30] [31] [32] [33] Finally, as the self-reported dataset only collected city and state information, I used U.S. Census and UPS postal data to match each city to a unique county FIPS code, allowing me to aggregate individual self-reported cases into county-month data similar to the institutionally reported elder fraud data.

---

[30] 8 entries with addresses recorded as 'nearly homeless' were removed as no county-level information was provided.

[31] 4,686 reports with only non-U.S. addresses were removed.

[32] For entries with 2 ages and addresses listed (e.g. 70 - 79 | 30 - 39; Florida | Texas), the FTC correspondent has clarified that the first address is likely the victim, while the second age/address refers to someone who filed the complaint on the victim's behalf. As a sanity check, the second age range listed is always younger if not the same as the first for every observation. The first age range is also always over 60 years old. Hence, these entries are retained.

[33] For entries with both a U.S. and foreign county listed, I included only the U.S. and its respective state. The FTC correspondent has confirmed that this is usually the case of someone abroad filing on behalf of an elder in USA. For the 8,388 entries listing two states, the first one was used.

The incidence of self-reported elder fraud has similarly increased steadily from 2019 to 2023. However, the total amount of fraud losses peaked in 2021 before gradually decreasing (see Figure A4). For self-reported elder fraud count, the top three states are Alaska, Arizona and Nevada. In terms of fraud losses, the top three states are Alaska, Arizona and California (see Table A10, Panel A). Across institutionally reported and self-reported data, Alaska ranks the highest among all states in terms of both fraud cases per elder and monetary losses. These results are further segmented by product, age group and payment method (see Table A10, Panels B, C, D) — bank wire transfers are the most common payment method (31%) while the age group 70 to 79 constitutes the largest concentration of elderly victims (38%).

6. Results

6.1 Main Effects on Institutionally Reported Elder Fraud

Table 4: Effects of Model Act on Institutionally Reported Fraud Per Elder (2014 to 2024)

	Institutionally Reported Fraud Per Elder				
	Total		By Provision		By Severity of Law
	(1)		(2)		(3)
Law In Place	0.0000221***	Mandatory Government Disclosures	0.0000365***	Mild Rank	-0.0000087
	(0.0000067)		(0.000013)		(0.0000081)
		Mandatory Third-Party Notifications	0.0000026	Moderate Rank	0.0000346***
			(0.000018)		(0.000012)
		Civil Penalties	0.0001018	Harsh Rank	0.0001362**
			(0.000073)		(0.0000694)
Education	-0.0000067		0.00000208		0.00000451
	(0.0000659)		(0.0000648)		(0.0000647)
Median HH Income	0.0000126***		0.0000121***		0.0000121***
	(0.0000025)		(0.0000023)		(0.0000024)
Social Associations	-0.0000021		-0.0000026		-0.00000262
	(0.0000021)		(0.0000021)		(0.0000021)
Poor Mental Health Days	0.0000029		0.00000456		0.00000492
	(0.0000054)		(0.0000051)		(0.0000049)
Debt-to-Income Ratio	-0.0000020		-0.00000215		-0.00000215
	(0.0000078)		(0.0000078)		(0.0000078)
Non-Elder Fraud Per Capita	0.0109173		0.0105044		0.0117049
	(0.0105097)		(0.0107496)		(0.010269)
Quarter 2	0.00000831***		0.00000832***		0.00000843***
	(0.0000029)		(0.0000030)		(0.0000030)
Quarter 3	0.0000216***		0.0000216***		0.0000219***
	(0.0000031)		(0.0000030)		(0.0000031)
Quarter 4	0.0000258***		0.0000256***		0.0000260***
	(0.0000034)		(0.0000033)		(0.0000034)
County FE	Yes		Yes		Yes
Year FE	Yes		Yes		Yes
Counties (#)	2,933		2,933		2,933
Observations	317,264		317,264		317,264
Adjusted R^2	0.0211		0.0226		0.0226
F-Test	F(10, 2932) = 94.23		F(12, 2932) = 85.14		F(12, 2932) = 93.81
	p-value = 0.0000		p-value = 0.0000		p-value = 0.0000

Standard errors are in parentheses, clustered by county

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Regression results suggest that the NASAA Model Act is effective in encouraging the reporting of elder fraud. The static difference-in-differences result in Column (1) indicates that instituting any provision of the Model Act leads to a statistically significant increase in the number of fraud reports per elder. This estimated effect is an increase of 0.000022 fraud reports per elder per month, which represents 13.81% (0.0000221/0.00016) of the mean. In line with the Model Act's purview, these effects are relevant specifically for the cases of elder abuse processed by financial professionals, not the entire scope of elder financial abuse.

Column (2) decomposes the main effect by the type of legal provision. Instituting mandatory government disclosures leads to a statistically significant 0.000037 increase in fraud reports per elder. The results find that mandatory third-party disclosures and civil penalties have no statistically significant effect on fraud reporting. This suggests that when financial professionals are explicitly required to report suspected and actual elder fraud to government authorities (compulsory disclosures), they are far more likely to do so compared to when such laws are merely permissive (voluntary disclosures) or simply absent.

I also analyze the effectiveness of the Model Act based on the severity of the overall law passed in Column (3). As each state passed different combinations of provisions, they were classified into one of three main categories: mild, moderate and harsh (see Table 1 and A2). States with mild laws, where reporting to government authorities was only voluntary, saw no statistically significant effect on reported elder fraud. Meanwhile, states with moderate laws, where reporting to government authorities was mandatory, saw a statistically significant increase of 0.000035 fraud reports per elder. Effecting harsh laws where financial professionals would face civil penalties for failing to report resulted in a statistically significant increase of 0.00014 fraud reports per elder.

To analyze elder fraud reporting during the COVID window, regressions were also run including a 'COVID' dummy (see Equation 5). Results indicate a positive and highly statistically significant interaction between COVID years and the level of elder fraud reporting (see Table A11), which suggests that the pandemic notably increased the incidence of actual elder fraud and/or the frequency of its reporting. The time trend and year fixed effects are therefore critical in capturing this significant uptick in fraud reporting during the COVID years of the sample period.

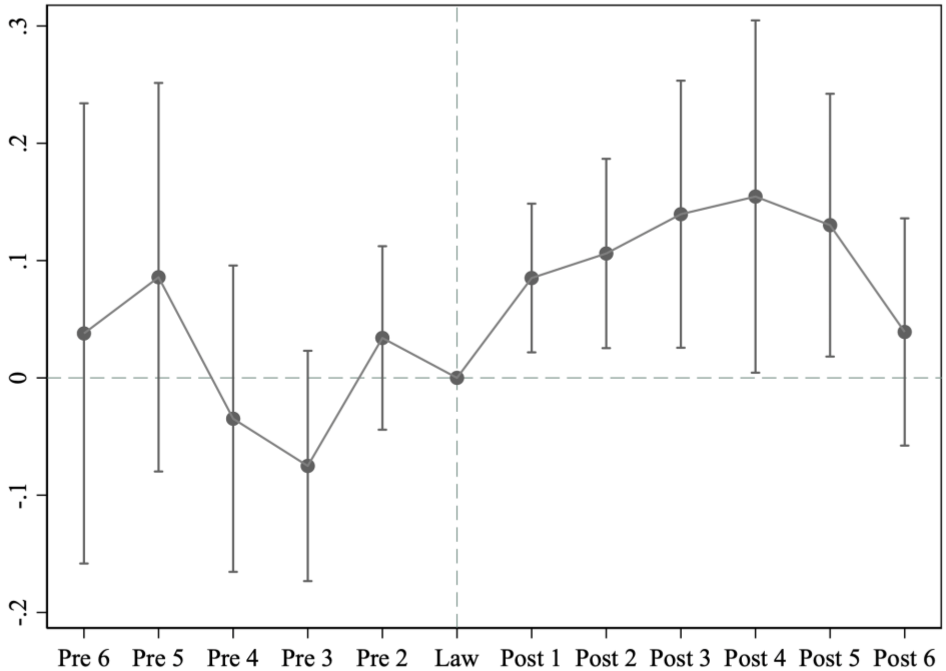
There is also a strong seasonality to the elder fraud, as we observe a stronger likelihood of elder fraud reports received in the 4th quarter of the year, followed by 3rd, 2nd and 1st. The months of October, November and December are the end-of-year and holiday periods, which may see higher financial transactions due to holiday shopping, year-end bonuses or fraudulent charitable giving. Fraud incidence might increase if scammers specifically target vulnerable elders during this period.

As the regression includes county fixed effects, the county-level control variables reflect only deviations within each county relative to its average level over time. Results in Column (1) indicate that the greater the average post-secondary education completion rates of a county, the lower the incidence of reported fraud per elder. As average county-level median household incomes increase and debt-to-income ratios decrease, the greater the incidence of fraud, potentially indicating greater financial resources available for exploitation. Greater county-level participation in social associations is associated with lower fraud levels, supporting previous research citing social participation as a 'protective factor' for financial abuse. Finally, counties with a higher average number of poor mental health days also see a higher incidence of reported fraud per elder, aligning with the literature linking poor mental health to both increased vulnerability among victims and fraudulent behavior among perpetrators. However, as the control variables are county-level demographic averages, they remain limited in capturing perpetrator risk factors should the perpetrator be out of state — i.e. fraud is not localized (see Footnote 19). More importantly, the controls primarily aim to account for factors that might affect the actual incidence of fraud and not its reporting, potentially explaining the lower R^2 value and model fit.

6.2 Dynamic Effects on Institutionally Reported Elder Fraud

To analyze the difference-in-differences estimates dynamically, the coefficients from the PPML regression are plotted in yearly intervals (6 years before and after the law's passage). 'Law' refers to the base period, defined as 0 to 11 months before a provision becomes effective in a state ('Pre-1'). There is no statistically significant pre-trend observed. After the first year of implementing the provision ('Post-1'), there is a 0.077 (0.034) increase in cases per county-month, which represents 2.4% of the mean and 0.3% of the standard deviation (see Table B1).

Figure 4: Effects of Model Act on Institutionally Reported Elder Fraud (6-Year Intervals Pre and Post)[34]



The effects of the increase appear to diminish over time, which has three possible explanations. First, there might be an early surge due to heightened awareness and publicity surrounding the new regulations. However, as enthusiasm and momentum fade, there might be normalization in reporting activity. Second, the initial increase in reports may be a result of surfacing previously unreported cases. As backlogs are gradually handled, the marginal rate of new reporting decreases. Finally, as perpetrators become aware of new reporting disclosures, they may adapt their tactics to avoid detection, resulting in a decline in identifiable and subsequently reportable fraud cases.

Analyzing the law's effect dynamically by state rank, the event plot shows that there is no statistically significant effect for states ranked as 'mild'. For states with moderate and harsh ranks, there is a distinct increase in reporting activity after the Model Act was passed. States ranked as

[34] All event-time plots show a 90% confidence interval based on standard errors clustered by county.

'moderate' see a clear upward trend in fraud reports. However, the confidence intervals are much larger for the 'harsh laws' category — likely due to the significantly smaller sample size of 4 states.

Figure 5: Effects of Model Act on Institutionally Reported Elder Fraud (Mild Rank — 14 States)

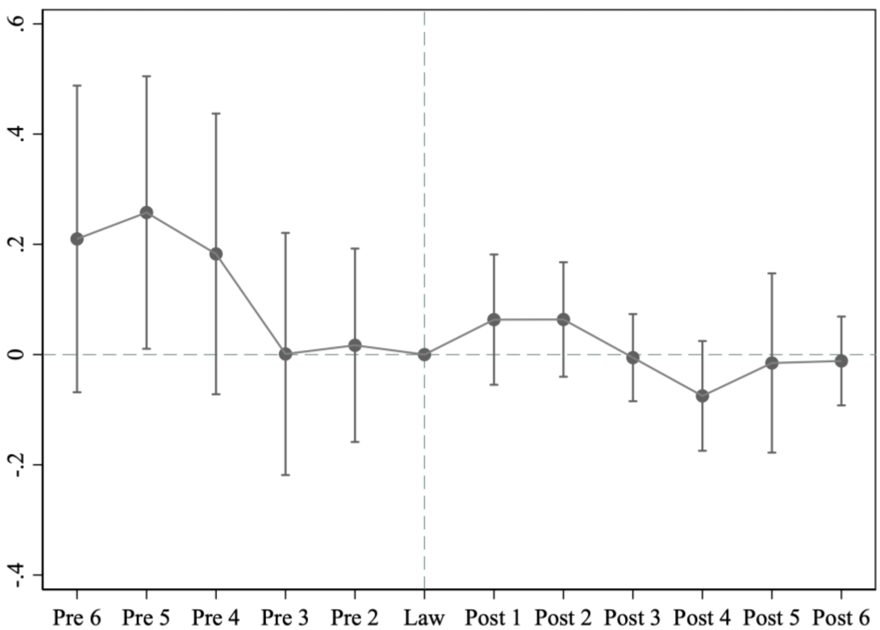


Figure 6: Effects of Model Act on Institutionally Reported Elder Fraud (Moderate Rank — 22 States)

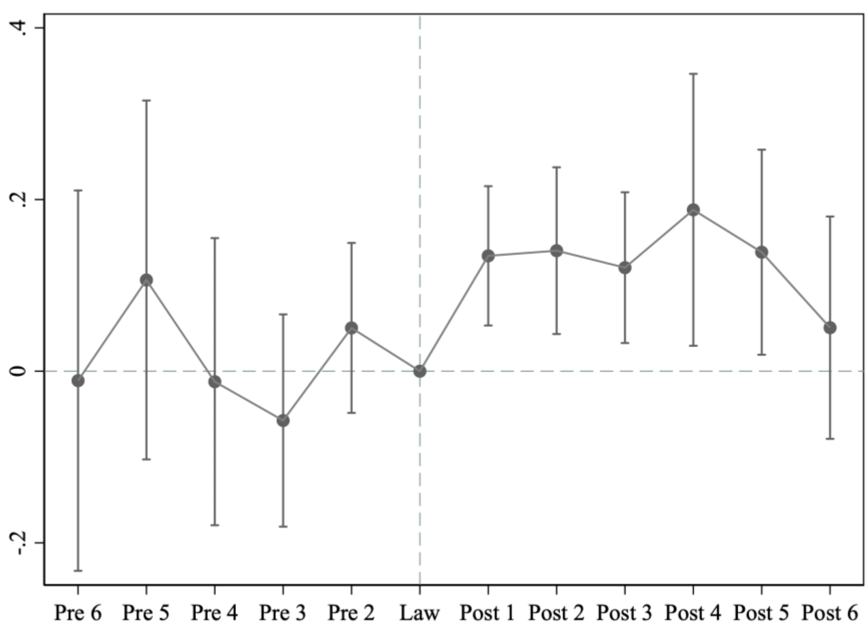
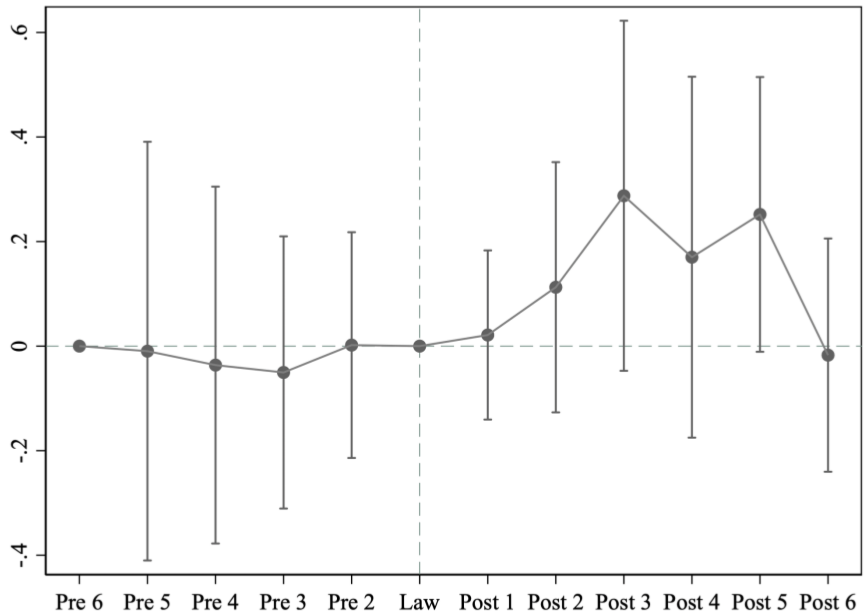


Figure 7: Effects of Model Act on Institutionally Reported Elder Fraud (Harsh Rank — 4 States)



These findings add a layer of nuance to our interpretation of the Model Act's effectiveness, revealing that while instituting provisions significantly encourages reporting, the type of provision also plays a crucial role. Mandatory government reporting requirements ultimately prove to be the most effective.

6.3 Main Effects on Self-Reported Elder Fraud

The same PPML regression specification as Equation (2) was used to analyze self-reported elder fraud, with the only difference being that the event panel plots 6-month instead of yearly intervals (see Equations 6 and 7). The same control variables, time trend, as well as county and year fixed effects were used. As all cases of elder fraud in this dataset are self-reported by victims and/or family members (see Table 2), these observations should function as a 'placebo' group with no expected change in number of fraud reports.

Table 5: Effects of Model Act on Self-Reported Fraud Per Elder (CSN)

	Self-Reported Fraud Cases Per Elder (1)	Self-Reported Fraud Amount Paid Per Elder (2)
Law In Place	0.00000212**	0.0934508
	(0.00000108)	(0.0792873)
Post-Secondary Education	-0.00000335	-1.525691
	(0.0000167)	(1.061855)
Median Household Income (000s)	0.000000723***	0.0037468
	(0.000000099)	(0.004319)
Social Associations	0.0000000451	-0.0215703
	(0.00000067)	(0.038617)
Poor Mental Health Days	0.00000659***	-0.0395574
	(0.00000093)	(0.050249)
Debt to Income Ratio	-0.00000155	-0.2098398**
	(0.0000019)	(0.0910605)
Non-Elder Fraud Per Capita	0.0035073***	202.9887***
	(0.0010312)	(76.91681)
Quarter 2	-0.0000008	-0.0498102
	(0.00000059)	(0.038628)
Quarter 3	0.0000024***	0.0194071
	(0.00000068)	(0.045020)
Quarter 4	0.000000631	-0.0467925
	(0.00000068)	(0.035524)
Time Trend	Yes	Yes
County FE	Yes	Yes
Year FE	Yes	Yes
Counties (#)	2,725	2,725
Observations	163,476	163,476
Adjusted R^2	0.0035	0.0000
F-Test	F(10, 2724) = 95.70	F(10, 2724) = 7.27
	p-value = 0.0000	p-value = 0.0000

Standard errors are in parentheses, clustered by county

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In line with this reasoning, Column (2) indicates that the passage of a Model Act provision leads to no statistically significant increase in total fraud amount paid. Column (1) indicates that there is a slightly statistically significant increase in self-reported fraud cases.[35] However, this result is not robust as prior to the law's passage, we observe a distinct pre-trend and differential trends between states that passed the Model Act and states that did not. Post-treatment, we also observe confidence intervals that overlap with 0 (see Figure X).

Though the results of Column (1) are inconclusive, it might suggest a potential spillover effect, where financial professionals who report suspected elder fraud also encourage elderly victims to self-report. As highlighted in Section 1.3, the Model Act also consists of third-party notifications where financial professionals are mandated/encouraged to notify designated third parties. As the elderly victim and/or their family members become aware of the suspected or confirmed fraud, they might also submit reports to the FTC for investigation, causing a slight uptick in self-reporting activity post-treatment. The above results are also reflected in the event-time plots below and in table form (see Table B2).

[35] The p-value for the coefficient 'Law In Place' is exactly 0.050, suggesting a borderline statistical significance at the 5% level.

Figure X: Effects of Model Act on Self-Reported Elder Fraud Count

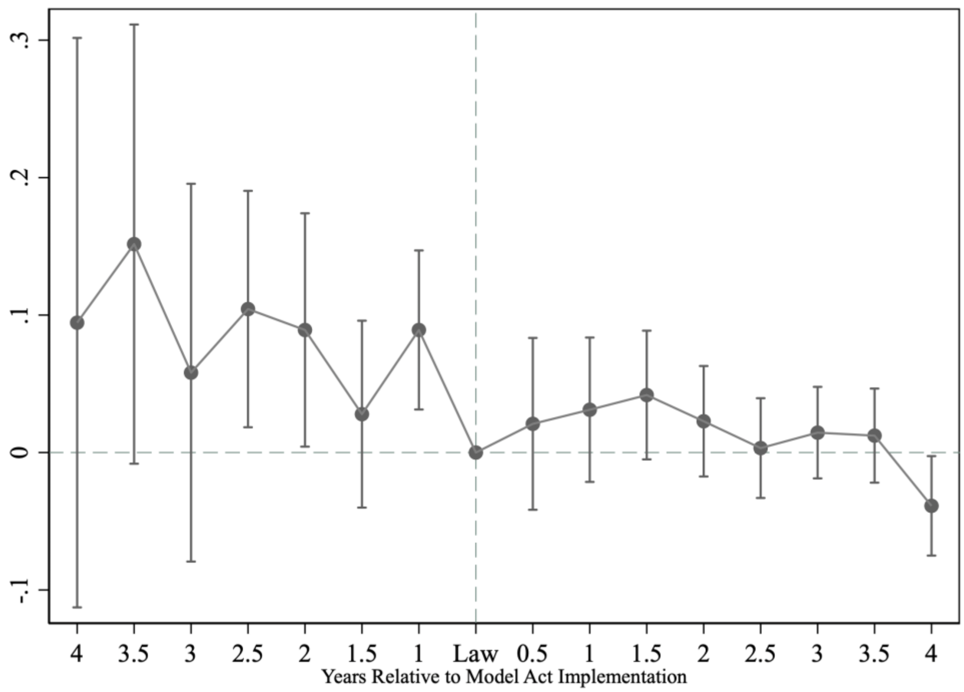
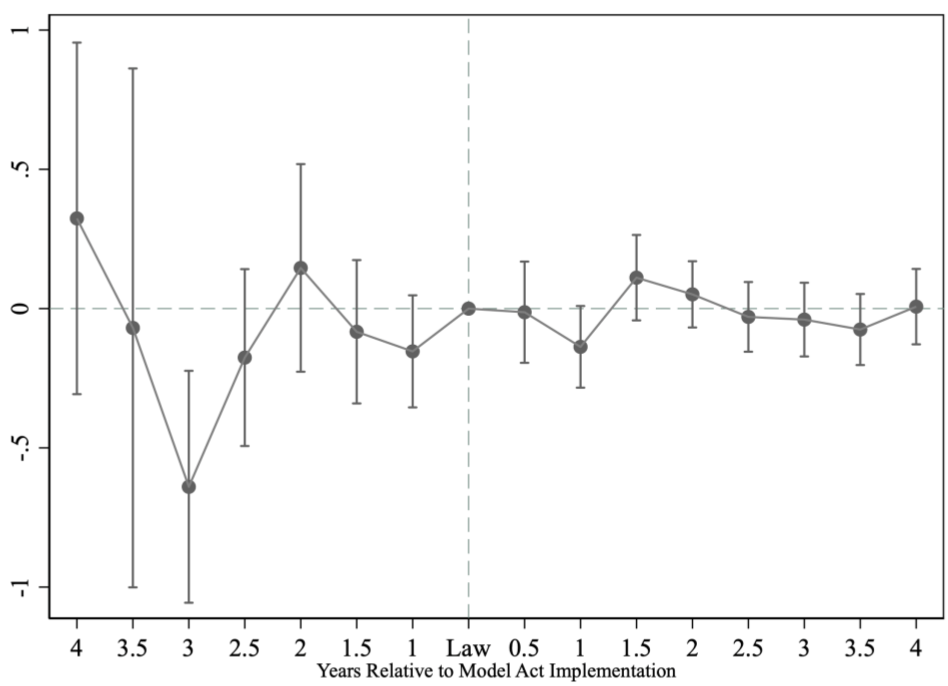


Figure Y: Effects of Model Act on Self-Reported Elder Fraud Losses Incurred



7. Conclusion

Our results suggest that the NASAA Model Act was successful in encouraging greater elder fraud reporting among financial professionals. This potentially indicates the effectiveness of the law's enabling function. As a robustness check, these results also hold under various regression specifications including panel data linear regression, PPML with high-dimensional fixed effects and fixed effects with interaction terms. However, it is difficult to determine if the law also had a deterrent function in reducing actual elder fraud occurrence and the magnitude of its effect. As both functions work in opposing directions, though the law might have successfully deterred some fraud from occurring, the increase in reporting appears to have been more substantial, leading to a net increase in elder fraud reports. Further research could attempt to quantify the Model Act's deterrent effect (i.e. whether the Model Act decreased the actual incidence of fraud in the long term). The outcome measure would focus on fraud attempts as opposed to fraud reporting, using proxies such as working with phone companies to analyze attempted scam calls.

The study provides additional nuance by decomposing the effect of the Model Act by the type of legal provision passed. There is especially strong evidence that mandatory government disclosures increase reporting activity. Meanwhile, states that implemented only voluntary disclosures observed no significant effects on elder fraud reporting. States that imposed civil penalties saw a statistically significant increase in fraud reports per elder — supporting the Public Investors Arbitration Bar Association's recommendation to impose civil penalties on financial professionals who fail to report. Further research might analyze the effectiveness of such laws in other countries and complement the quantitative findings with qualitative interviews to gain insights from state regulators and financial professionals on the ground.

Analyzing the time frame of the pandemic, elder fraud reports increased significantly during COVID-19 and remained elevated (see Table 3). The regression included year fixed effects and a time trend accounting for the overall rise in elder and non-elder fraud cases. Controlling for this, the increase in reporting activity remained robust both during and after the pandemic. Importantly, the regressions which included a dummy specifically intended to capture the effects of COVID found a positive and statistically significant interaction between COVID years and levels of fraud reporting across all specifications (see Table A11). As shown in the event-time graphs, we also observe a statistically significant increase in elder fraud reporting even five years post-law implementation, which aggregates data from both the COVID and post-pandemic periods. This suggests that the law's provisions remained resilient amidst the extreme rise in actual fraud cases, as financial professionals continued to report cases at sustained levels.

Finally, the paper analyzed data from the Consumer Sentinel Network which collects self-reported elder fraud instead of fraud reported by financial professionals. I hypothesized that the passage of Model Act provisions which apply only to financial professionals would not affect self-reporting activity. The findings are mostly consistent with this 'placebo' scenario, as there was no statistically significant effect on total fraud losses incurred. However, there is a slightly significant increase in fraud reports, suggesting the possibility of a small spillover effect if financial professionals' reporting encourages elderly victims and/or their family members to also file their own reports. This aligns with the Model Act provision surrounding third-party notifications which encourages or mandates that financial professionals notify select trusted contacts in the event of suspected fraud. However, as there are notable pre-trends and only slightly significant effects post-treatment, this result remains inconclusive.

Overall, the difference-in-differences estimates suggest that the Model Act has a positive enabling effect, especially for states that passed mandatory government disclosures. This creates a strong case for states to not only pass Model Act provisions but to enforce obligatory, not simply permissive reporting requirements. States may also consider instituting enforcement mechanisms such as civil penalties for failure to report, or when evidence of financial abuse has been willfully ignored. Altogether, this study demonstrates support for the effectiveness of legal provisions in encouraging greater reporting of elder fraud. Given the unique position of financial professionals to detect elder fraud, as well as the scale and severity of harm done to its victims, there remains a strong economic and ethical case supporting such legal interventions.

8. References

Acierno, R., Hernandez, M. A., Amstadter, A. B., Resnick, H. S., Steve, K., Muzzy, W., & Kilpatrick, D. G. (2010). Prevalence and correlates of emotional, physical, sexual, and financial abuse and potential neglect in the United States: The National Elder Mistreatment Study. *American Journal of Public Health*, *100*(2), 292–297. https://doi.org/10.2105/ajph.2009.163089

American Bankers Association. (2024, April 18). FinCEN: Financial institutions reported $2.7 billion in elder financial exploitation. *ABA Banking Journal*. https://bankingjournal.aba.com/2024/04/fincen-financial-institutions-reported-27-billion-in-elder-financial-exploitation/

Anderloni, L., Bacchiocchi, E., & Vandone, D. (2012a). Household financial vulnerability: An empirical analysis. *Research in Economics*, *66*(3), 284–296. https://doi.org/10.1016/j.rie.2012.03.001

Carlin, B., Umar, T., & Yi, H. (2023). Deputizing financial institutions to fight elder abuse. *Journal of Financial Economics*, *149*(3), 557–577. https://doi.org/10.1016/j.jfineco.2023.06.004

Conrad, K. J., & Conrad, K. M. (2019). Abuser risk measure: Reports by alleged victims to adult protective services. *The Gerontologist, 59*(5), 403–414. 10.1093/geront/gny091

Consumer Financial Protection Bureau. (2019). *Suspicious activity reports on elder financial exploitation: Issues and trends* (Technical Report). https://files.consumerfinance.gov/f/documents/cfpb_suspected-elder-financial-exploitation-financial-institutions_report.pdf

DeLiema, M., Deevy, M., Lusardi, A., & Mitchell, O. S. (2020). Financial fraud among older Americans: Evidence and implications. *The Journals of Gerontology: Series B*, *75*(4), 861–868. https://doi.org/10.1093/geronb/gby151

Donnelly, A. (2016, March 23). *Nearly 1 in 5 seniors swindled financially*. NBC Boston. https://www.nbcboston.com/investigations/nearly-1-in-5-seniors-swindled-financially/57792/

FBI Internet Crime Complaint Center. (2020). *Elder Fraud Report 2020.* Federal Bureau of Investigation. https://www.ic3.gov/AnnualReport/Reports/2020_IC3ElderFraudReport.pdf

FBI Internet Crime Complaint Center. (2023). *Elder Fraud Report 2023*. Federal Bureau of Investigation. https://www.ic3.gov/AnnualReport/Reports/2023_IC3ElderFraudReport.pdf

Financial Crimes Enforcement Network (2024, April 18). *Financial Institutions Report $27 Billion in Elder Financial Exploitation Suspicious Activity in One-Year Period.* https://www.fincen.gov/news/news-releases/fincen-issues-analysis-elder-financial-exploitation

Financial Crimes Enforcement Network. (2019). *Elders Face Increased Financial Threat from Domestic and Foreign Actors* (Technical Report). https://www.fincen.gov/sites/default/files/shared/FinCEN%20Financial%20Trend%20Analysis%20Elders_FINAL%20508.pdf

Gamble, K. J., Boyle, P. A., Yu, L., & Bennett, D. A. (2014). *The causes and consequences of financial fraud among older Americans* (Working Paper). Boston College Center for Retirement Research. http://crr.bc.edu/wp-content/uploads/2014/11/wp_2014-13.pdf

H.B. 2205, 2015 Bill, 2013 Reg. Sess. (Ore. 2015) https://olis.oregonlegislature.gov/liz/2013R1/Downloads/MeasureDocument/HB2205/Enrolled

Heisler, C. J. (2017). Moving forward: Recommendations for advancing late-life polyvictimization practice, policy, and research. *Journal of Elder Abuse & Neglect*, *29*(5), 351–363. https://doi.org/10.1080/08946566.2017.1388013

Lachs, M. S., & Pillemer, K. (2015). Elder abuse. *New England Journal of Medicine*, *373*(20), 1947–1956. https://doi.org/10.1056/NEJMra1404688

Lim, A. C., Mosqueda, L., Nguyen, A. L., Mason, T. B., Weissberger, G. H., Fenton, L., Lichtenberg, P., & Han, S. D. (2022). Interpersonal dysfunction predicts subsequent financial exploitation vulnerability in a sample of adults over 50: A prospective observational study. *Aging & Mental Health*, *27*(5), 983–991. https://doi.org/10.1080/13607863.2022.2076210

NASDAQ Verafin 2024 global financial crime report. Nasdaq. (2024). https://www.nasdaq.com/global-financial-crime-report

North American Securities Administrators Association. (2019). *NASAA Model Act to Protect Vulnerable Adults from Financial Exploitation: Legislative text and commentary for the 2019 legislative session*. https://www.nasaa.org/wp-content/uploads/2019/07/NASAA-Model-Act-Updated-Commentary-for-2019-Session.pdf

North American Securities Administrators Association. (2021). *2021 NASAA Activity Report.* https://www.nasaa.org/wp-content/uploads/2022/07/NASAA-2021-Activity-Report-FINAL.pdf

North American Securities Administrators Association. (2024). *NASAA Enforcement Report and Top Threats for 2024. https://www.nasaa.org/wp-content/uploads/2024/10/FINAL_2024-Enforcement-Report.pdf*

Peterson, J. C., Burnes, D. P. R., Caccamise, P. L., Mason, A., Henderson, C. R., Wells, M. T., Berman, J., Cook, A. M., Shukoff, D., Brownell, P., Powell, M., Salamone, A., Pillemer, K. A., & Lachs, M. S. (2014). Financial exploitation of older adults: A population-based prevalence study. *Journal of General Internal Medicine*, *29*(12), 1615–1623. https://doi.org/10.1007/s11606-014-2946-2

Pinsker, D. M., Pachana, N. A., Wilson, J., Tilse, C., & Byrne, G. J. (2010). Financial capacity in older adults: A review of clinical assessment approaches and considerations. *Clinical Gerontologist, 33*(4), 332–346. http://doi.org/10.1080/07317115.2010.502107

Public Investors Arbitration Bar Association. (2015, October 29). *Comment letter: Regarding NASAA's proposed model legislation or regulation to protect vulnerable adults from financial exploitation*. Public Investors Arbitration Bar Association. https://piaba.org/comment-letter-regarding-nasaas-proposed-model-legislation-or-regulation-protect/

S.B. 951, 2017 Bill, 2017 Reg. Sess. (Mary. 2017) https://mgaleg.maryland.gov/2017RS/chapters_noln/Ch_838_sb0951T.pdf

Storey, J. E. (2020). Risk factors for elder abuse and neglect: A review of the literature. *Aggression and Violent Behavior*, *50*, 101339. https://doi.org/10.1016/j.avb.2019.101339

Title 46. Welfare, State St. § 46-454 (2010). https://www.azleg.gov/ars/46/00454.htm

U.S. Census Bureau. (2017, March 9). *Facts for features: 2017 profile of the U.S. population aged 65 and older*. U.S. Census Bureau. https://www.census.gov/newsroom/facts-for-features/2017/cb17-ff08.html

U.S. Department of the Treasury. (2024, July 16). *Treasury Sanctions Cartel Accountants, Announces Joint Notice on Timeshare Fraud in Mexico*. https://home.treasury.gov/news/press-releases/jy2465

U.S. Government Accountability Office. (2011). *Elder justice: Stronger federal leadership could enhance national response to elder abuse* (GAO-11-208). https://www.gao.gov/new.items/d11208.pdf

U.S. Securities and Exchange Commission. (2018, June). *Elder Financial Exploitation Why it is a concern, what regulators are doing about it, and looking ahead*. https://www.sec.gov/files/elder-financial-exploitation.pdf

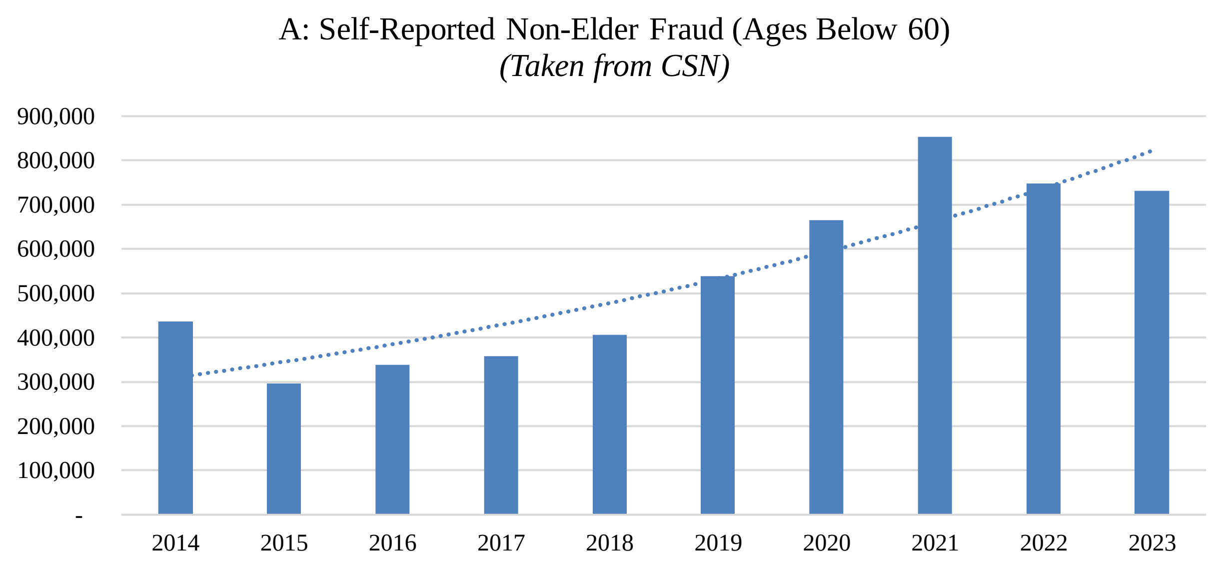
Wood, S. A., Liu, P.-J., Hanoch, Y., & Estevez-Cores, S. (2016). Importance of numeracy as a risk factor for elder financial exploitation in a community sample. *The Journals of Gerontology: Series B, 71*(6), 978–986. https://doi.org/10.1093/geronb/gbv041

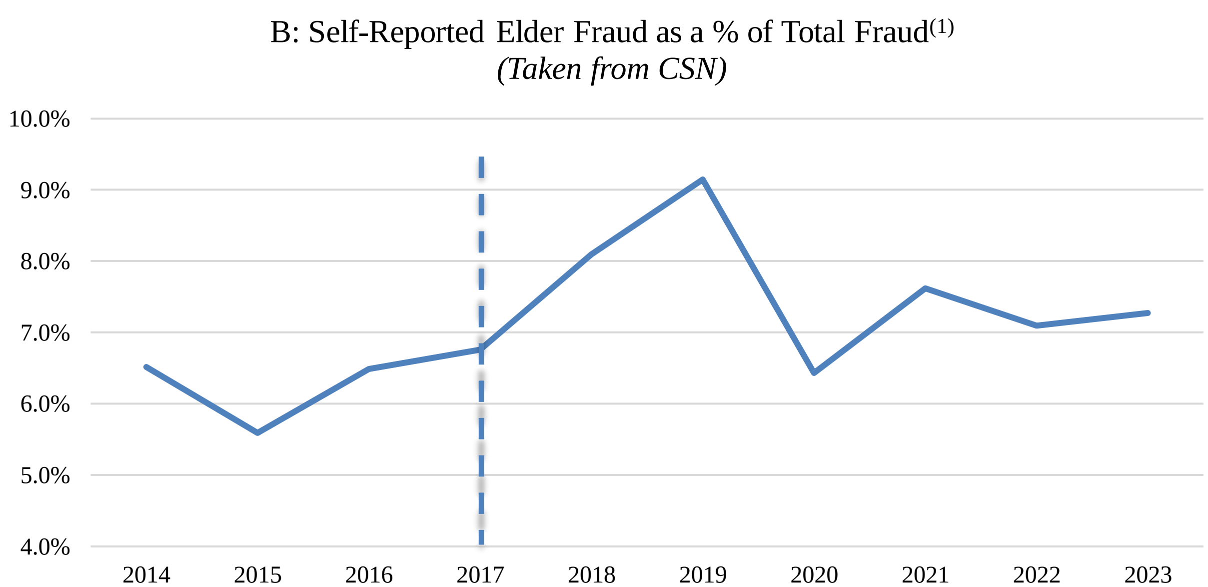
Yu, L., Mottola, G., Bennett, D. A., & Boyle, P. A. (2021). Adverse impacts of declining financial and health literacy in old age. *The American Journal of Geriatric Psychiatry*, *29*(11), 1129–1139. https://doi.org/10.1016/j.jagp.2021.02.042

9. Appendix

Appendix I: Figures

Figure A1: Measures of Overall Fraud Incidence from 2014 to 2023

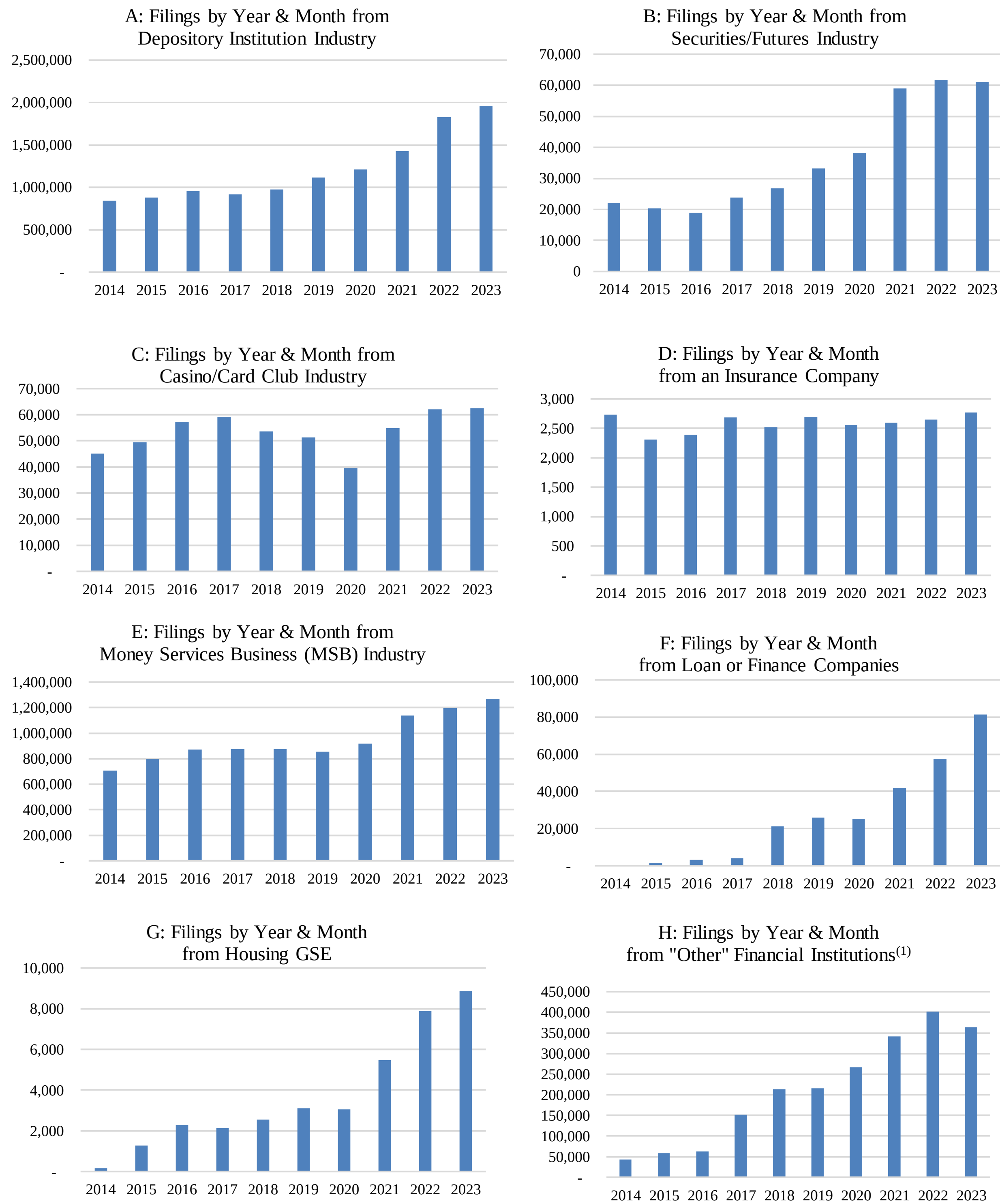




(1) Note: 2017 is the year when most states implemented Model Act provisions. CSN data from both these graphs are aggregated totals taken from annual reports. My sample only includes 2019 to 2023 due to the 5-year data retention policy (see Figure A4)

Figure A2: Total Reported Elder Fraud from 2014 to 2023

(By Reporting Entity, taken from FinCEN)[37]



(1) Note: "Other" Financial Institutions refer to various primary federal regulators such as Commodity Futures Trading Commission, Comptroller of the Currency, Federal Deposit Insurance Corporation, Federal Housing Finance Agency, Federal Reserve Board, Internal Revenue Service, National Credit Union Administration, Securities and Exchange Commission and other unspecified regulators.

Figure A3: Total Reported Elder Fraud from 2014 to 2023
(By Product Type, taken from FinCEN)

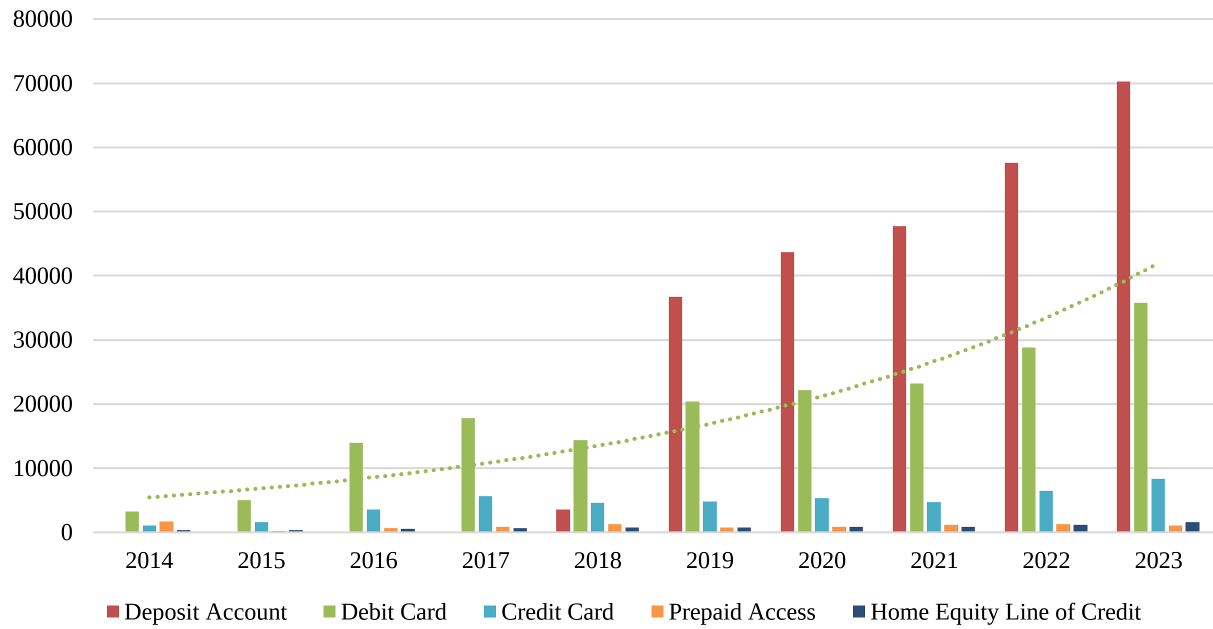
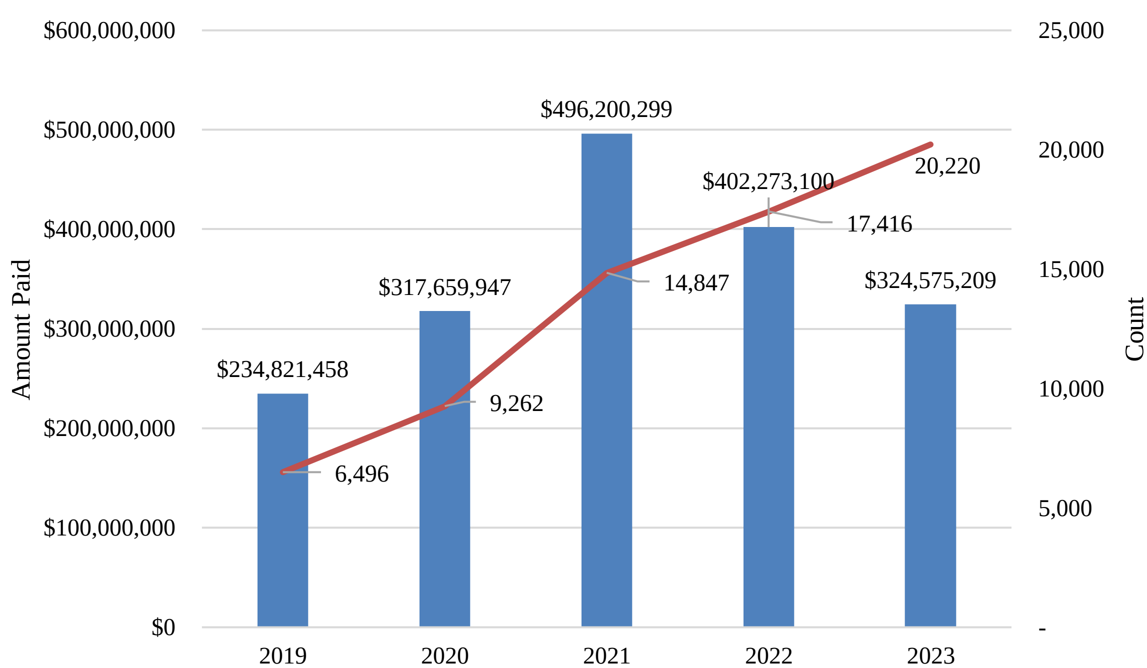


Figure A4: Total Reported Elder Fraud Cases and Amount Paid from 2019 to 2023
(Taken from CSN)[(1)]



---

(1) Note: CSN data sample only includes 2019 to 2023 due to the 5-year data retention policy (see Footnote 22). Data from earlier graphs (Figure A1) are aggregated totals taken from annual reports.

Appendix II: Tables

Table A1: Staggered Adoption of the NASAA Model Act

Name	Passage Date	Effective Date	Relevant Institutions	Age Cutoff For Elderly
Alabama Act 2016-141	Apr-2016	Jul-2016	Broker-dealers and Investment Advisers	65
Alaska HB 170	Apr-2017	Jan-2018	Broker-dealers and Investment Advisers	60
Arizona SB 1483	May-2019	Aug-2019	Broker-dealers and Investment Advisers	65
Arkansas SB 151	Mar-2017	Aug-2017	Broker-dealers and Investment Advisers	65
California SB 496	Sep-2019	Jan-2020	Broker-dealers and Investment Advisers	65
Colorado HB 17-1253	Jun-2017	Jul-2017	Broker-dealers and Investment Advisers	70
Delaware HB 332	Jul-2014	Sep-2014	Financial Institutions	62
Florida HB 813	Jun-2020	Jul-2020	Broker-dealers and Investment Advisers	65
Georgia SB84	May-2023	Jul-2023	Broker-dealers and Investment Advisers	65
Hawaii HB 940	Apr-2021	Jun-2021	Broker-dealers and Investment Advisers	62
Indiana HB 1526	Apr-2017	Jul-2017	Broker-dealers and Investment Advisers	65
Indiana HB 221	Mar-2016	Jul-2016	Broker-dealers	65
Iowa HF839	Apr-2021	May-2021	Broker-dealers and Investment Advisers	65
Kentucky HB 93	Apr-2018	Jul-2018	Financial Institutions	65
Louisiana Act 580	Jun-2016	Jan-2017	Broker-dealers and Investment Advisers	60
Maine LD 566	Apr-2019	Sep-2019	Broker-dealers and Investment Advisers	65
Maryland HB 1149 & SB 951	May-2017	Oct-2017	Broker-dealers and Investment Advisers	65
Michigan Act 344	Dec-2020	Sep-2021	Financial Institutions	65
Minnesota HF3833	May-2018	Aug-2018	Broker-dealers and Investment Advisers	60
Mississippi SB 2911	Mar-2017	Jul-2017	Broker-dealers and Investment Advisers	Vulnerable Person
Missouri SB 244	Jun-2015	Aug-2015	Broker-dealers	60
Montana SB 0024	Mar-2017	Mar-2017	Broker-dealers and Investment Advisers	60
Nebraska LB 297	Mar-2021	Mar-2021	Broker-dealers and Investment Advisers	65
Nevada Chapter 362		May-2015	Broker-dealers and Investment Advisers	60
New Hampshire SB252	Jul-2019	Sep-2019	Broker-dealers and Investment Advisers	65
New Jersey A-5091	Dec-2019	Jan-2020	Broker-dealers and Investment Advisers	65
New Mexico HB 0326	Apr-2017	Jul-2017	Broker-dealers and Investment Advisers	65
North Dakota SB 2322	Apr-2017	Aug-2017	Broker-dealers and Investment Advisers	65
Ohio HB110		Sep-2021	Broker-dealers and Investment Advisers	60
Okla. Admin. Code § 660:11-15-2	Sep-2020	Nov-2020	Broker-dealers and Investment Advisers	62
Oregon SB0095	Jun-2017	Jan-2018	Financial Institutions	65
Rhode Island S. 433	Jul-2019	Jul-2019	Broker-dealers	60
South Carolina S425	May-2021	May-2021	Broker-dealers and Investment Advisers	55
Tennessee SB1192 & HB 0304	May-2017	May-2017	Broker-dealers and Investment Advisers	65
Texas HB 3291	Jun-2017	Sep-2017	Financial Institutions	65
Utah SB 88	Mar-2018	May-2018	Broker-dealers and Investment Advisers	65
V.S.R. § 8-5		Jul-2016	Broker-dealers and Investment Advisers	65
Virginia SB 1490 & HB 1987	Mar-2019	Jul-2019	Financial Institutions	60
Washington SB 6202	Mar-2010	Jun-2010	Broker-dealers and Investment Advisers	60
West Virginia HB 4377	Mar-2020	Jun-2020	Broker-dealers and Investment Advisers	65
Wyoming SF0024	Feb-2023	Jul-2023	Broker-dealers and Investment Advisers	60

Table A2: NASAA Model Act Provisions and Ranking by State

State	Reporting to Government Authorities	Immunity for Government Reporting	Third-Party Notifications	Immunity for Third-Party Notifications	Disbursement Delay	Civil Penalties	Rank
AL	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
AK	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
AZ	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
AR	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
CA	Mandatory	Yes	Voluntary	Yes	Yes	Yes	Harsh
CO	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
CT	No	No	No	No	No	No	None
DE	Mandatory	Yes	No	No	Yes	No	Moderate
FL	Mandatory	Yes	Mandatory	Yes	Yes	No	Moderate
GA	Mandatory	Yes	Mandatory	Yes	Yes	No	Moderate
HI	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
ID	No	No	No	No	No	No	None
IL	No	No	No	No	No	No	None
IN	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
IN	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
IA	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
KS	No	No	No	No	No	No	None
KY	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
LA	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
ME	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
MD	Mandatory	Yes	Voluntary	Yes	Yes	Yes	Harsh
MA	No	No	No	No	No	No	None
MI	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
MN	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
MS	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
MO	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
MT	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
NE	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
NV	Mandatory	Yes	No	No	No	Yes	Harsh
NH	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
NJ	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
NM	Mandatory	Yes	Mandatory	Yes	Yes	No	Moderate
NY	No	No	No	No	No	No	None
NC	No	No	No	No	No	No	None
ND	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
OH	Mandatory	Yes	No	No	Yes	No	Moderate
OK	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
OR	Mandatory	Yes	Voluntary	Yes	Yes	Yes	Harsh
PA	No	No	No	No	No	No	None
RI	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
SC	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
SD	No	No	No	No	No	No	None
TN	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
TX	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
UT	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
VT	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
VA	Voluntary	Yes	Voluntary	Yes	Yes	No	Mild
WA	Voluntary	Yes	No	No	Yes	No	Mild
WV	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate
WI	No	No	No	No	No	No	None
WY	Mandatory	Yes	Voluntary	Yes	Yes	No	Moderate

Table A3: Descriptive Statistics for Institutionally Reported Elder Fraud (FinCEN)
County-Month Elder Fraud Reports and Demographic Variables (2014 to 2023)

	(1) Mean	(2) Median	(3) SD	(4) Min	(5) Max	(6) N
Elder Fraud Cases (#)	3.2	0.0	25.8	0.0	2,622.0	357,826
Fraud Per Elder (#)	0.00016	0.0	0.00055	0.0	0.059	357,826
Fraud per 100,000 elderly (#)	11.6	0.0	54.5	0.0	5,920.2	357,826
Probability of Elder Fraud (%)	27.1	0.0	44.5	0.0	100.0	357,826
Population Above 65 (%)	18.2	17.9	4.5	3.2	58.3	357,826
Post-Secondary Education (%)	57.3	57.4	11.5	12.2	95.7	357,632
Median Household Income	51,689.5	49,512.0	14,244.1	22,045.0	167,605.0	357,608
Unemployment (%)	5.6	5.1	2.4	0.8	28.3	357,632
Debt-to-Income Ratio	1.8	1.7	0.9	0.4	3.4	357,826
Social Associations (# per 10,000)	12.7	11.8	6.1	0.0	65.1	322,484
Poor Mental Health Days (# in last 30 days)	4.1	4.1	0.9	1.0	10.1	347,228
Excessive Drinking (%)	17.6	17.7	3.8	3.2	56.2	338,972
Female (%)	50.0	50.3	2.1	29.1	57.8	357,632
Rural (%)	56.7	57.3	30.7	0.0	100.0	357,344
Non-Hispanic Black (%)	9.0	2.3	14.2	0.0	85.9	357,632
American Indian / Alaska Native (%)	2.1	0.6	6.8	0.0	88.0	357,632
Native Hawaiian / Other Pacific Islander (%)	0.1	0.1	0.4	0.0	13.1	357,632
Asian (%)	1.5	0.7	2.8	0.0	43.9	357,632
Hispanic (%)	9.2	4.2	13.4	0.3	96.4	357,632
Non-Hispanic White (%)	76.7	83.9	19.7	2.7	98.6	357,632
Age Cutoff Delta	3.4	5.0	2.7	-5.0	10.0	274,988

Table A4: Descriptive Statistics for Institutionally Reported Elder Fraud (FinCEN)
County-Month Elder Fraud Reports (Segmented by Pre- and Post-COVID periods)

Panel A: Pre-COVID *(Jan 2014 to Dec 2019)*

	Mean	Median	SD	Min	Max	N
Elder Fraud Cases	1.4	0.0	7.2	0.0	555.0	211,176
Fraud per 100,000 elderly	5.6	0.0	26.0	0.0	1,924.1	211,176
Probability of Elder Fraud (%)	20.1	0.0	40.1	0.0	100.0	211,176

Panel B: Post-COVID *(Jan 2020 to Feb 2024)*

	Mean	Median	SD	Min	Max	N
Elder Fraud Cases	5.8	0.0	39.2	0.0	2,622.0	146,650
Fraud per 100,000 elderly	20.2	0.0	78.4	0.0	5,920.2	146,650
Probability of Elder Fraud (%)	37.3	0.0	48.4	0.0	100.0	146,650

Table A5: Descriptive Statistics for Institutionally Reported Elder Fraud (FinCEN)
County-Month Elder Fraud Reports (Segmented by Law Severity)

Panel A: Model Act Not Passed

	Mean	Median	SD	Min	Max	N
Elder Fraud Cases	3.4	0.0	32.1	0.0	2,306.0	73,078
Fraud per 100,000 elderly	10.5	0.0	45.1	0.0	2,502.2	73,078
Probability of Elder Fraud (%)	29.4	0.0	45.6	0.0	100.0	73,078

Panel B: Model Act Passed (Mild Rank)

	Mean	Median	SD	Min	Max	N
Elder Fraud Cases	1.7	0.0	10.2	0.0	622.0	119,560
Fraud per 100,000 elderly	10.0	0.0	34.7	0.0	1,797.6	119,560
Probability of Elder Fraud (%)	22.2	0.0	41.5	0.0	100.0	119,560

Panel C: Model Act Passed (Moderate Rank)

	Mean	Median	SD	Min	Max	N
Elder Fraud Cases	2.8	0.0	12.8	0.0	849.0	149,206
Fraud per 100,000 elderly	12.2	0.0	65.7	0.0	5,920.2	149,206
Probability of Elder Fraud (%)	27.3	0.0	44.5	0.0	100.0	149,206

Panel D: Model Act Passed (Harsh Rank)

	Mean	Median	SD	Min	Max	N
Elder Fraud Cases	16.1	1.0	87.9	0.0	2,622.0	15,982
Fraud per 100,000 elderly	22.6	3.0	88.4	0.0	2,388.2	15,982
Probability of Elder Fraud (%)	52.6	100.0	49.9	0.0	100.0	15,982

Table A6: CFPB Analysis of Suspected Perpetrators and Median Loss per Elderly Victim

Suspected Perpetrators	**Percent by Suspect[39]**	**Average / Median Loss per Elderly Victim[40]**
Stranger	51%	$17,000 / $8,500
Known Person	36%	$50,200 / $23,200
Family Members	25%	$42,700 / $24,900
Fiduciary	7%	$83,600 / $33,800
Non-Family Caregivers	4%	$57,800 / $21,800

[39] Percentages add up to more than 100 percent because some reports indicate multiple types of suspects.
[40] Report by the Consumer Financial Protection Bureau studying a random sample of 1,051 elder fraud cases from 2013 to 2017. Median loss amounts per older adult are based on the FinCEN Elder Financial Exploitation Suspicious Activity Reports where the entire amount reported is a monetary loss to the older adult, and excludes SARs with no losses, partial losses or any loss to the filer (CFPB, 2019).

Table A7: List of Control Variables and their Data Sources

Control Variables	Data Source
Post-Secondary Education *Risk Factor: Educational Attainment* Research has shown that lower numeracy skills correlate with greater financial fraud risk (Wood et al., 2015). In a study on community-dwelling older adults, declining literacy rates were also strongly correlated with poorer decision-making and greater vulnerability to financial fraud (Yu et al., 2021).	**American Community Survey, 5-Year Estimates** Measures the percentage of adults with post-secondary education, including vocational or technical schools, community colleges or four-year universities. It includes individuals who both completed and did not complete their degrees.
Debt-to-Income Ratio *Risk Factor: Economic Status* A higher debt-to-income ratio indicates that the individual likely has incurred substantial debt relative to their income. Higher ratios could suggest lower financial reserves available to exploit.	**Federal Reserve System[41]** The FED calculates household debt from FRBNY Consumer Credit Panel/Equifax Data and household income from the Bureau of Labor Statistics from 1999 to 2024.
Median Household Income *Risk Factor: Economic Status* This income measure is particularly significant for the elderly population, as calculations account for Social Security or Railroad Retirement benefits, Supplemental Security Income (SSI), welfare payments and pensions for retirement. Higher incomes may indicate a larger amount of financial resources available to exploit.	**American Community Survey, 5-Year Estimates** The Small Area Income and Poverty Estimates (SAIPE) data includes a county-level income measure, factoring in standard salary income, interest dividends, and rental income from real estate.
Social Associations *Risk Factor: Social Isolation* In 2022, medical researchers at the Keck School of Medicine of USC pioneered a study relating social connectedness and problems of social isolation amongst older adults to greater financial vulnerability over time. (Lim et al., 2022). Conversely, embedded community networks have been cited as 'protective factors', which instead reduce the risk of elder abuse (Heisler, 2017).	**County Business Patterns** This dataset records sub-national economic data for businesses with paid employees by industry. The measure 'Social Associations' measures the number of membership associations per 10,000 population, acting as a proxy for the extent of social involvement with others and broader community life.
Poor Mental Health Days *Risk Factor: Mental Health* Researchers have also found correlations between diminished psychological health, cognitive impairment and mental health problems such as depression and anxiety and higher rates of elder fraud for both victims and offenders (Acierno et al., 2010; Gamble et al., 2014). *Note: Self-reported health outcomes are subject to individual discretion, as different people/cultures can have varying interpretations of what constitutes psychological well-being.*	**CDC Behavioral Risk Factor Surveillance System** BRFSS is the nation's premier system of health-related, self-reported surveys. This measure records the average number of mentally unhealthy days reported in the past 30 days, aiming to capture the frequency of mental distress and overall psychological well-being.

[41] Figures were provided for both high and low debt-to-income ratios. DTI ratios used were the average of both.

Table A8: Institutionally Reported Elder Fraud (FinCEN)

Total Elder Fraud Reports by State (2014 to 2023)
Arranged in Decreasing Fraud Per Elder

State	Total Count (#)	Percent (%)	Fraud Per Elder (#)
Alaska	2,780	0.5	0.03
Delaware	4,136	0.7	0.02
South Dakota	3,143	0.5	0.02
Virginia	24,426	3.9	0.02
Georgia	25,704	4.1	0.02
Nebraska	5,343	0.9	0.02
Utah	6,025	1	0.02
Colorado	13,372	2.2	0.02
Rhode Island	3,045	0.5	0.02
Oregon	11,933	1.9	0.02
North Dakota	1,825	0.3	0.02
Maryland	14,000	2.3	0.02
Nevada	7,006	1.1	0.02
Wyoming	1,369	0.2	0.02
North Carolina	24,229	3.9	0.01
Idaho	3,934	0.6	0.01
Washington	16,561	2.7	0.01
Indiana	14,720	2.4	0.01
South Carolina	12,209	2	0.01
Iowa	7,355	1.2	0.01
Kansas	6,233	1	0.01
Minnesota	11,873	1.9	0.01
New Mexico	4,775	0.8	0.01
Ohio	25,909	4.2	0.01
Arkansas	6,531	1.1	0.01
Montana	2,489	0.4	0.01
Missouri	12,914	2.1	0.01
Alabama	10,288	1.7	0.01
Wisconsin	11,745	1.9	0.01
Texas	42,321	6.8	0.01
Kentucky	8,142	1.3	0.01
California	62,302	10	0.01
New Jersey	16,029	2.6	0.01
Tennessee	12,137	2	0.01
West Virginia	3,897	0.6	0.01
Hawaii	2,787	0.5	0.01
Oklahoma	6,571	1.1	0.01
New Hampshire	2,569	0.4	0.01
Pennsylvania	24,719	4	0.01
Florida	44,546	7.2	0.01
Michigan	17,225	2.8	0.01
Mississippi	4,528	0.7	0.01
Arizona	11,752	1.9	0.01
Massachusetts	10,638	1.7	0.01
Maine	2,546	0.4	0.01
Connecticut	5,492	0.9	0.01
Louisiana	6,226	1	0.01
Illinois	17,099	2.8	0.01
New York	24,516	3.9	0.01
Vermont	676	0.1	0.01
Total	622,590	100.0%	

Table A9: Institutionally Reported Elder Fraud (FinCEN)

Total Elder Fraud Reports by Industry, Regulator, Instrument and Product (2014 to 2023)

Panel A: Reported Elder Fraud by Industry

Industry	Count	Percent (%)
Depository Institution	534,696	85.9
Money Services Business (MSB)	63,974	10.3
Securities/Futures	19,328	3.1
Insurance Company	721	0.1
Loan or Finance Company	268	0.0
Casino/Card Club - State Licensed Casino	70	0.0
Casino/Card Club - Tribal Authorized Casino	64	0.0
Casino/Card Club - Other Casino/Card Club	6	0.0
Housing Government Sponsored Enterprise GSE	4	0.0
Other	3,459	0.6
Total	622,590	100.0%

Panel B: Reported Elder Fraud by Regulator

Regulator	Count	Percent (%)
OCC	255,296	41.0
FRB	158,713	25.5
FDIC	72,365	11.6
IRS	66,662	10.7
NCUA	58,767	9.4
SEC	9,956	1.6
Not Applicable	805	0.1
FHFA	24	0.0
CFTC	2	0.0
Total	622,590	100.0%

Panel C: Reported Elder Fraud by Instrument

Instrument	Count	Percent (%)
U.S. Currency	187,554	30.1
Funds Transfer	161,891	26.0
Personal/Business Check	125,269	20.1
Bank/Cashier's Check	67,392	10.8
Money Orders	21,732	3.5
Government Payment	10,000	1.6
Foreign Currency	7,552	1.2
Gaming Instruments	143	0.0
Travelers Checks	113	0.0
Other	40,944	6.6
Total	622,590	100.0%

Panel D: Reported Elder Fraud by Product

Product	Count	Percent (%)
Deposit Account	269,795	43.6
Debit Card	189,565	30.6
Credit Card	47,199	7.6
Prepaid Access	9,962	1.6
Home Equity Line of Credit	8,041	1.3
Insurance/Annuity Products	2,905	0.5
Mutual Fund	2,870	0.5
Stocks	1,979	0.3
Home Equity Loan	1,338	0.2
Residential Mortgage	1,166	0.2
Bonds/Notes	788	0.1
Forex Transactions	426	0.1
Options on Securities	293	0.1
Commercial Paper	221	0.0
Security Futures Products	219	0.0
Futures/Options on Futures	126	0.0
Microcap Securities	81	0.0
Commercial Mortgage	62	0.0
Hedge Fund	44	0.0
Swap, Hybrid, or Other Derivative	17	0.0
Other	82,412	13.3
Total	622,590	100.0%

Table A10: Self-Reported Elder Fraud and Amount Paid (CSN)
Total Elder Fraud Reports and Amount Paid by State, Product, Age and Payment Method (2019 to 2023)

Panel A: Self-Reported Elder Fraud and Amount Paid by State
Arranged in Decreasing Fraud Per Elder (#)

State	Fraud Reports (#)	Percent (%)	Fraud Per Elder (#)	Amount Paid ($)	Percent (%)	Losses Per Elder (#)
Alaska	170	0.2	0.0021	$4,984,090	0.3	$60
Arizona	2,451	3.6	0.0020	$71,973,779	4.1	$60
Nevada	888	1.3	0.0019	$22,651,769	1.3	$50
New Mexico	685	1	0.0019	$17,402,463	1	$49
Washington	2,092	3.1	0.0019	$59,506,231	3.4	$53
Colorado	1,434	2.1	0.0019	$38,127,473	2.1	$49
Maryland	1,599	2.3	0.0018	$39,329,083	2.2	$44
Utah	584	0.9	0.0017	$15,309,937	0.9	$46
Oregon	1,219	1.8	0.0017	$25,883,475	1.5	$36
California	8,965	13.1	0.0016	$312,325,575	17.6	$57
Virginia	2,011	2.9	0.0016	$56,847,141	3.2	$45
Delaware	273	0.4	0.0016	$6,996,993	0.4	$40
New Hampshire	351	0.5	0.0015	$8,393,589	0.5	$36
Texas	4,927	7.2	0.0014	$137,744,120	7.8	$40
Idaho	372	0.5	0.0014	$6,020,469	0.3	$23
Florida	5,895	8.6	0.0014	$161,962,659	9.1	$39
Montana	267	0.4	0.0014	$4,314,598	0.2	$23
Minnesota	1,202	1.8	0.0014	$26,024,290	1.5	$30
North Carolina	2,228	3.3	0.0014	$59,163,902	3.3	$36
Wyoming	122	0.2	0.0013	$2,197,337	0.1	$24
Hawaii	337	0.5	0.0013	$11,840,370	0.7	$47
South Carolina	1,137	1.7	0.0013	$24,245,615	1.4	$28
Georgia	1,837	2.7	0.0013	$41,578,426	2.3	$30
Vermont	153	0.2	0.0013	$2,074,627	0.1	$18
Maine	345	0.5	0.0013	$7,579,817	0.4	$28
North Dakota	143	0.2	0.0013	$4,463,110	0.3	$40
Massachusetts	1,396	2	0.0013	$29,740,891	1.7	$27
Kansas	564	0.8	0.0013	$8,953,285	0.5	$20
Connecticut	744	1.1	0.0012	$19,029,459	1.1	$32
Nebraska	363	0.5	0.0012	$5,986,304	0.3	$20
Wisconsin	1,153	1.7	0.0012	$22,073,261	1.2	$23
Rhode Island	208	0.3	0.0012	$3,864,795	0.2	$22
Pennsylvania	2,664	3.9	0.0012	$55,296,477	3.1	$24
New Jersey	1,630	2.4	0.0012	$57,199,126	3.2	$41
Tennessee	1,232	1.8	0.0011	$22,237,071	1.3	$21
Oklahoma	687	1	0.0011	$17,686,157	1	$29
Missouri	1,146	1.7	0.0011	$23,718,323	1.3	$24
New York	3,575	5.2	0.0011	$97,219,621	5.5	$31
Illinois	2,154	3.2	0.0011	$55,188,001	3.1	$28
Michigan	1,794	2.6	0.0011	$28,590,472	1.6	$17
West Virginia	378	0.6	0.0011	$4,852,969	0.3	$14
Indiana	1,078	1.6	0.0011	$18,891,070	1.1	$18
Alabama	833	1.2	0.0010	$35,467,908	2	$44
Louisiana	716	1	0.0010	$12,332,092	0.7	$18
Ohio	1,982	2.9	0.0010	$39,611,679	2.2	$20
Iowa	530	0.8	0.0010	$15,000,107	0.8	$29
Arkansas	491	0.7	0.0010	$12,265,167	0.7	$25
Kentucky	690	1	0.0010	$11,046,207	0.6	$16
South Dakota	129	0.2	0.0009	$2,858,200	0.2	$20
Mississippi	417	0.6	0.0009	$7,454,884	0.4	$16
Total	68,241	100.0%		$1,775,504,462	100.0%	

Panel B: Self-Reported Elder Fraud and Amount Paid by Product

Fraud Product	Fraud Reports (#)	Percent (%)	Amount Paid ($)	Percent (%)
Miscellaneous Investments	3,978	5.8	393,000,000	22.1
Romance Scams	6,243	9.1	359,000,000	20.2
Business Imposters	25,653	37.6	349,000,000	19.7
Government Imposters	8,846	13.0	249,000,000	14.0
Prizes, Sweepstakes	5,162	7.6	154,000,000	8.7
Tech Support Scams	7,531	11.0	103,000,000	5.8
Family and Friend Imposters	3,812	5.6	37,500,000	2.1
Fake Check Scams	1,568	2.3	34,300,000	1.9
Computer Equipment	644	0.9	13,400,000	0.8
Banks, Credit Unions and S&Ls	313	0.5	11,600,000	0.7
Real Estate	145	0.2	11,300,000	0.6
Unwanted Telemarketing Calls	310	0.5	8,850,000	0.5
Privacy and Data Security	733	1.1	8,450,000	0.5
Creditor Debt Collection	551	0.8	6,720,000	0.4
Foreign Money and Inheritance Scams	357	0.5	6,010,000	0.3
Stocks and Community Futures Trading	98	0.1	5,910,000	0.3
Job Scams and Employment	670	1.0	4,780,000	0.3
Other Misc.	94	0.1	3,640,000	0.2
Malware and Computer Exploits	195	0.3	2,410,000	0.1
Bank and Credit Lending	77	0.1	2,150,000	0.1
Unsolicited Email	108	0.2	1,850,000	0.1
Unsolicited Text Messages	43	0.1	1,730,000	0.1
Online Payment Services	315	0.5	1,670,000	0.1
Finance Company Lending	14	0.0	968,000	0.1
Online Shopping	143	0.2	836,000	0.0
Misc. Institution Lending	136	0.2	800,000	0.0
Credit Cards and Loss Protection	139	0.2	594,000	0.0
Phone Devices, Accessories and Services	13	0.0	526,000	0.0
Timeshare Resales	6	0.0	457,000	0.0
Third Party Debt Collection	48	0.1	341,000	0.0
Broadband Internet Access	39	0.1	321,000	0.0
Creditor Debt Collection	57	0.1	243,000	0.0
Non-Educational Grants	27	0.0	205,990	0.0
Timeshare Sales	3	0.0	145,212	0.0
Student Loans	21	0.0	143,000	0.0
Broadband Internet Cost	15	0.0	141,000	0.0
Business and Job Opportunities	8	0.0	134,900	0.0
Used Auto Sales	23	0.0	107,233	0.0
Advance-Fee Credit	24	0.0	87,870	0.0
Charitable Solicitations	11	0.0	66,660	0.0
Broadband Internet Speed	5	0.0	54,826	0.0
Phone Billing	6	0.0	41,755	0.0
Payday Loans	3	0.0	41,300	0.0
Cable and Satellite TV	18	0.0	25,516	0.0
Website Design and Promotion	1	0.0	20,000	0.0
Mortgage Modification and Foreclosure Relief	2	0.0	16,600	0.0
Immigration Services	1	0.0	10,500	0.0
Social Networking Services	3	0.0	6,500	0.0
Pyramids and Multi-Level Marketing	4	0.0	6,050	0.0
Vacation and Timeshare Plans	1	0.0	4,500	0.0
Auto Parts and Repairs	5	0.0	4,440	0.0
Property and Inheritance Tracers	1	0.0	3,050	0.0
New Auto Sales	2	0.0	2,250	0.0
Auto Renting and Leasing	3	0.0	2,123	0.0
Health Care: Other Products	1	0.0	1,736	0.0
Insurance (excl. Medical)	3	0.0	1,125	0.0
Website Content	2	0.0	379	0.0
Utilities	1	0.0	350	0.0
Auto Service and Warranties	2	0.0	320	0.0
Medical Insurance	1	0.0	207	0.0
Home Appliances and Connected Devices	1	0.0	160	0.0
Internet Information Services	1	0.0	29	0.0
Medical Treatments	1	0.0	14	0.0
Total	68,241	100.0%	$1,775,631,595	100.0%

Note: For reports where more than one fraud category was listed, the first category was used

Panel C: Self-Reported Elder Fraud and Amount Paid by Age

Age Bracket	Count (#)	Percent (%)	Amount Paid ($)	Percent (%)
60 - 64	16,132	23.6	$408,998,808	23.0
65 - 69	17,556	25.7	$434,506,569	24.5
70 - 79	25,558	37.5	$675,394,470	38.0
80 and Over	8,995	13.2	$256,604,613	14.5
Total	68,241	100.0%	$1,775,504,460	100.0%

Panel D: Self-Reported Elder Fraud and Amount Paid by Payment Method

Payment Method	Count (#)	Percent (%)	Amount Paid ($)	Percent (%)
Bank Wire Transfer or Payment	6,263	9.2	543,709,351	30.6
Cryptocurrency	5,438	8.0	295,046,744	16.6
Wire Transfer - Other	2,369	3.5	198,977,184	11.2
Other Payment Method	4,786	7.0	161,625,844	9.1
Gift Card or Reload Card	3,468	5.1	128,167,973	7.2
Check	18,657	27.3	119,314,324	6.7
Cash	3,017	4.4	106,869,268	6.0
Credit Card	2,775	4.1	101,666,743	5.7
Bank Transfer Other	9,292	13.6	26,979,117	1.5
Debit Card	530	0.8	24,282,291	1.4
Payment App or Service	4,181	6.1	16,868,295	1.0
Money Order	3,254	4.8	16,776,869	0.9
Wire Transfer - MoneyGram	692	1.0	14,788,567	0.8
Bank Account Debit	1,564	2.3	7,673,526	0.4
Not Reported	939	1.4	3,350,069	0.2
Wire Transfer - Western Union	221	0.3	3,021,147	0.2
Cash Advance - Credit Card	142	0.2	2,769,986	0.2
Internet Payment Services (e.g., PayPal)	95	0.1	1,460,179	0.1
Mobile Payment Services (e.g., Google Wallet)	281	0.4	1,069,155	0.1
MoneyPak	104	0.2	517,251	0.0
Cash Advance - Other	109	0.2	255,967	0.0
Phone Bill - Mobile Devices	45	0.1	238,895	0.0
Payroll Allotment	15	0.0	68,002	0.0
Unknown	4	0.0	7,713	0.0
Total	68,241	100.0%	$1,775,504,460	100.0%

Table A11: Effects of Model Act on Institutionally Reported Fraud Per Elder (2014 to 2024)
Regression Specification including COVID Dummy (Equation 5)

	Institutionally Reported Fraud Per Elder				
	Total		By Provision		By Severity of Law
	(1)		(2)		(3)
Law In Place	0.0000236***	Mandatory Government Disclosures	0.0000373***	Mild Rank	-0.00000673
	(0.0000067)		(0.0000129)		(0.0000081)
		Mandatory Third-Party Notifications	0.00000485	Moderate Rank	0.0000359***
			(0.0000179)		(0.000012)
		Civil Penalties	0.0000996	Harsh Rank	0.0001353*
			(0.0000729)		(0.000069)
Education	-0.00000357		0.0000053		0.00000721
	(0.0000660)		(0.0000649)		(0.000065)
Median HH Income	0.0000124***		0.0000119***		0.0000119***
	(0.0000025)		(0.0000023)		(0.0000023)
Social Associations	-0.00000115		-0.00000166		-0.00000169
	(0.0000021)		(0.0000021)		(0.0000021)
Poor Mental Health Days	0.0000010		0.00000277		0.00000306
	(0.0000054)		(0.0000050)		(0.0000050)
Debt-to-Income Ratio	-0.00000285		-0.00000292		-0.00000292
	(0.0000078)		(0.0000078)		(0.0000078)
Non-Elder Fraud Per Capita	-0.0118994		-0.0109226		-0.0097232
	(0.0107981)		(0.0107823)		(0.0101541)
COVID	0.0000413***		0.0000392***		0.0000388***
	(0.0000050)		(0.0000048)		(0.0000048)
Quarter 2	0.00000777***		0.00000783***		0.00000791***
	(0.0000030)		(0.0000030)		(0.0000030)
Quarter 3	0.000021***		0.000021***		0.0000213***
	(0.0000031)		(0.0000030)		(0.0000031)
Quarter 4	0.0000252***		0.0000251***		0.0000254***
	(0.0000034)		(0.0000033)		(0.0000034)
County FE	Yes		Yes		Yes
Counties (#)	2,933		2,933		2,933
Observations	317,264		317,264		317,264
Adjusted R^2	0.0213		0.0228		0.0228
F-Test	F(11, 2932) = 86.09		F(13, 2932) = 79.49		F(13, 2932) = 87.54
	p-value = 0.0000		p-value = 0.0000		p-value = 0.0000

Standard errors are in parentheses, clustered by county

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix III: Dynamic Difference-in-Differences Results

Table B1: Institutionally Reported Elder Fraud Count (FinCEN)
6 Years Prior to and After the Law Provision was Passed (Yearly Intervals, 2014 to 2023)

	Institutionally Reported Elder Fraud Count			
	Law In Place	Mild Rank	Moderate Rank	Harsh Rank
	(1)	(2)	(3)	(4)
Panel A: Pre-Law				
Pre-6	0.0153174	0.2098331	-0.0109864	N/A
	(0.1078909)	(0.169123)	(0.1347185)	
Pre-5	0.0899173	0.2577068	0.1062593	-0.0095973
	(0.1022234)	(0.1502782)	(0.1271012)	(0.2434708)
Pre-4	-0.0167243	0.1826283	-0.0122144	-0.036289
	(0.0812812)	(0.154775)	(0.1016999)	(0.2074917)
Pre-3	-0.0714797	0.0011187	-0.0574458	-0.050363
	(0.061364)	(0.1335239)	(0.0751685)	(0.1582724)
Pre-2	0.0358098	0.0168885	0.0503955	0.0019543
	(0.0491613)	(0.1066518)	(0.0601959)	(0.1312541)
Panel B: Post-Law				
Post-1	0.0770856**	0.0633975	0.1344036***	0.0212995
	(0.0342864)	(0.0718402)	(0.0493331)	(0.0983382)
Post-2	0.1048773**	0.0636582	0.1400415**	0.1126014
	(0.0482284)	(0.0631321)	(0.059053)	(0.1454916)
Post-3	0.1360083**	-0.0055304	0.1206246**	0.2875784
	(0.068297)	(0.0480462)	(0.0533899)	(0.2035636)
Post-4	0.1418025	-0.0749491	0.1880158*	0.1700919
	(0.0869875)	(0.0650367)	(0.0963059)	(0.2098351)
Post-5	0.1260352*	-0.0152845	0.1386224*	0.2519161
	(0.0654186)	(0.0988457)	(0.0726221)	(0.1597536)
Post-6	0.0372513	-0.0115577	0.0507033	-0.0172376
	(0.0572048)	(0.0489732)	(0.0787326)	(0.1355928)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	316,776	171,026	196,318	79,100

Table B2: Self-Reported Elder Fraud Count and Amount Paid (CSN)

4 Years Prior to and After the Law Provision was Passed (6-Month Intervals, 2019 to 2023)

	Self-Reported Elder Fraud Count (1)	Self-Reported Elder Fraud Amount Paid (2)
Panel A: Pre-Law		
Pre-8	0.0944721	0.3238492
	(0.1259301)	(0.3836996)
Pre-7	0.1516271	-0.0694244
	(0.0971228)	(0.5663326)
Pre-6	0.0581066	-0.6398189***
	(0.0835405)	(0.2531325)
Pre-5	0.1043796**	-0.1758606
	(0.0522752)	(0.1930696)
Pre-4	0.0891633*	0.1460103
	(0.0516042)	(0.2265805)
Pre-3	0.0279273	-0.0831937
	(0.0413356)	(0.1564524)
Pre-2	0.0891662***	-0.1535919
	(0.0351684)	(0.1223187)
Panel B: Post-Law		
	0.0208697	-0.0129383
Post-1	(0.0380073)	(0.1104985)
	0.0311355	-0.1372845
Post-2	(0.0319268)	(0.089122)
	0.0418288	0.1110061
Post-3	(0.0284592)	(0.0932266)
	0.0227678	0.0511626
Post-4	(0.0244332)	(0.0722724)
	0.0032312	-0.029756
Post-5	(0.0220684)	(0.0760929)
	0.0144826	-0.0395147
Post-6	(0.0202367)	(0.0804585)
	0.0123116	-0.0751253
Post-7	(0.0208045)	(0.0775528)
	-0.038781*	0.0070097
Post-8	(0.0220001)	(0.0823032)
County FE	Yes	Yes
Year FE	Yes	Yes
Observations	163,476	163,476