The Effectiveness of White-Collar Crime Enforcement: Evidence from the War on Terror

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Abstract

This paper studies the deterrent effect of criminal enforcement on white-collar criminal activities. Using the 9/11 terrorist attacks as a shock to the FBI's allocation of investigative resources and priorities, and variations in the Muslim population in the United States as a measure of geographic variations in the shock, I examine two questions: (1) Does the bureau's shift to counter-terrorism investigations after 9/11 lead to a reduction in the enforcement of laws targeting white-collar crime? (2) Does white-collar crime increase as a result of less oversight? Using a difference-in-differences estimation approach, I find that there is a significantly greater reduction in white-collar criminal cases referred by FBI field offices that shift their investigative focus away from white-collar crime to counter-terrorism. I also find that areas overseen by FBI field offices that shift their attention from white-collar crime to counter-terrorism experience a significantly greater increase in wire fraud, illegal insider trading activities, and fraud within financial institutions.

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1 Introduction

White-collar crime, which consists primarily of financially motivated illegal actions characterized by deceit and fraud, ranging from wire fraud and Ponzi schemes to illegal insider trading and accounting fraud, can have devastating consequences for investors and the financial market. After high-profile financial failures and corporate fraud scandals, such as the Enron accounting scandal, the Madoff Ponzi scheme, and the mortgage fraud epidemic that precipitated the recent financial crisis, many observers call for stricter regulation and increased enforcement of laws against white-collar crime. However, whether white-collar crime can be effectively deterred by plausible variations in enforcement efforts and, if so, at what cost and with what deterrent effects remain largely unresolved questions.

On the one hand, researchers have found evidence suggesting that white-collar criminals are responsive to the cost of committing crime and can be deterred by regulators' enforcement actions (Kedia and Rajgopal, 2011). The idea that criminals respond to changes in the cost of committing crime is formalized in Becker's (1974) model, which depicts criminals as rational agents who maximize their expected utilities and weigh the benefits and costs of committing a crime. Edward Swanson, a white-collar criminal defense attorney at Swanson & McNamara LLP, believes that the deterrent effect of criminal prosecution is high for white-collar crime because "white-collar crime prosecutions heavily affect behavior in the business community, and the knowledge that you might be prosecuted is an effective deterrent."

On the other hand, given that the punishments for and negative consequences of financial misconduct are quite severe, it remains a puzzle why financial fraud still persists. Psychologists and criminologists consider criminals to have at most limited rationality, finding it difficult to assign monetary value to the potential cost of committing a crime (Carroll, 1978). Behavioral economists believe that bounded rationality and bounded willpower might explain criminals' departure from Becker's model (Jolls, Sunstein, and Thaler, 1998). A fundamental attribution error and moral pessimism can lead criminals to underestimate the probability of being caught. Legal scholars also find that white-collar defendants do not seem to hear the deterrence message that punishments by the legal system are intended to communicate to them (Henning, 2015).

In their review of the financial misconduct literature, Amiram, Bozanic, Cox, Dupont, Karpoff, and Sloan (2017) suggest behavioral biases and personal traits as potential explanations of why white-collar crime is difficult to deter; hence, the relatively low current level of criminal enforcement does not have a significant deterrent effect. These personal traits and behavioral biases can lead white-collar criminals down what Schrand and Zechman (2012) coined "the slippery slope." For example, overconfident CEOs unintentionally issue financial statements that are optimistically biased, and are then later pressured to issue increasingly optimistic statements to hide the initial bias. Interviews with white-collar defendants further reveal that they do not behave rationally (Soltes, 2016).

It is, however, difficult to answer these questions empirically since the cost of criminal behavior is usually unobservable and difficult to estimate, while it is relatively easy to estimate the benefits of such behavior. Even criminals themselves have trouble mapping the cost of committing crime to the monetary value such behavior brings (Carroll, 1978). More importantly, the endogenous relationship between the enforcement of laws against financial crimes and the decision to commit financial crimes makes it challenging for researchers to draw causal conclusions or estimate the magnitude of the deterrent effect of enforcement.

In this paper, I provide insights into both (1) whether financial crime can be effectively deterred, and, if so, (2) what the magnitude of the deterrent effect is, by examining changes in white-collar criminal activities following the FBI's diversion of resources and investigative focus from white-collar crime to counter-terrorism after the 9/11 terrorist attacks.

Following the 9/11 terrorist attacks, the FBI is revealed to have directed its field offices to count the number of mosques and Muslims in their jurisdictions to gauge the expected number of terrorism-related investigations and intelligence warrants that each office was expected to produce.[1] The distribution of Muslim American communities can be partly explained by their immigration history. Detroit, Michigan illustrates how historical immigration patterns can explain variations in the distribution of the Muslim American population today. There is a story about Henry Ford's meeting with a Yemeni sailor, who spread the word about Ford's auto factory jobs that paid five dollars a day, eventually leading to a series of Arab migrations to the city.[2] Although it is unclear whether that chance encounter actually happened, Henry Ford was indeed more willing to hire Arabs than some other immigrants. And it followed that many Muslim American communities began to form around his factory in Highland Park. As Ford moved and built the Rouge Complex in Dearborn, the Arab Americans followed him there.

The Muslim population within an FBI office's jurisdiction is likely driven by similar migration patterns that happened well in the past, and hence, is unrelated to the economic determinants of changes in white-collar crime in the present.[3] I use the density of local or regional Muslim populations as an exogenous "treatment" that captures variations in the diversion of investigative focus and resources away from investigating white-collar crime towards counter-terrorism investigations. I conduct a difference-in-differences analysis and compare differences in changes in both the extent of enforcement and the prevalence of certain

[1] http://www.nytimes.com/2003/01/28/us/threats-responses-american-muslims-fbi-tells-offices-count-local-muslims-mosques.html

[2] http://michiganradio.org/post/what-explains-michigans-large-arab-american-community

[3] Through robustness tests in a later section I find that areas reflecting differences in treatment do not differ regarding changes in economic conditions that have been found in previous research to predict crime, lending support to this assumption.

types of white-collar crime across geographic areas that are subject to varying levels of treatment.

I find that there is a significant decline in the number of white-collar criminal cases referred by the FBI for prosecution after 2002. The treatment year is set at 2002 because it was in 2002 that Congress approved the FBI's reallocation of agents from ordinary criminal investigations to counter-terrorism work. I find that the decrease in white-collar criminal cases referred by the FBI after 2002 is significantly greater in judicial districts whose corresponding FBI field offices' jurisdictions have higher Muslim population densities, even after controlling for variables that capture variations in the demographics and economic conditions across judicial districts. A one-standard-deviation increase in the treatment is associated with an 11.54 percent greater decrease in the number of white-collar criminal cases referred for prosecution. I also examine changes in securities and financial institution–related fraud cases, which are sub-categories of white-collar crime, and obtain similar results. A one-standard-deviation increase in the treatment is associated with 14.28 percent and 7.28 percent greater decreases in the number of financial institution and securities fraud cases, respectively, referred for prosecution by the FBI. Because the FBI did not formally reallocate agents to counter-terrorism until 2002 and because a white-collar criminal investigation can take more than a year to complete,[4] I expect the variation in the reduction in white-collar criminal cases across districts to become pronounced in 2003 or 2004. Consistent with this prediction, I find no significant variations in changes in the number of cases in 2001 or 2002 (in comparison with the baseline year of 2000), but I do find statistically significant variations in the reduction of white-collar crime prosecutions starting in 2003 and 2004.

I then proceed to evaluate the effect of this reduction in enforcement efforts on changes in white-collar crimes such as wire fraud, opportunistic insider trading, and suspicious activity reports filed by financial institutions. I find that counties located in the jurisdictions of FBI offices that are exposed to higher levels of the treatment – with higher-density Muslim populations – see a greater increase in the rate of wire fraud. A one-standard-deviation increase in the treatment is associated with a 25.19 percent greater increase in the rate of wire fraud. This variation in the increase in wire fraud cases starts to turn upward significantly in 2003 but is not statistically significant in 2001 and 2002, as expected. Similarly, I study the effect of the reduction in enforcement of laws against corporate fraud such as insider trading and stock options grant date timing. While unlawful insider trading has been investigated by the FBI for a long time and is listed as one of the agency's top corporate fraud priorities, the FBI began cracking down on options grant timing only in 2006. Since the treatment year is 2002, and the period that I examine spans from 2000 through 2005, an effect on insider trading is plausible but no effect on options timing is expected.

In my analysis of changes in opportunistic insider trading, I use Cohen, Malloy, and Pomorski's (2012)

[4] https://www.businessknowhow.com/security/whitecollarcrime.htm

approach to classify insider trades into opportunistic trades (trades based on insider information) and routine trades (innocuous trades). My difference-in-differences analysis finds that firms located in the jurisdictions of FBI offices with higher levels of the treatment see greater increases in the probability of having an opportunistic trade, in the number of opportunistic trades, and in the profits obtained from opportunistic trades after 2002. A one-standard-deviation increase in the treatment is associated with a 1.3 percent greater increase in the probability of executing an opportunistic trade, the occurrence of 4.1 percent more opportunistic trades, and a US$261,900 greater increase in monthly profits from opportunistic insider trading. As expected, the variation in the change in the number of opportunistic trades starts to turn upward in 2003, but is not statistically significant in 2001 and 2002. I observe no such effect for opportunistic options grant date timing, which is proxied by options granted on the day with the lowest stock price of the month.

In the analysis of changes in fraud reported by financial institutions, I find that a one-standard-deviation increase in the treatment is associated with a 25 percent greater increase in the rate of suspicious activity reports involving such crimes as checking fraud, commercial loan fraud, credit card fraud, debit card fraud, self-dealing, and the like, filed by financial institutions.

I also conduct robustness tests to examine whether there are any differences in changes in economic conditions across the treated areas and find no differences in changes in the unemployment rate, the poverty rate, bank and savings deposits, or the number of banks and savings institution's offices across areas subject to varying levels of treatment.

This paper contributes to the debate over how effective the enforcement of laws against white-collar crime is at deterring it. My findings suggest that, given the FBI's previous level of enforcement efforts, the agency is effective at deterring white-collar crime. White-collar criminals respond quickly, however, to any reduction in enforcement activity: when the FBI reduced white-collar crime investigations following the approval to reallocate agents from criminal investigations, including white-collar crime, to counter-terrorism in 2002, I observe a greater increase in wire fraud and opportunistic insider trading in high treatment areas starting shortly after, in 2003.

The findings of the paper also contribute to the debate over whether the FBI's diversion of resources from investigating white-collar crime to counter-terrorism prevented the agency from going after banking- and mortgage-related fraud in the years leading up to the financial crisis. Although I am unable to establish a direct link between the FBI's reallocation of resources and the observed increase in risky banking practices and mortgage fraud, the paper provides evidence consistent with there being an increase in wire fraud, opportunistic insider trading, and fraud within financial institutions after the bureau's reallocation of its resources. These findings suggest that the FBI plays an important role in the prevention of white-collar crime and that allocating more resources to the FBI's white-collar crime enforcement program could help the agency prevent certain types of white-collar crime.

This paper also provides insight into the effect of a shock to a major law enforcement agency's internal allocation of resources on the effectiveness of its enforcement of laws against various types of crime, and on changes in the behavior of criminals who consequently receive less oversight. This internal resource allocation problem is not unique to the FBI, and is relevant to other regulators and gatekeepers such as the SEC, the IRS, and internal auditors.

This paper contributes to two streams of literature. First, I add to the literature that studies the effectiveness of regulatory agencies and law enforcers' investigations of white-collar criminals. Empirical studies in accounting and finance focus on the SEC and the IRS and examine the deterrent effect of these government agencies' enforcement actions (Kedia and Rajgopal, 2011; Blackburne, 2014; Hoopes et al., 2012; Nguyen and Nguyen, 2017). I contribute to this literature by focusing on the FBI, a major criminal law enforcement agency that investigates white-collar crime. Although regulators such as the SEC cover a larger number of corporate and securities cases, the FBI investigates cases that can be referred for criminal prosecution. With this study, I seek to provide a better understanding of the FBI's white-collar-related law enforcement activities and examine whether they have any deterrent effect. This paper is also a response to a call by Amiram et al. (2017) for researchers to look into several puzzles and research questions in the financial misconduct literature; one such puzzle concerns why financial misconduct persists even though the punishment for and negative consequences of financial misconduct can be quite severe. This paper provides new insights into this puzzle and suggests that constraints on law enforcers and inconsistent enforcement are potential explanations.

Second, I also contribute to the stream of literature that studies the effect of a shock to police vigilance on crime. Di Tella et al. (2004) uses an increase in police protection at Jewish institutions following a terrorist attack in Buenos Aires as an exogenous shock to police force, and finds a large deterrent effect of the ensuing heavier police presence on car theft. The present paper, on the other hand, studies white-collar crime and examines whether law enforcers' *reduction* in the enforcement of laws against white-collar crime due to the diversion of resources towards counter-terrorism investigations leads to an *increase* in white-collar crime.

The paper is organized as follows. Section 2 presents some background information on the FBI and other law enforcement agencies. Section 3 develops the hypotheses. Section 4 discusses the data sources and the variables used in the paper. Section 5 presents the empirical strategy. Section 6 analyzes the main results. Section 7 presents robustness tests. Section 8 discusses additional analyses. Section 9 concludes. Figures and tables are presented at the end.

2 Institutional Details: Background on Enforcement Agencies

2.1 What is white-collar crime and who investigates it?

White-collar crime is financially motivated and typically committed by businesses or professionals, and is characterized by "deceit, concealment, or violation of trust, and is not dependent on the application or threat of physical force and violence." The FBI is the major law enforcement agency that investigates white-collar crime and covers the broadest range of such crimes: public corruption; money laundering; securities and corporate fraud; mortgage fraud; institutional financial fraud such as wire fraud, credit card fraud, bank fraud and embezzlement; fraud against the government; election law violations; mass marketing fraud; and healthcare fraud, etc.[5] The pie charts in Figure 1 show that, among federal agencies, the FBI refers the highest number of white-collar criminal cases for prosecution.

Other agencies that are responsible for enforcing laws against various types of white-collar crime will often cooperate with the FBI on case investigations. For instance, the SEC investigates civil violations of laws against securities fraud. Securities fraud includes insider trading, Ponzi schemes, accounting fraud, and broker embezzlement, among other activities. Other government agencies also involved in securities fraud investigations are the Commodity and Futures Trading Commission, the Financial Industry Regulatory Authority (FINRA), the Internal Revenue Service, and the U.S. Postal Inspection Service. Although it is spread more thinly across a wide range of areas, the FBI enjoys certain advantages over these agencies because it can employ criminal investigative tactics such as wiretapping, tailing suspects, obtaining information through search warrants, and so on.

State and local law enforcement agencies also investigate financial fraud, but they do not have sufficient resources or jurisdictional authority to complete such investigations.[6] State and local law enforcement agencies also must contend with violent crime, which incites the sentiments of local populations and voters to a greater extent than white-collar crime. The FBI, on the other hand, has broader jurisdiction and is more capable of investigating crimes involving financial fraud. It typically obtains information from financial institutions that are victims of fraud through suspicious activity reports. Victims who are civilians often file complaints to report fraud. The FBI also receives complaints from the Federal Trade Commission. The agency also has its own informant network, conducts data mining and investigative journalism, and obtains intelligence information from prior investigations.[7]

The SEC and the FBI work in parallel to investigate securities fraud. In many cases, SEC lawyers

[5] https://www.fbi.gov/investigate/white-collar-crime

[6] https://oig.justice.gov/reports/FBI/a0537/final.pdf

[7] https://www.crowehorwath.com/folio-pdf/Examining_the_FBI_AS-16002-002A.pdf

and accountants discover misconduct through information obtained from tips, complaints, whistleblower submissions, and referrals from self-regulatory organizations and then alert the FBI. The SEC and the FBI work independently, but in cooperation.

Among securities fraud cases that are investigated by both the FBI and the SEC, unlawful insider trading is the staple for both civil and criminal enforcers.[8] Many civil and criminal investigations of unlawful insider trading start with referrals from FINRA or the Options Regulatory Surveillance Authority ("ORSA"), or from the SEC's own trade data analytics. When the SEC receives information about such cases, it refers some of them to the FBI. The FBI can then employ criminal investigative tactics to investigate suspicious individuals.[9]

2.2 The FBI: white-collar crime and counter-terrorism

2.2.1 Shift in focus to counter-terrorism

In addition to white-collar crime, the FBI investigates a wide range of criminal violations, including terrorism, the manufacture and possession of weapons of mass destruction, violent crime, theft, Mafia and gang activity, government fraud, corruption, and civil rights violations. Following the 9/11 terrorist attacks the FBI has felt significant pressure to focus on counter-terrorism and national security, causing a shift in the agency's investigative focus and staff allocation from other investigative areas, including white-collar crime, to counter-terrorism and national security.

The New York Times reports that after the 9/11 attacks, the FBI shifted more than 1,800 agents (nearly one-third of all agents in criminal programs) to terrorism and intelligence duties. Officials say that the cutbacks left the bureau seriously exposed in its efforts to investigate other areas of crime. Internal FBI data reveal that the cutbacks in agents was particularly severe in staffing for investigations of white-collar crime, with a loss of 36 percent from its 2001 levels. Due to this reduction in the number of white-collar criminal investigators, executives in the private sector have difficulty attracting the bureau's attention even in cases of fraud involving millions of dollars.[10]

The FBI also finds it difficult to request additional funding from the government. An internal administration budget document shows that, although the FBI requested US$1.5 billion in 2001 to create 2,024 positions, the White House Office of Management and Budget cut that request to US$531 million. Congress also gave the FBI only US$745 million out of the US$20 billion dollar approved as part of the response to the

[8] https://www.sec.gov/news/speech/2014-spch033114mjw
[9] http://www.businessinsider.com.au/how-fbi-gets-hedge-fund-traders-to-cooperate-2016-1
[10] http://www.nytimes.com/2008/10/19/washington/19fbi.html?scp=2&sq=FBI&st=cse

9/11 attacks. Former Attorney General John D. Ashcroft also did not agree with the FBI's request for an increase of US$588 million for 2003 that included funds to hire 54 translators and 248 counter-terrorism agents and support staff.[11] The squeeze in funding and lack of agents working on counter-terrorism investigations explains the FBI's reallocation of agents from criminal investigations to terrorism investigations.

The Department of Justice (DOJ) also says that the shift of FBI agents to anti-terrorism duties has undermined investigations of corporate miscreants and fraud, and that investigators are taking longer to complete cases. Los Angeles prosecutors say that with more agents moving to anti-terrorism duty, corporate fraud cases are routinely put on hold. James M. Sheehan, FBI special agent in charge of the Los Angeles office's criminal division, says that resource constraints have prevented the agency from taking on white-collar criminal cases that would meet the U.S. attorney's guidelines. A key former supervisor in Los Angeles said that the local FBI office had reduced the number of agents who once worked on white-collar crime and public corruption cases by nearly 60 percent.[12]

The FBI's diversion of resources and investigative focus to counter-terrorism led to a significant reduction in the bureau's enforcement of laws against white-collar crime. It is therefore an interesting and important empirical question whether the void in policing white-collar crimes left behind by the FBI has any significant effect on the deterrence of crime or whether this void can be filled by other agencies, such as the SEC.

2.2.2 Cross-sectional variations in the shift in focus: Mosques and the Muslim American population

FBI field offices vary in their focus on terrorism investigations. The FBI ordered its field office supervisors to count the number of mosques and Muslims in their areas as part of the anti-terrorism effort. In a closed briefing given to Congressional staff members in 2003, Wilson Lowery Jr., executive assistant director of the bureau, told the briefing that the bureau was collecting information on mosques and Muslims in 56 field offices. Mr. Lowery told Congressional officials that the information would be used to help establish a yardstick for the number of terrorism investigations and intelligence warrants that a field office would be expected to produce, and that failure to live up to those numbers would trigger an automatic inspection from headquarters.[13] Civil rights advocates and Arab American groups have called on the FBI to determine its investigative priorities based on probable cause, not the number of mosques or Muslims in a region or area, which Mr. Lowery admitted is "pure profiling" in its worst form.

[11] https://www.washingtonpost.com/archive/politics/2004/03/22/fbi-budget-squeezed-after-911/169ac386-cab7-4c93-bcda-9801b5d5969d/?utm_term=.10721fbbb194

[12] http://articles.latimes.com/2004/aug/30/business/fi-fbi30

[13] http://www.nytimes.com/2003/01/28/politics/28MOSQ.html

For example, agents from the San Francisco office of the FBI regularly attended meetings and services at mosques to collect intelligence about the local Muslim community. The *Los Angeles Times* reports that an FBI document released by the American Civil Liberties Union (ACLU) contains lists of 20 mosques with names and phone numbers of Muslim Americans affiliated with centers of worship from San Francisco to Seaside, California.[14]

The ACLU has documented the use of crude stereotypes by FBI agents regarding crimes and the bureau's collection of demographic data to map where those groups live. A document associated with the "Detroit Domain Management" process asserts that "because Michigan has a large Middle-Eastern and Muslim population, it is prime territory for attempted radicalization and recruitment" by State Department-designated terrorist groups originating in the Middle East and Southeast Asia. Despite these unsubstantiated assertions, the Detroit FBI office initiated a "Domain Assessment" process in Michigan to collect intelligence. After an investigation into its terrorism training, the FBI had to remove hundreds of training materials about Muslims because some of them characterize Muslims as prone to violence and terrorism.[15,16]

Leaving aside debates and controversies about ethical and national security issues surrounding the FBI's activities, I use these observations as institutional details on the basis of which to design my empirical strategy. More specifically, I use variations in the density of Muslim Americans in FBI field offices' jurisdictions as a proxy for variations in the diversion of investigative focus and resources from white-collar crime to counter-terrorism after 9/11 and examine the effects of this diversion on the bureau's efforts to enforce laws against white-collar crime. I then examine whether this exogenous shift in investigative efforts is associated with an increase in white-collar criminal activities.

3 Hypotheses

I first test whether there is a decrease in white-collar criminal enforcement activities after the re-allocation of resources away from white-collar crime to counter-terrorism, which can be formalized in the following two hypotheses:

H1a: There is a decrease in the number of white-collar criminal cases investigated after the rise in terrorism investigations due to the 9/11 attacks.

H1b: The reduction in the number of cases involving white-collar crime was significantly greater at FBI field offices whose jurisdictions have higher Muslim population densities, i.e., were exposed to higher levels

[14] http://articles.latimes.com/2012/mar/28/local/la-me-fbi-california-mosques-20120328
[15] https://www.brennancenter.org/analysis/testimony-hearing-ending-racial-profiling-america
[16] https://www.wired.com/2012/02/hundreds-fbi-documents-muslims/

of treatment after 2002.

My analysis relies not only on changes in enforcement efforts but also on cross-sectional variations in such changes, so I test whether there is a greater decline in the number of cases referred for prosecution in areas where FBI field offices likely diverted more attention and resources from white-collar crime to counter-terrorism. I then examine whether there is an increase in white-collar crime and in particular whether there is a greater increase in areas where local FBI field offices diverted more resources and focus from white-collar crime to counter-terrorism.

Following the 9/11 terrorist attacks in 2001, the FBI faced significant public and political pressure to focus on terrorism investigations. A 9/11 congressional hearing concluded that the attacks were preventable but were not detected because of a failure in communication between the FBI and the CIA. The report concluded that if the two agencies had shared intelligence and if the FBI had been more aggressive, the 9/11 plot would very likely have been unraveled. The report criticized the two agencies for not acting aggressively enough to collect intelligence. In response, then FBI director Mueller made anti-terrorism the top priority of the bureau, and added agents and analysts to focus on counter-terrorism investigations.[17]

Since the FBI did not have sufficient resources to add new agents, the bureau had to shift agents who were working in other areas, including white-collar crime, to counter-terrorism. These changes in the bureau's organization point to a possible decline in the number of white-collar criminal cases investigated by the FBI. However, the magnitude of the impact is unclear. To learn about the magnitude of the impact, I examine the number of cases that were investigated before and after the bureau's reorganization of its priorities as well as the magnitude of the reduction in the number of cases.

A reduction in the number of white-collar criminal cases might also be attributed to a reduction in the prevalence of white-collar crime. Contemporaneous factors such as economic conditions in the early 2000s could have affected the prevalence of white-collar crime and contributed to the overall decline in the number of cases investigated after 2002. To rule out this alternative explanation, I test Hypothesis 1b using a difference-in-differences econometric approach to estimate the differences in the changes in the number of cases investigated by FBI field offices that vary in treatment, that is, offices that differ in regards to the shock to white-collar criminal investigative focus due to the shift to counter-terrorism investigations. Because FBI field offices were required to count the number of Muslims in their jurisdictions to provide a yardstick for the number of counter-terrorism investigations that each office was expected to conduct,[18] variations in the Muslim population can be used as a proxy for variations in the diversion of resources and

[17] http://www.nytimes.com/2003/07/24/us/9-11-congressional-report-faults-fbi-cia-lapses.html?mcubz=0

[18] http://www.nytimes.com/2003/01/28/us/threats-responses-american-muslims-fbi-tells-offices-count-local-muslims-mosques.html

investigative focus from white-collar crime to counter-terrorism. I therefore use the size and density of the Muslim population in FBI field office jurisdictions as treatment variables. If Hypothesis 1b is true, then the treatment variable can also be used to study cross-sectional variations in changes in white-collar crime: areas with "high" treatment will likely experience a greater increase in white-collar crime because FBI field offices in those areas experienced bigger shocks to their investigative focus, as proposed in Hypothesis 1b.

Next, I examine whether there is an increase in white-collar crime following a reduction in enforcement efforts, which can be formally presented as follows:

H2a: There was an increase in white-collar crime rates after 2002.

H2b: Counties in the jurisdictions of FBI offices that focused more resources on terrorism investigations experienced a greater increase in white-collar crime rates after 2002.

Inferences drawn from Hypothesis 2a can potentially be confounded by time-varying factors such as changes in overall economic conditions. For example, the stock market crash of the Internet bubble between 2001 and 2002 could have led to a deterioration in economic conditions and an increase in overall crime, although for white-collar crime the prediction is less clear: economic hardships can lead to an increase in white-collar crime; on the other hand, poor economic conditions may make it unprofitable to steal money from individuals or corporations that are lacking in funding themselves. With Hypothesis 2b, I attempt to overcome this problem by examining changes in the cross-section, and test whether there are differences in changes in white-collar crime across U.S. counties overseen by FBI field offices that vary in levels of treatment.

To test Hypotheses 2a and 2b, I examine the rate of wire fraud across U.S. counties. In Hypothesis 3, I explore whether I observe the same effect for securities fraud by examining changes in illegal insider trading:

H3: There was a greater increase in the occurrence of securities fraud at firms located in jurisdictions of FBI offices that allocated more resources to terrorism investigations.

4 Data

4.1 Data sources

The data used in this paper come from several sources. First, data on the number of cases referred to all district attorney offices are taken from the Transactional Records Access Clearinghouse (TRAC). For each case, TRAC provides an identifier, the judicial district that handles the case, the agency that refers the case, the date of referral, the fiscal year in which the case is still open, the program category of the case (e.g., securities fraud, bankruptcy fraud, etc.), the number of defendants, the charge, and the court type (district court, magistrate, out of court). I identify each case by the identifier, the district code that handles the case, the date of referral, and the date when a referral was received. The total number of cases referred to a district by the FBI in each year is then aggregated by crime category to create the dependent variable for the analysis of changes in the FBI's investigations of white-collar crime.

Figure 1 shows the top agencies that refer the highest numbers of white-collar criminal cases during the years 2000 through 2002 and the years 2003 through 2005. The FBI refers the highest number of cases, outranking the agency that refers the second-highest number of cases.

Data on the Muslim population in each county are obtained from the Religious Congregations and Membership Study 2000, which is available on the website of the Association of Religion Data Archives.[19] The study, which was designed and completed by the Association of Statisticians of American Religious Bodies (ASARB), represents statistics for 149 religious bodies regarding the number of congregations within each county of the United States.

I collect FBI offices' jurisdictions from the FBI website.[20] The FBI provides information on offices' names and locations as well as the counties that each office covers. I link each FBI office with U.S. district attorney offices through the counties that FBI offices' jurisdictions and judicial districts have in common. To link a given judicial district to the counties it covers, I use the judicial district-county crosswalk file from the United States District Court Boundary Shape files (1900-2000), which is available on the Inter-university Consortium for Political and Social Research (ICPSR) website.[21] There are 94 judicial districts in the United States but I perform analysis on only 90 of them and leave out four judicial districts – Guam, Northern Mariana Islands, Virgin Islands, and Puerto Rico – due to missing county-level data.

The unemployment rate, the number of banks and savings institutions' offices, the population density, the median household income, the proportion of the population with a high school education, and the divorce rate are obtained from the Census Bureau's USA Counties Data File Downloads.[22] County crime incident data are obtained from the National Incident-Based Reporting System (NIBRS) from the ICPSR.[23] State-level data on financial institutions reported suspicious activities are obtained from FinCEN's website.[24]

Insider trading data are obtained from Thomson Reuters' Insider Filing Data Feed, Table 1 - Stock

[19] http://www.thearda.com/Archive/Files/Descriptions/RCMSCY.asp
[20] https://www.fbi.gov/contact-us/field/jurisdictions
[21] http://doi.org/10.3886/E30426V1
[22] https://www.census.gov/support/USACdataDownloads.html
[23] https://www.icpsr.umich.edu/icpsrweb/ICPSR/series/57
[24] https://www.fincen.gov/suspicious-activity-reports-sars

Transactions. The Insider Filing Data Feed (IFDF) is designed to capture all U.S. insider activity as reported on SEC Forms 3, 4, 5, and 144 in line-by-line detail. Stock option grant date data are obtained from Thomson Reuters' Insider Filing Data Feed, Table 2. Company address, GVKEY identifiers, and financial variables such as size – the natural logarithm of market equity – and book to market are obtained from Compustat. Company stock returns are obtained from CRSP.

Insider trading litigation releases by the SEC are hand-collected from the SEC's annual reports.

4.2 Matching units of observation

In the analyses throughout this paper, I use a variety of data sources whose units of observation vary from firms to counties, judicial districts, and states. This section provides a brief overview of the units of observation and their corresponding tests. Table D1 summarizes the various units of analysis.

To test for changes in the FBI's enforcement of laws against white-collar crime after 2002, I use mainly data on cases referred by the FBI for prosecution to U.S. federal district courts. As noted above, there are 94 judicial districts and 56 field offices. I leave out four judicial districts – Guam, Northern Mariana Islands, Virgin Islands, and Puerto Rico – due to missing county-level data. A given judicial district can be covered by one to three FBI offices. When a judicial district is covered by only one FBI office, the value of the "treatment" variable – the density of the Muslim population assigned to that district – equals the treatment value of the corresponding FBI office. When a judicial district is covered by more than one FBI office, that judicial district's treatment is the population-weighted average treatment of all the corresponding FBI offices.

Tests for changes in white-collar crime after 2002 use data with observations at the county level, the firm level, and the state level. In my main tests, I explore several measures of white-collar crime: wire fraud, insider trading, and financial institutions reported fraud. The wire fraud data come from the NIBRS and are collected at the county level. Insider Trading data are collected at the firm level and come from Thomson Reuters' Insider Filing Data Feed. Fraud within financial institutions come from FinCEN's Suspicious Activity Reports and are collected at the state level. For observations at the county and firm levels, there is a one-to-one matching between these observations and the corresponding FBI office. On the other hand, when the unit of analysis is the state, one observation can be matched with more than one FBI office. When the unit of analysis is matched to more than one FBI office, the treatment variable is a population-weighted average density of all the corresponding FBI offices.

5 Empirical Strategy

The empirical approach adopted for this paper consists of two parts. In the first part, I examine whether there is a change in enforcement due to the re-allocation of resources from white-collar crime to counter-terrorism investigations. In the second part of the analysis, I examine whether white-collar crime increases following the reduction in enforcement efforts, and I attempt to measure the economic magnitudes of any such increases.

5.1 Decrease in FBI investigations and variation in white-collar criminal cases across judicial districts

The ideal data for observing the FBI's investigative activities related to white-collar crime indicate the total number of white-collar criminal cases investigated by the agency. The data that are observed, however, indicate the total number of cases referred to federal district attorneys' offices for criminal prosecution by the FBI. I do not observe cases that are investigated by the FBI but are not referred for prosecution. If the FBI refers only a subset of cases that it investigates, then the number of referred cases is an underestimation of the FBI's investigative efforts. However, for the purpose of this study, this is a not a concern, and the total number of referred cases is a good proxy for the FBI's investigative activities.

The timeline for changes in enforcement at the FBI after 9/11 is presented in Figure 2. In May 2002, the FBI director reprogrammed the bureau's human resources function. A month later, Congress approved the agency's reorganization and reprogramming, and reassigned agents and support positions from criminal to counter-terrorism investigations in June 2002. In December 2002, Congress approved another FBI counter-intelligence reprogramming step, and reassigned additional agents and support positions from criminal to counterintelligence work.[25,26] Since the investigation of a white-collar crime case can take more than a year to complete,[27] I expect to see a significant decline in the number of cases referred for prosecution starting in 2003 or 2004.

Attributing the magnitude of the change in the number of cases to the FBI's resource reallocation alone can potentially be problematic because other contemporaneous factors around 2002 could also potentially explain why fewer cases are referred for prosecution. For instance, one might raise the concern that the dot-com bubble burst of 2000-2002 might have led to a decrease in opportunities for white-collar crime after 2002, and this, in turn, might have led to a decline in white-collar crime law enforcement.

[25] https://www.fbi.gov/file-repository/stats-services-publications-fbi_ct_911com_0404.pdf/view
[26] https://oig.justice.gov/reports/FBI/a0439/final.pdf
[27] https://www.businessknowhow.com/security/whitecollarcrime.htm

To address potential problems with these confounding factors, I examine variations in white-collar criminal cases referred for prosecution by the FBI across judicial districts whose corresponding FBI field offices differ regarding their counter-terrorism investigative focus after 9/11. I expect to observe a greater decline in white-collar crime case referrals at judicial districts whose corresponding FBI offices were expected to focus more narrowly on terrorism investigations based on the Muslim population density in their jurisdictions.

There are 56 FBI field offices. Each office's jurisdiction covers a certain number of counties. Although civil rights advocates and Arab Americans have objected to the FBI's focus on mosques and Muslims for counter-terrorism investigations, the FBI is reported to have ordered its field supervisors to count the number of mosques and Muslims in their areas to gauge the number of anti-terrorism investigations that each office was expected to conduct.[28] I use variations in Muslim population density, measured as the total number of Muslims divided by the total population in each FBI field office's jurisdiction as a variation in "treatment" intensity across FBI field offices. Because FBI field offices covering areas with larger Muslim populations were expected to conduct more terrorism investigations, I expect these offices to have investigated fewer white-collar criminal cases. Having access to data on staffing and budget reallocation associated with each program category at each FBI field office would perhaps be ideal for capturing variations in FBI offices' resource and agent reallocation changes after 9/11.[29]

The Office of the Inspector General (OIG), in its report, "The External Effects of the Federal Bureau of Investigation's Reprioritization Efforts,"[30] presents a table with data on agent- and support-funded staffing levels for several FBI field offices but the table does not present data on the reallocation of staff from white-collar to counter-terrorism investigations, which would capture staff and agents diverted from white-collar to counter-terrorism work. Lacking office-level data on the number of agents reallocated from white-collar crime to counter-terrorism investigations, I use the Muslim population density in each field office's jurisdiction as an approximation of changes in FBI field offices' investigative focus. I use some of the limited information in the aforementioned OIG report in a robustness test in the later portion of my analysis.

The ideal dependent variable to proxy for the FBI's enforcement activities would be the number of cases opened at each FBI field office. I do not have data on FBI office-level case openings. The next best proxy

[28]http://www.nytimes.com/2003/01/28/politics/28MOSQ.html

[29]I filed a Freedom of Information Act (FOIA) Request with the FBI to learn the number of agents assigned to each unit of criminal investigation but the request was rejected. A conversation with TRACFed, a data-gathering and data research organization at Syracuse University whose mission is to provide the public, the media, and scholars with information on staffing, spending, and enforcement activities of the federal government through information obtained from FOIA requests and FOIA lawsuits, reveals that TRACFed was also not able to obtain information on annual office-level staffing by crime category from the FBI, and that the agency has become somewhat more sensitive in the period after 2003 regarding the release of information on staffing allocation. The DOJ's OIG report titled "The Internal Effects of the Federal Bureau of Investigation's Reprioritization" reports the number of agents and support funded staffing levels for FBI field offices for fiscal years 2000 and 2003 but does not specify the number of agents by program category.

[30]https://oig.justice.gov/reports/FBI/a0537/final.pdf

for which I have data is the number of white-collar criminal cases referred for prosecution by the FBI at the 94 judicial districts across the United States. I link each judicial district to the corresponding FBI offices based on the counties over which their jurisdictions overlap. The FBI website provides each FBI field office's jurisdictions by listing the counties that each FBI office oversees. I link FBI offices to judicial districts using FBI office jurisdictions and the judicial district-county crosswalk file from the United States District Court Boundary Shape files (1900-2000).

To test whether there is a greater decline in the number of cases referred for prosecution by FBI field offices that are exposed to higher levels of treatment, that is, offices in areas with higher Muslim population densities, I perform the following regression analysis:

$$Cases\ Referred_{it} = \alpha + \beta_1 D_i * After_{2002} + \beta_2 D_i + \beta_3 After_{2002} + \beta Control_{it} + \epsilon_{it} \tag{1}$$

where $Cases\ Referred_{it}$ is the number of cases referred to district i by the FBI. Because one district can be linked to more than one FBI office, for a given district, the treatment variable D is a continuous variable and equals the population-weighted average Muslim population density of the district's corresponding FBI offices, and is calculated as follows:

$$D_i = \sum_{j=1}^{j=n} w_j D_{FBI_j} \tag{2}$$

where w_j is the weight and equals the total population of the counties that are common to FBI office j and judicial district i, divided by the total population of judicial district i. $After_{2002}$ is an indicator variable that is equal to one for the years after 2002 and zero otherwise. $Control_{it}$ is a vector of control variables that includes variables that have been found to be predictive of crime, and consists of the rate of the population with a high school education, the district divorce rate, the population density, the percentage of the population that lives in poverty, the median income, and the unemployment rate (Ehrlich, 1975; Sjoquist, 1973; Fleisher, 1966; Simpson and Weisburd, 2010; Cohen and Felson, 1979; Agnew et al., 2009). Including variables that control for district characteristics that have been found to be linked with crime alleviates the concern that variations in local economic condition and demographics could have led to differences in opportunities for white-collar crime across districts, in turn leading to variations in white-collar crime law enforcement.

I expect the coefficient β_1 to be significantly negative. In other words, I expect to see a greater decline in the number of white-collar criminal cases in judicial districts whose FBI field offices are more likely to divert attention to terrorism investigations, as proxied by the Muslim population density in their jurisdictions. The assumption underlying a difference-in-differences econometric approach is the parallel trend assumption, which assumes that the treated and the control group, or in this case, groups exposed to varying levels of treatment, would follow the same trend in the absence of any treatment. Although the parallel trend assumption is not testable, I test for whether there is a parallel trend pattern among areas exposed to varying treatment levels in the period before the treatment, and whether variation in the treatment effect replaces this parallel pattern when the treatment is expected to take effect, by running the following regression:

$$
\begin{aligned}
\mathit{Cases\ Referred}_{ijt} = \alpha + \beta_{t+\tau} \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} D_j * Y_{t+\tau} + \gamma_{t+\tau} \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} Y_{t+\tau} \\
+ \beta Control_{ijt} + \epsilon_{ijt}
\end{aligned} \tag{3}
$$

where $\tau = 0$ for the year 2002. $Y_{t+\tau}$ are indicator variables that equal one if the year is Υ. Υ_{min} and Υ_{max} are the earliest and latest years of the data sample, which run from 2000 through 2005. The indicator variable for the year 2000 is set at 0 such that all the other coefficients are measured incrementally to that of 2000. I expect to see the coefficients on the interaction of D and year indicators to turn positive and statistically significant starting from β_{t+1} or β_{t+2}, which corresponds to the years 2003 or 2004, respectively. If the decrease is gradual over the years after 2002, I might not observe a statistically significant effect on β_{t+1} or β_{t+2}, but only an average effect over the after-treatment period. I do not expect the coefficients β_{t-1} and β_t to be statistically significant. If there is an overall reduction in enforcement activities over all districts following the diversion of resources from white-collar crime to terrorism, then γ_{t+1} could also be positive and statistically significant.

5.2 White-collar crime in response to lax enforcement

5.2.1 Changes in wire fraud

The previous subsection explains the empirical approaches I adopted to test whether there are greater declines in the extent of white-collar crime investigations in areas where FBI field offices were likely allocating more resources to terrorism investigations, that is, offices that were exposed to higher treatment levels. In this section, I explain empirical strategies I adopted to test whether I observe an increase in white-collar criminal activities after 2002, and whether there is a greater increase in white-collar crime in areas where FBI field offices allocated more of their resources to terrorism investigations. I conduct the following regression analysis:

$$\begin{aligned} \textit{White-Collar Crime}_{ijt} = \alpha + \beta_1 D_j * After_{2002} \\ + \beta_2 After_{2002} + \beta_3 D_j + \beta Control_{ijt} + \epsilon_{ijt} \end{aligned} \tag{4}$$

To control for unobservable time-invariant cross-sectional differences across FBI offices, I run the following regression:

$$\begin{aligned} \textit{White-Collar Crime}_{ijt} = \alpha_j + \beta_1 D_j * After_{2002} \\ + \beta_2 After_{2002} + \beta Control_{ijt} + \epsilon_{ijt} \end{aligned} \tag{5}$$

where $\textit{White-Collar Crime}_{ijt}$ is the rate of white-collar crime incidents in county i located in the jurisdiction of FBI office j in year t. D_j is the level of treatment and equals the Muslim population density in the jurisdiction of FBI office j. $After_{2002}$ is an indicator variable that equals one for years after 2002 and zero otherwise. $Control_{ijt}$ are the control variables for county i in FBI office j in year t, and include a county's unemployment rate, the population density, the percentage of the population living in poverty, the median household income, the divorce rate, and the proportion of the population with a high school education. These control variables are included to account for possible differences in county-level economic conditions and demographics that were found in prior research to be predictors of crime (Ehrlich, 1975; Sjoquist, 1973; Fleisher, 1966; Simpson and Weisburd, 2010; Cohen and Felson, 1979; Agnew et al., 2009). I also include the number of banks and savings institutions' offices in each county to account for possible differences in profitability from white-collar crimes such as wire fraud and fraud related to financial institutions. α_j are FBI office fixed effects.

The main identification assumption of the difference-in-differences estimation approach in equations 4 and 5 is that counties treated at varying levels follow a parallel trend. In other words, the parallel trend assumption requires that counties with varying treatment levels follow the same dynamics, and that for any given county the average change in the outcome variable would have been the same as that for other counties with different treatment levels, if there had been no treatment. This comes from the requirement that the treatment be exogenous. Formally, the assumption is that the potential outcomes in the absence of treatment are independent of the assignment of treatment, or that $D_j \perp (\textit{White-Collar Crime}_{0i,j,aft} - \textit{White-Collar Crime}_{0i,j,bef})$.

The parallel trend assumption is not testable. However, I provide evidence consistent with this assumption by examining the trend in the before period. More specifically, in the analysis associated with equation 6, I estimate the time-varying effect of the treatment in relation to the years before the treatment, a period in which I expect to see no difference in the outcome variable.

Potential criminals can learn about the reduction in white-collar crime investigations through many sources. How soon they react to a perceived decrease in enforcement efforts is likely determined by the speed at which they learn. Since newspaper articles are one source of information from which they can learn, I search through newspaper articles on Factiva using the following keywords: "FBI," "agent," "shift," and "terrorism" and find that there are articles starting at the end of 2001 that discuss the FBI's focus on terrorism.[31]

A *Wall Street Journal* article in 2003 that explicitly discusses the consequences of the FBI's resource diversion towards counter-terrorism and reports that "the bureau's new focus on terrorism is proving to be a burden on local law enforcement [...] inevitably, crimes will go unsolved because of the lack of manpower and less access to the FBI's high-tech forensic labs,"[32] suggesting that other government agencies were indeed burdened by the FBI's reduction in white-collar crime investigations.

If white-collar criminals learn of the FBI's re-allocation of resources from information that become publicly available at around the same time the above articles are published and respond quickly, we can expect to see white-collar crime increase in late 2002 or 2003.[33]

I expect the difference in the increase in white-collar crime across areas overseen by FBI offices with varying levels of treatment to turn upward significantly around 2003. This will be captured by the coefficient on the interaction term between treatment D and the year indicator in the regression model below:

$$\begin{aligned} \textit{White-Collar Crime}_{ijt} = \alpha + \beta_{t+\tau} \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} D_j * Y_{t+\tau} + \gamma_{t+\tau} \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} Y_{t+\tau} \\ + \beta Control_{ijt} + \epsilon_{ijt} \end{aligned} \tag{6}$$

where variables that appeared in the previous regression model are defined as they were above. $\tau = 0$ for

[31] An article published on December 5, 2001 in the *Washington Post* reports: "With thousands of FBI agents concentrating on terrorism, the bureau's field offices across the country have put aside a wide array of other matters...the FBI has been relying on state and local police departments, and other local law enforcement agencies to fill the gaps." The articles do not, however, discuss whether other law enforcement agencies have the ability to absorb all the cases no longer pursued by the FBI. Another article published in the *St. Louis Post-Dispatch* on June 15, 2002 reports that "the FBI is about to pull back from the drug war because it has a much bigger battle to wage against terrorists. Agency Director Robert S. Mueller III says the shift means hundreds of agents will be moved to antiterrorism duties from drug and white-collar crime investigations."

[32] https://www.wsj.com/articles/SB10569207093804000

[33] If white-collar criminals anticipate the FBI's shift in investigative focus shortly after the 9/11 terrorist attacks, the effect can show up after 2001. If they need more time to process the information and assess the changes in the enforcement activities, the effect can show up later than 2003. Depending on the speed of the reactions of potential criminals, then, the increase in white-collar crime could be sharp or gradual. If the increase in crime is slow and gradual, we might only observe a significant coefficient on the after treatment indicator, rather than a significant coefficient on any particular interaction term between the treatment variable and the after treatment indicator.

the year 2002. $Y_{t+\tau}$ are indicator variables that equal one if the year is Υ. And Υ_{min} and Υ_{max} are the earliest and last years of the data sample, which runs from 2000 through 2005.

The ideal dependent variable would be the total number of white-collar crime incidents, caught or not caught. Because I do not observe all white-collar crime incidents, I use the number of reported white-collar crime incidents in the NIBRS as a proxy. I am interested in examining white-collar crime that involves the defrauding of money from consumers or corporations. I focus on wire fraud because it is a federal crime, which is under the jurisdiction of the FBI, not under the jurisdiction of local law enforcement agencies, and is therefore more likely to be affected by the FBI's diversion of resources. The government was also concerned about the potential effect of the FBI's reprioritization regarding wire fraud, and the DOJ's OIG conducted a survey to determine whether the change regarding wire fraud affected other law enforcement agencies.[34]

5.2.2 Changes in insider trading

In addition to changes in wire fraud at the county level, I also examine changes in crimes related to securities law violations. More specifically, I examine changes in illegal insider trading using the following regression model:

$$\begin{aligned} \textit{Opportunistic Insider Trades}_{ijt} = \alpha + \beta_1 D_j * After_{2002} + \beta_2 After_{2002} + \beta_3 D_j \\ + \beta Control_{ijt} + \epsilon_{ijt} \end{aligned} \tag{7}$$

where $\textit{Opportunistic Insider Trades}_{ijt}$ are the number of opportunistic trades at firm i that is located in the jurisdiction of FBI office j in month-year t. D_j is the level of treatment and equals the Muslim population density in the jurisdiction of FBI office j. $\textit{After}_{2002}$ is an indicator variable that equals one for years after 2002 and zero otherwise. $Control_{ijt}$ are firm-level controls and include firm size, firm's natural logarithm of book to market, the previous month's return, and an indicator of whether any firm in the same FBI office's jurisdiction has been investigated for illegal insider trading by the SEC.

I use Cohen, Malloy and Pomorski's (2012) approach to classify insider trades into routine (or normal) trades and opportunistic trades based on inside information. Trades that are made in the same month as those made in the previous three consecutive years are classified as routine trades and trades that are made in other months are classified as opportunistic trades. The authors find that a portfolio strategy that is based on opportunistic insider trades yields value-weighted abnormal returns of 82 basis points per month, whereas returns associated with routine trades in effect equal 0. In a regression framework, the difference

[34]https://oig.justice.gov/reports/FBI/a0537/final.pdf

between the coefficients translates to an increase of 158 basis points per month in the predictive ability of opportunistic trades compared with routine trades (Cohen et al., 2012).

I expect to find no effects on violations of securities laws that the FBI does not cover. Since the FBI did not enforce opportunistic stock options grant date timing until 2006, I check whether there are any differences in changes in opportunistic stock options grant date timing across firms located in the jurisdictions of differentially treated FBI offices around 2002.

I also examine differences in changes in profits from insider trading. I calculate the value of insider transactions for a given firm in each month to obtain the total profits gained and the total losses avoided from the excess returns in the following month. I then perform the following regression analysis:

$$Profit_{ijt+1} = \alpha + \beta_1 D_j * After_{2002} + \beta_2 After_{2002} + \beta_3 D_j + \beta Control_{ijt} + \epsilon_{ijt} \tag{8}$$

where $Profit_{ijt+1}$ is the total profit gained and loss avoided at firm i located in the jurisdiction of FBI office j in month-year t+1. D_j is the treatment variable and equals the Muslim population density in the corresponding FBI field office's jurisdiction. $After_{2002}$ equals one for years after 2002. $Control_{ijt}$ is a vector of control variables for firm i located in the jurisdiction of FBI office j in month-year t.

5.2.3 Changes in fraud reported by financial institutions

I also examine changes in unlawful behavior that financial institutions report via the Suspicious Activity Reports (SARs), one of the main sources of financial institution- reported white-collar crime used by law enforcement agencies. The SARs data are at the state level. I match FBI offices to states through county overlap, and estimate the difference-in-differences in the amount of suspicious activities reported around 2002 across states with varying levels of treatment intensity based on the differences in the Muslim population density at the corresponding FBI field offices' jurisdictions. I find results consistent with the proposition that states exposed to higher levels of treatment experience a greater increase in suspicious activity reports. The regression model for this analysis is as follows:

$$\begin{aligned} All\ SAR\ Cases\ Over\ Pop_{it} = \alpha + \beta_1 D_i * After_{2002} + \beta_2 After_{2002} + \beta_3 D_i \\ + \beta Control_{it} + \epsilon_{it} \end{aligned} \tag{9}$$

where $All\ SAR\ Cases\ Over\ Pop_{it}$ is the total number of suspicious activities reported by financial institutions in state i divided by the total population in state i in year t. D_i is the treatment variable, and is the weighted

Muslim population density in the jurisdictions of FBI offices that cover state i. $After_{2002}$ equals one for years after 2002 and zero otherwise. $Control_{it}$ is a vector of control variables for state i in year t.

6 Analysis of Results

6.1 Changes in white-collar crime investigations after 9/11

Table 1 presents the coefficient estimates for testing whether there is a greater reduction in the number of cases referred for prosecution in districts where the corresponding FBI field offices are exposed to higher levels of treatment, that is, have likely allocated more resources to terrorism investigations based on the Muslim population density in their jurisdictions. As expected, the coefficients on the interaction term *D*After* are all negative and statistically significant, suggesting that districts whose corresponding FBI offices allocated more resources to terrorism investigations exhibit a greater reduction in the number of white-collar criminal cases referred for prosecution. In terms of magnitude, a one-standard-deviation increase in the treatment is associated with an 11.54 percent greater decrease in the number of white-collar criminal cases referred for prosecution. I also consider changes in cases classified as financial institution fraud and securities fraud, two categories under the rubric of white-collar crime and find that a one-standard-deviation increase in the treatment is associated with a 14.28 percent and a 7.82 percent greater decrease in the number of financial institution fraud cases and securities fraud cases, respectively.

In models (2), (4), and (6), I include district fixed effects to control for unobservable cross-sectional variations. Including district fixed effects does not change the significance of the results and produces coefficients with similar economic magnitudes: models (2), (4), and (6) show that a one-standard-deviation increase in the treatment effect is associated with an 11.4 percent, a 12.23 percent, and a 10.18 percent greater decrease in the number of white-collar criminal cases, financial institution fraud and securities fraud cases referred for prosecution, respectively.

Table 2 tests for when the number of cases referred for prosecution in districts overseen by FBI offices that are exposed to varying levels of treatment start to differ. The indicator variable for the year 2000, which corresponds to t-2, is set at 0, so that all coefficients are measured incrementally to that of 2000. Since I do not expect to observe any significant differences across districts in the years prior to 2002 in comparison with 2000, I predict that the coefficients on D*Y will be statistically insignificant for 2001 (t-1) and possibly also for 2002 (t). Table 2 shows that, as expected, the coefficients on the treatment variable, when interacted with year indicators, is negative and statistically significant in year t+1 in model (2), which corresponds to the year

2003 for white-collar crime. For financial institution fraud, the coefficients on the interaction between the treatment variable and the after-treatment indicator are negative and become statistically significant in 2004 in models (3) and (4). For securities fraud, the coefficients on the interaction term between the treatment variable and the year 2003 indicator are negative and greater in magnitude than for the previous years, and are statistically significant with the district fixed effect in model (6). Results shown in table 2 suggest that, compared with the year 2000, in 2001 and 2002 there are no significant differences in the numbers of cases referred for prosecution in districts whose FBI offices are subject to varying levels of treatment. However, after 2002, more than a year after 2001 and after Congress approved the reallocation of FBI agents from criminal investigation to counter-terrorism, districts whose FBI offices are subject to higher treatment levels, that is, districts with higher Muslim population densities, exhibit a statistically significant greater decrease in the number of cases referred for prosecution.

6.2 Changes in white-collar crime activities

In table 3, the coefficient on the interaction term between the treatment variable and the after-treatment indicator is positive and statistically significant, as expected, suggesting that counties in the jurisdictions of FBI offices experiencing higher levels of treatment, that is, those that are more likely to have allocated more resources to terrorism investigations, experience a greater increase in wire fraud rates. A one-standard-deviation increase in the treatment is associated with a 25.19 percent greater increase in the rate of wire fraud.

In Table 4, I split the sample into two groups based on the treatment variable: one group with "high" treatment and the other group with "low" treatment. The high treatment group has an increase in the rate of wire fraud that is 1.72 times that in the low treatment group. The increase in the wire fraud rate after treatment for the high treatment group is 91.5 percent of the mean wire fraud, whereas the increase for the low treatment group is 53.19 percent that of the mean.

In Table 5, I test for when there begin to be significant differences in the rate of wire fraud across counties overseen by FBI offices exposed to varying treatment levels. The indicator variable for the year 2000 (t-2) is set at 0 so that all other coefficients are measured incrementally to it. Since I do not expect to observe any significant differences across counties in the years prior to 2002 in comparison with 2000, I predict that the coefficients on D*Y will be statistically insignificant for 2001 (t-1) and possibly also for 2002 (t), especially if criminals need time to assess changes in government enforcement and confirmation of enforcement changes from the news or public releases by the government.[35] As expected, the coefficient on the interaction term between the treatment variable and the year indicator turns positive and statistically significant in 2003; the coefficient on the interaction term is still large but not significant in 2004 and is again statistically significant in 2005. The results are consistent with there being no significant differences in wire fraud rates across counties located in the jurisdictions of FBI offices exposed to varying levels of treatment before the treatment period in 2001 and 2002 (compared with 2000), and is consistent with counties in the jurisdictions of FBI offices experiencing higher levels of treatment having statistically significant higher wire fraud rates starting in 2003.

In Tables 6 and 7, I examine changes in insider trading activities. As expected, the coefficient on the interaction term between the treatment variable and the after-treatment indicator is positive and statistically significant for opportunistic trades, while it is negative and statistically significant for routine trades, suggesting that firms located in the jurisdictions of FBI offices exposed to higher levels of treatment, that is, those in jurisdictions with higher Muslim population densities, experience a greater *increase* in opportunistic trades and a greater *decrease* in routine trades. Table 6 shows that a one-standard-deviation increase in the treatment, or a 0.009 increase in the Muslim population density, is associated with a 1.3 percent greater increase in the probability that opportunistic trades occur, 4.1 percent more opportunistic trades, a 6.54 percent greater decrease in the probability that routine trades occur, and 3.79 percent fewer routine trades. These results suggest that firms located in the jurisdictions of FBI offices that likely allocated more resources to terrorism investigation seem to experience a shift from routine to opportunistic insider trading. Table 7, which includes FBI office fixed effects to control for unobservable cross-sectional differences across FBI offices, shows very similar results, with a one-standard-deviation increase in the treatment associated with a 1.1 percent greater increase in the likelihood of having an opportunistic trade and a 4.5 percent greater increase in the number of opportunistic trades.

In Table 8, I show the results of testing for when changes in opportunistic trades begin to diverge among firms located in the jurisdictions of FBI offices with varying levels of treatment. The indicator variable for the year 2000 is set at 0 so that all the other coefficients are measured incrementally to that of 2000. I expect the coefficients on the interaction term between the treatment variable and year indicators for opportunistic trade to increase in size for the years after 2002 (after treatment). The coefficients on the interaction terms for 2001 and 2002 are not statistically significant, suggesting that there were no differences across firms in high and low treatment groups in those years. However, the coefficient on the interaction term turns positive in 2003 (t+1) and statistically significant in 2004 (t+2) for model (1), and is positive

[35] Please see section 5 for examples of news articles that discuss the FBI's diversion of resources and investigative focus from criminal investigation to counter-terrorism.

and statistically significant for 2003, 2004, and 2005 for model (3). For routine trades, the coefficients on the interaction terms are negative for 2003, 2004, and 2005. Overall the results are consistent with the proposition that firms located in the jurisdictions of FBI offices with higher levels of treatment experience greater increases in opportunistic trades and greater decreases in routine trades around the beginning of the after-treatment period.

Tables 9 and 10 test for changes in insider trading profits for opportunistic and routine trades, respectively. The profits generated by insider trades in a given firm are the total profits from share purchases and losses avoided by sales, in millions of dollars, calculated as the total value of insider purchases and sales multiplied by excess returns in the following month.

For opportunistic trades, the coefficients on the interaction term between the treatment and the after-treatment indicator are positive and statistically significant for profits from overall opportunistic trades and profits from opportunistic sales, but not statistically significant for opportunistic buys. Table 9 shows that a one-standard-deviation increase in the treatment, which is an increase of 0.009 in the Muslim population density, is associated with a US$261,900 greater increase in profits from opportunistic insider trading based on model (1) or a US$249,300 greater increase in profits based on model (2), and is associated with a US$208,800 greater increase in profits from opportunistic insider sales based on model (3) or a US$235,800 greater increase in sales profits based on model (4). Table 10 suggests that there do not seem to be any significant differences in changes in profits obtained from routine trades.

Table 11 reports the coefficient estimates for changes in suspicious activities reported by financial institutions. In model (1), where the treatment variable is the Muslim population density, a one-standard-deviation increase in the treatment is associated with a 25 percent greater increase in the rate of suspicious activities reported by financial institutions. In model (2), where the treatment variable is the number of Muslims in the relevant area, a one-standard-deviation increase in the treatment is associated with a 64.64 percent greater increase in the rate of suspicious activity reports.

7 Robustness Tests

To lend support to the argument that the results obtained in the analysis of differences in changes in the number of cases referred for prosecution across judicial districts is specific for the treatment years, in table R1 I conduct a placebo test using data from 1995-2000, with 1997 as the pseudo-treatment year, and find that there are no differences in changes in white-collar crime, securities fraud, or financial institution fraud across districts located in the jurisdictions of FBI offices exposed to varying levels of treatment based on the number of Muslims in their jurisdictions in 2000.

In table R2, I present the results of testing for whether there are any differences in changes in local economic conditions that are captured by variables such as the unemployment rate, median household income, the percentage of the population in poverty, bank deposits, and the number of banks and savings institutions' offices across districts whose FBI offices are exposed to varying levels of treatment. The table shows that there are no significant differences across such districts.

Model (1) in table R3 presents the coefficient estimates for a prediction model for the rate of wire fraud in the after-treatment period, 2003-2005, based on covariates and the rate of wire fraud in the pre-treatment period, 2000-2002. The residual between the real and predicted wire fraud rates in the after-treatment period is then regressed on the treatment variable and covariates in models (2) and (3). The coefficient estimates presented in models (2) and (3) suggest that the unexpected portion of wire fraud is greater, and significant, in counties overseen by FBI offices exposed to higher levels of treatment.

In table R4, I split counties into higher and lower treatment groups. The higher treatment group is assigned to the treatment group, whereas the lower treatment group is the control group. The variable *Treat* is an indicator variable that equals one for the treatment group and zero for the control group. I then use propensity score matching to match the two groups by the covariates shown in the regression. The coefficient on the interaction term between the treatment variable and the after-treatment indicator is positive and statistically significant, suggesting that counties in the higher treatment group experience a greater increase in the rate of wire fraud. Counties in the treatment group experience a 43.9 percent greater increase (as a percentage of the mean wire fraud rate) in the rate of wire fraud compared with the control group.

To mitigate concerns that differences in local economic conditions potentially drive differences in changes in a given county's rate of wire fraud, I test whether there are any differences in changes in variables that proxy for local economic and financial conditions such as the unemployment rate, the poverty rate, the median household income, bank and savings deposits, and the number of banks and savings institutions' offices. The coefficient estimates shown in table R5 suggest that there are no significant differences in changes in those variables.

I expect the FBI's reduction in criminal enforcement to have a small or no effect on the types of crime that other law enforcement agencies also have the jurisdiction and ability to enforce, such as credit card fraud, embezzlement, and robbery. I test this by looking at changes in credit card fraud, embezzlement, and robbery. The coefficient estimates in models (1)-(4) of table R6 suggest that there are no differences in the change in credit card fraud or embezzlement across counties overseen by differentially treated FBI offices. Similarly, in models (5) and (6), I find no effects on robberies, which makes sense because robberies are covered by local police and are therefore less likely to be affected by changes in the FBI's enforcement practices. Finding no effects also alleviates concerns about possible variations in economic conditions that might subsequently lead to differences in crime across higher and lower treatment groups.

In Table R7, I show the results of conducting a placebo test for the wire-fraud analysis using data from 1995-2000 and 1997 as the pseudo-treatment year. Coefficient estimates shown in table R7 suggest that there are no differences in changes in wire fraud across counties overseen by FBI offices subject to varying levels of treatment in the pseudo-treatment period.

In Table R8, I show the results of conducting a placebo test for the insider trading analysis using observations from 1995-2000 and 1997 as the pseudo-treatment year. The coefficient estimates shown in table R8 suggest that there are no differences in changes in opportunistic insider trading in the period after the pseudo-treatment year.

In Table R9, I also omit Internet firms from my main insider trading analysis to eliminate concerns about how the Dot-com bubble might have affected Internet firms differentially and how that might explain the differences in changes in opportunistic insider trading across firms that are obtained in the main analysis. Table R9 shows that excluding Internet firms does not change the results of the analysis.

Because the FBI did not begin cracking down on stock options grant date timing until 2006, I do not expect to see any differences in changes in stock options grant date timing after 2002 and, therefore, I use the analysis of changes in the extent of stock options grant date timing as a placebo test. The coefficient estimates shown in table R10 suggest that there are no significant differences in the extent of stock options grant date timing after 2002.

7.1 Relationship between the reduction in agent utilization and changes in wire fraud

Establishing a direct relationship between data on agents diverted from white-collar crime to counter-terrorism investigations and data on increases in white-collar crime helps support the argument that the diversion of agents to counter-terrorism contributed to the increase in white-collar crime, especially if the decision to divert agents from white-collar crime is determined by the expected number of counter-terrorism investigations, and not by the expected incidents of white-collar crime. I was able to obtain data on agent utilization but not on agent allocation related to financial crime investigations for 2000 and 2004 for seven

FBI offices from the DOJ's OIG's report titled "The External Effects of the Federal Bureau of Investigation's Reprioritization Efforts."[36] I link these FBI offices to counties and perform the following regression analysis:

$$\begin{aligned} \textit{Wire Fraud}_{it} = \alpha + \beta_1(\textit{Decrease in Agent})_i * After_{2002} + \beta_2 After_{2002} \\ + \beta_3(\textit{Decrease in Agent})_i + \beta Control_{it} + \epsilon_{it} \end{aligned} \tag{10}$$

where *Wire Fraud*$_{it}$ is the rate of wire fraud in county i year t. *Decrease in Agent* is the percentage reduction in agent utilization associated with the FBI office that covers county i. *After*$_{2002}$ equals one for years after 2002 and zero otherwise. *Control*$_{it}$ is a vector of control variables for county i in year t. The coefficient estimates in table R11 suggest that a one-standard-deviation increase in the treatment (a 14 percent decrease in agent utilization) is associated with a 166 percent greater increase in wire fraud.

8 Additional Analyses

The regression tables and analyses of the results for this section are in the online appendices.

I test whether areas with higher Muslim population densities experience a greater increase in hate crimes related to the religion of Islam. If hate crimes increase more sharply in those areas, then another reason for the FBI's greater reduction in white-collar crime investigation could be their occupation with hate crimes. I don't find any differences in the change in hate crimes targeting Islam across counties overseen by FBI offices that are differentially treated. Finding no differences in the change in hate crimes also alleviates concerns about differences in changes in the attitude or behavior of individuals living in Muslim- populated areas driving the differences in the change in white-collar crime across the differentially treated areas.

To provide additional evidence that criminal prosecution of securities fraud such as insider trading does have a deterrent effect, I examine insider trading activities at firms located near firms that are prosecuted for illegal insider trading. I identify criminal prosecution of insider trading using the following method. First, I find firms that are neighbors of firms previously prosecuted for unlawful insider trading. I hand-collect data on all SEC insider trading releases from 1998 through 2006 from the SEC's annual reports. I then identify people and firms that were involved in each insider trading case by reading the releases and hand-collecting individual and company names. I search for these individuals and firms in all criminal dockets of U.S. federal district courts by name and by restricting the time period of the search to two years before and two years after the SEC releases. I do this by carefully modifying the middle initials and full middle names in the

[36] https://oig.justice.gov/reports/FBI/a0537/final.pdf

search for individuals, since there are cases in which middle names are mentioned in SEC releases, but only middle initials are used in court dockets. To confirm that a given case is the right case, I check the types of charges mentioned in it. I then find the GVKEYs of the firms involved in each insider trading case by hand-matching the names of the firms with company names in Compustat. I was able to identify 530 litigation releases during this period, and have matched 235 of those litigation releases to 347 GVKEY-years. I use companies' addresses as listed in Compustat to identify the longitudes and latitudes of their locations. I then find all "neighboring" firms by calculating the distances between the prosecuted firm and firms from my sample of classified insider trades. Firms that are within 50 km of the prosecuted firms are then identified as the "neighboring" firms. This is the treatment sample. I then find a group of control firms for the treatment firms by identifying firms that are in the same industry, have classified insider trading data, are in the same size and book-to-market quintile, and are not geographically close to any prosecuted firms during the time period of interest. I then compare changes in insider trades at the treated and the control sample around the time of the local firm's prosecution, and find that, for cases that involve a criminal prosecution in addition to the SEC litigation release, there is a greater decrease in the probability of opportunistic trades at treated firms compared with control firms.

I also examine whether punishment and fines for securities fraud violations in areas where FBI offices are exposed to higher levels of treatment increase in severity to a greater degree. This hypothesis can be explained as follows: FBI offices exposed to higher levels of treatment reduce investigation efforts that target small cases; U.S. attorneys' offices located in the jurisdictions of FBI offices subject to higher levels of treatment are more likely to choose only serious securities and corporate fraud cases to prosecute, or are more likely to issue harsher sentences to deter securities and corporate fraud, perhaps in an effort to mitigate potential consequences of the reduction in enforcement efforts. I don't find any differences in the change in fines or sentences across districts overseen by differentially treated FBI offices.

As an additional robustness check, I replace Muslim population density with the number of Muslims as the treatment variable, and repeat the main tests to check whether results differ based on the treatment variable used. The results for these tests are very similar to those obtained in the main tests when the treatment variable used is the Muslim population density.

9 Conclusion

I study changes in investigative priorities and internal resource allocation at the FBI to examine whether plausible variations in the level of criminal enforcement activity can effectively deter white-collar crime and, if so, what the magnitude of the deterrent effect is. These questions are important because they have policy implications and can potentially inform discussions about whether law enforcement agencies should receive and allocate more resources towards fighting white-collar crime.

Whether white-collar crime can be effectively deterred, given plausible variations in enforcement efforts, is a matter of debate among academic researchers and legal scholars. There are two sides to this debate. One side argues that white-collar crime can be easily deterred because white-collar criminals are more rational actors and, hence, are more responsive to the potential cost of committing a crime. The other side of the debate, however, asserts that due to behavioral biases, low psychic costs, and less social stigma, white-collar crime is harder to deter; hence, the relatively low current level of criminal enforcement of relevant laws does not have a significant deterrent effect. I contribute to this debate by examining whether white-collar crime increases following the FBI's diversion of resources from white-collar crime to counter-terrorism after the 9/11 terrorist attacks. I also shed light on the magnitude of the deterrent effect by examining the relationship between a proxy for geographic variations in the diversion of investigative focus away from white-collar crime and variations in the increase in white-collar crime.

I use variations in Muslim population densities across the jurisdictions of FBI offices as variations in "treatment," that is, variations in the extent of the shock to FBI field offices' white-collar crime investigative focus and resources, to examine whether FBI field offices with higher levels of treatment refer fewer white-collar criminal cases for prosecution and whether areas located in the jurisdictions of FBI offices with higher levels of treatment see a greater increase in white-collar crime as a result of the greater reduction in enforcement efforts.

I find that there is a significant decline in the number of white-collar criminal cases referred by the FBI for prosecution after 2002. The decrease in white-collar cases referred by the FBI after 2002 is significantly greater in judicial districts overseen by FBI field offices whose jurisdictions have higher Muslim population densities, even after controlling for relevant variables that capture variations in demographics and economic conditions across judicial districts.

I also study the effects of this reduction in enforcement activity on changes in white-collar crimes such as wire fraud, opportunistic insider trading, and suspicious activity reports filed by financial institutions. My findings suggest that counties located in the jurisdictions of FBI offices that are exposed to higher levels of treatment see a greater increase in the rate of wire fraud. I find that firms located in the jurisdictions of FBI offices that are exposed to higher levels of treatment experience a greater increase in the probability of having an opportunistic trade, a greater increase in the number of opportunistic trades, and a greater increase in profits from opportunistic trades after 2002. I also find that states overseen by FBI offices that are exposed to higher levels of treatment experience a greater increase in the rate of suspicious activity reports about fraud that consists of checking fraud, commercial loan fraud, credit card fraud, debit card fraud, self-dealing, and other crimes filed by financial institutions.

The findings of the paper suggest that the FBI is effective at deterring certain types of white-collar crime, such as wire fraud, illegal insider trading, and fraud within financial institutions. The paper provides insights into the effects of a shock to an enforcement agency's internal resource allocation on the effectiveness of the agency's monitoring role, and the effect on the types of crime that consequently receive less oversight. The paper also adds to the literature on the effectiveness of regulatory agencies and law enforcement agencies' enforcement of laws against white-collar crime by providing a better understanding of the FBI, a major law enforcement agency that has received less attention in the accounting literature.

References

Agarwal, Sumit, and Robert Hauswald, 2010, Distance and Private Information in Lending, *Review of Financial Studies* 23, 2757–2788.

Agnew, Robert, Nicole L Piquero, and Francis Cullen, 2009, *General Strain Theory and White-Collar Crime* (In: The Criminology of White-Collar Crime.: New York, NY).

Amiram, Dan, Zahn Bozanic, James D Cox, Quentin Dupont, Jonathan M Karpoff, and Richard Sloan, 2017, Financial Reporting Fraud and Other Forms of Misconduct: A Multidisciplinary Review of the Literature, *(forthcoming) Review of Accounting Studies*.

Bebchuk, L A, Y Grinstein, and U Peyer, 2010, Lucky CEOs and lucky directors, *The Journal of Finance*.

Becker, Gary S., 1968, Crime and Punishment: An Economic Approach, *Journal of Political Economy* 76, 169–217.

Bhattacharya, Utpal, and Hazem Daouk, 2002, The World Price of Insider Trading, *The Journal of Finance* 57, 75–108.

Blackburne, Terrence, 2014, Regulatory Oversight and Reporting Incentives: Evidence from SEC Budget Allocations, *Working Paper*.

Carroll, John S, 1978, A Psychological Approach to Deterrence: The Evaluation of Crime Opportunities, *Journal of Personality and Social Psychology* 36, 1512–1520.

Choi, Stephen J., and A. C. Pritchard, 2003, Behavioral Economics and the SEC, *Stanford Law Review* 56, 1–73.

Cohen, Lauren, Christopher J. Malloy, and Lukasz Pomorski, 2012, Decoding Inside Information, *The Journal of Finance* 67, 1009–1043.

Cohen, Lawrence E., and Marcus Felson, 1979, Social change and crime rate trends: A routine activity approach, *American Sociological Review* 44, 588–608.

Correia, Maria M, 2014, Political connections and SEC enforcement, *Journal of Accounting and Economics* 57, 241–262.

DeMarzo, Peter M, Michael J Fishman, and Kathleen M Hagerty, 1998, The Optimal Enforcement of Insider Trading Regulations, *Journal of Political Economy* 106, 602–632.

Di Tella, Rafael, and Ernesto Schargrodsky, 2004, Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack, *The American Economic Review* 94, 115–133.

Duro, Miguel, Jonas Heese, and Gaizka Ormazabal, 2017, Does the Public Disclosure of the SEC's Oversight Actions Matter?, *Working Paper* pp. 1–61.

Ehrlich, Isaac, 1973, Participation in Illegitimate Activities: A Theoretical and Empirical Investigation, *Journal of Political Economy* 81, 521–565.

———, 1975, The Deterrent Effect of Capital Punishment: A Question of Life and Death, *The American Economic Review* 65, 397–417.

———, and George D Brower, 1987, On the Issue of Causality in the Economic Model of Crime and Law Enforcement: Some Theoretical Considerations and Experimental Evidence, *The American Economic Review* 77, 99–106.

Ferris, Stephen P, Murali Jagannathan, and A C Pritchard, 2003, Too Busy to Mind the Business? Monitoring by Directors with Multiple Board Appointments, *The Journal of Finance* 58, 1087–1111.

Fich, Eliezer, and Anil Shivdasani, 2006, Are Busy Boards Effective Monitors?, *The Journal of Finance* 61, 689–724.

Fleisher, Belton M, 1970, The Effect of Income on Delinquency: Reply, *The American Economic Review* 60.

Freeman, Richard B, 1996, Why Do So Many Young American Men Commit Crimes and What Might We Do About It?, *The Journal of Economic Perspectives* 10, 25–42.

Garoupa, Nuno, 2003, Behavioral Economic Analysis of Crime: A Critical Review, *European Journal of Law and Economics* 15, 5–15.

Garrett, Brandon, Nan Li, and Shivaram Rajgopal, 2017, Do Heads Roll? An Empirical Analysis of CEO Turnover and Pay When the Corporation is Federally Prosecuted, *Working Paper*.

Henning, Peter J, 2015, Is Deterrence Relevant in Sentencing White-Collar Criminals?, *Working Paper* pp. 1–34.

Hoopes, Jeffrey L, Devan Mescall, and Jeffrey A Pittman, 2012, Do IRS Audits Deter Corporate Tax Avoidance?, *The Accounting Review* 87, 1603–1639.

Jagolinzer, Alan D, David F Larcker, Gaizka Ormazabal, and Daniel J Taylor, 2016, Political Connections and the Informativeness of Insider Trades, *Rock Center for Corporate Governance* Working Paper Series No. 222, 1–56.

Jolls, Christine, Cass R Sunstein, and Richard Thaler, 1998, A behavioral approach to law and economics, *Stanford Law Review* 50, 1471–1550.

Kedia, Simi, and Shiva Rajgopal, 2011, Do the SEC's enforcement preferences affect corporate misconduct?, *Journal of Accounting and Economics* 51, 259–278.

Klick, Jonathan, and Alexander Tabarrok, 2005, Using Terror Alert Levels to Estimate the Effect of Police on Crime, *The Journal of Law and Economics* 48, 267–279.

Levitt, Steven D, 1998, The relationship between crime reporting and police: Implications for the use of Uniform Crime Reports, *Journal of Quantitative Criminology* 14, 61–81.

Ljungqvist, Alexander, and suffix Jr suffix William J Wilhelm, 2003, IPO Pricing in the Dot-Com Bubble, *The Journal of Finance* 58, 723–752.

Lopez, Dennis M, and Gary F Peters, 2011, Auditor Workload Compression and Busy Season Auditor Switching, *Accounting Horizons* 25, 357–380.

McAdams, Richard H, and Thomas S Ulen, 2008, Behavioral Criminal Law and Economics, *University Of Chicago Law School John M. Olin Law & Economics Working Paper* pp. 1–46.

Nguyen, Trung, and Quoc Nguyen, 2017, It is Easy to Be Brave from a Safe Distance: Proximity to the SEC and Insider Trading, *Working Paper*.

Schoepfer, Andrea, Stephanie Carmichael, and Nicole Leeper Piquero, 2007, Do perceptions of punishment vary between white-collar and street crimes?, *Journal of Criminal Justice* 35, 151–163.

Schrand, Catherine M, and Sarah L C Zechman, 2012, Journal of Accounting and Economics, *Journal of Accounting and Economics* 53, 311–329.

Simpson, Sally S, and David Weisburd, 1975, *The Criminology of White-Collar Crime* (Springer).

Sjoquist, David Lawrence, 1973, Property Crime and Economic Behavior: Some Empirical Results, *The American Economic Review* 63, 439–446.

Skaife, H A, D Veenman, and D Wangerin, 2013, Internal control over financial reporting and managerial rent extraction: Evidence from the profitability of insider trading, *Journal of Accounting and Economics* 55, 91 – 110.

Soltes, Eugene, 2016, *Why They Do It: Inside the Mind of the White-Collar Criminal* (PublicAffairs).

Witte, Ann Dryden, 1980, Estimating the Economic Model of Crime with Individual Data, *The Quarterly Journal of Economics* 94, 57–84.

Figure 1: Top Agencies - White-Collar Crime

This table reports the proportion of white-collar criminal cases referred to judicial districts by the top agencies based on the number of cases referred.

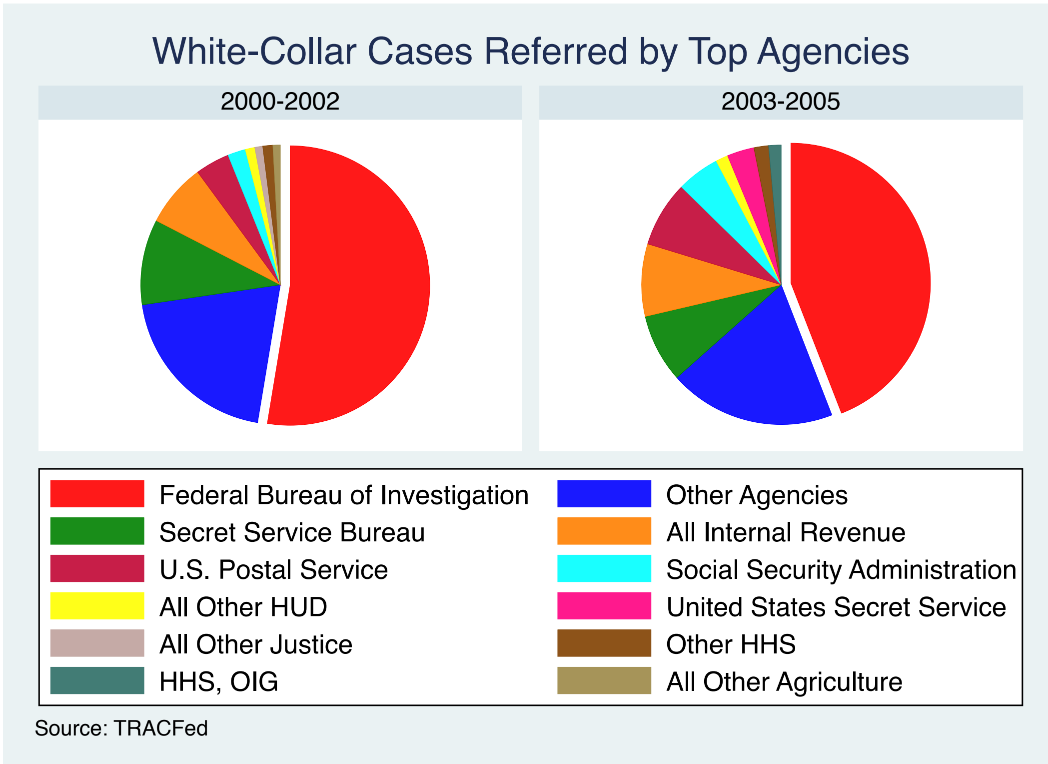

Figure 2: FBI Reorganization Timeline

This figure shows the timeline for the FBI's reorganization after the 9/11 terrorist attacks.

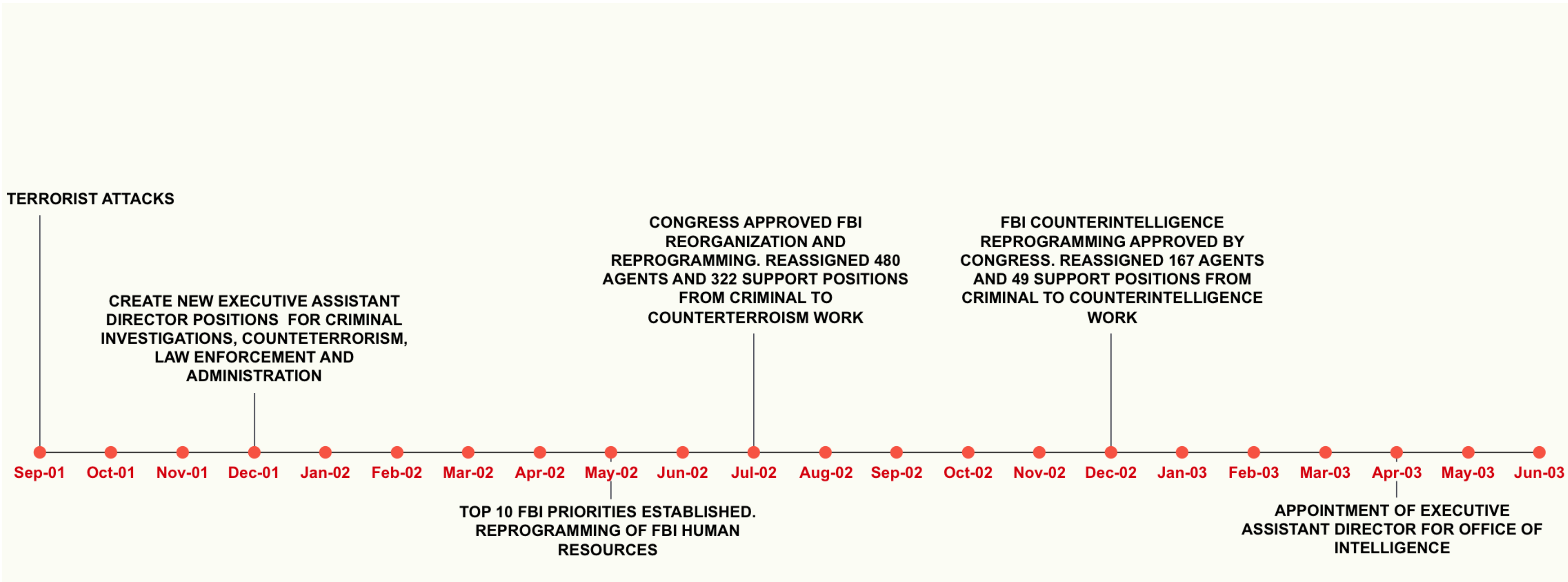

Figure 3: White-collar criminal cases referred by the FBI over the years
This graph shows the number of white-collar criminal cases referred for prosecution by the FBI over the years.

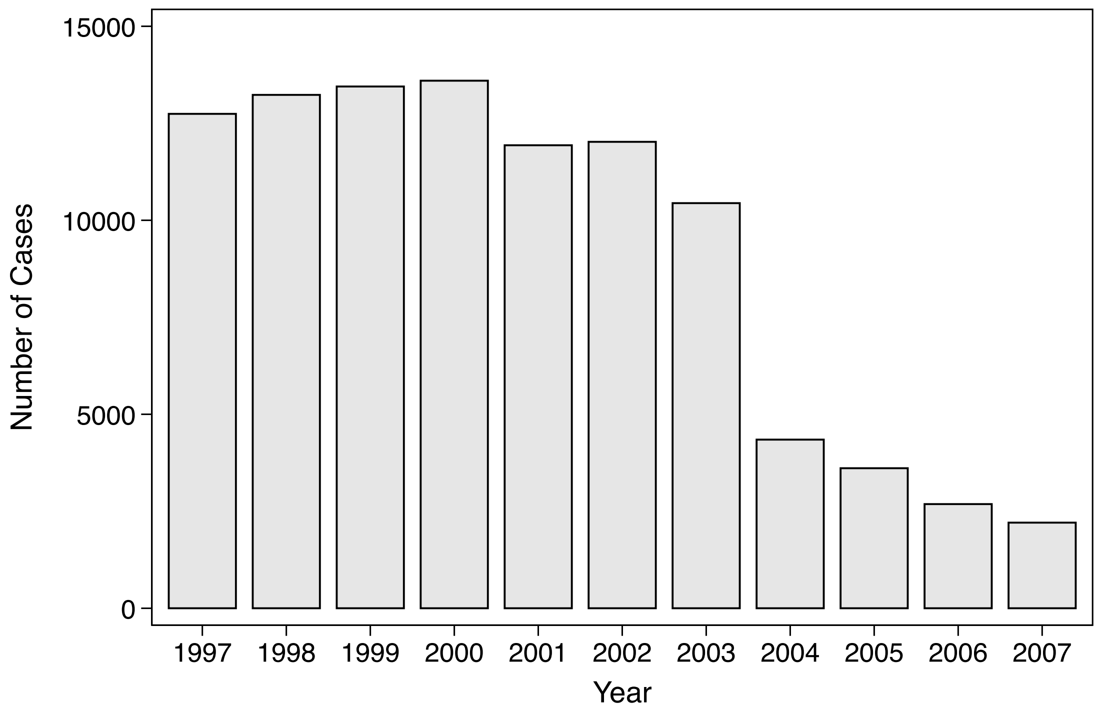

Figure 4: Coefficients on D*Year in the analysis of differences in changes in cases referred for prosecution across districts

This figure presents the coefficients on the interaction of the treatment variable D, the Muslim population density in the jurisdiction of FBI offices corresponding to a given district, and year indicators in the analysis of changes in the number of cases referred for prosecution. The regression model is as follows:

$$Cases\ Referred_{ijt} = \alpha_j + \beta_1 \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} D_j * Y_{t+\tau} + \beta_2 \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} Y_{t+\tau} + \beta Control_{ijt} + \epsilon_{ijt}$$

Bandwidths of standard errors at a 10% significance level are shown.

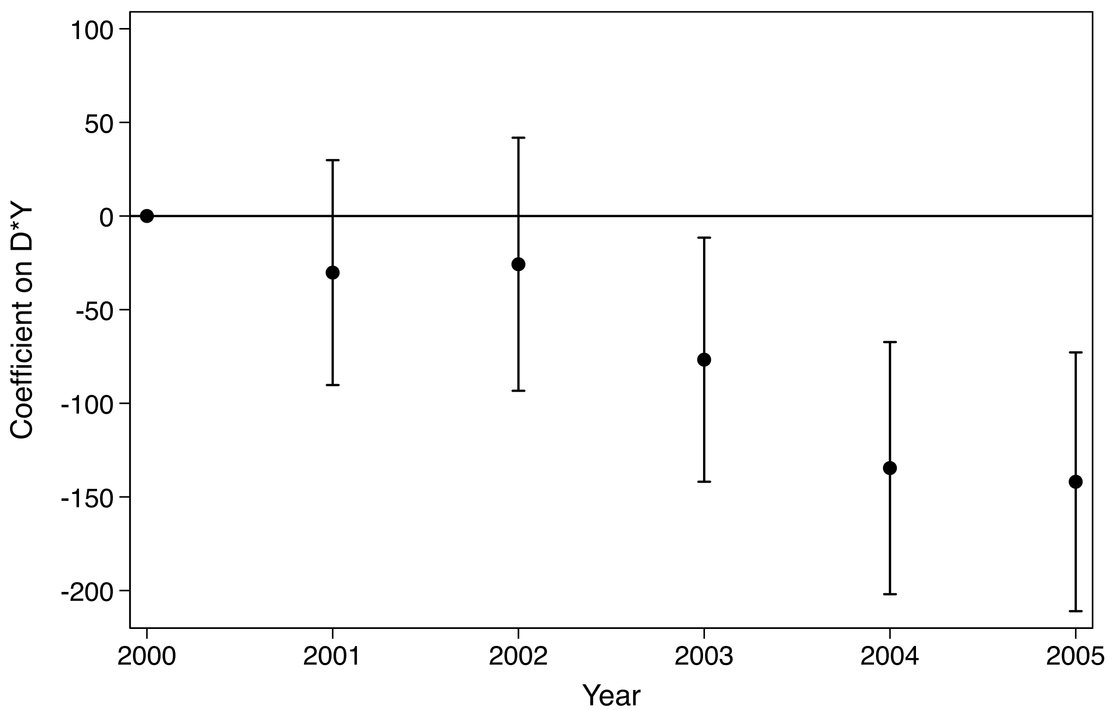

Figure 5: Coefficients on D*Year in the analysis of differences in changes in wire fraud rates across counties

This figure presents the coefficients on the interaction of the treatment variable D, the Muslim population density in the jurisdiction of FBI offices corresponding to a given county, and year indicators in the analysis of changes in the rate of wire fraud. The regression model is as follows:

$$Wire\ Fraud_{ijt} = \alpha_j + \beta_1 \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} D_j * Y_{t+\tau} + \beta_2 \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} Y_{t+\tau} + \beta Control_{ijt} + \epsilon_{ijt}$$

Bandwidths of standard errors at a 10% significance level are shown.

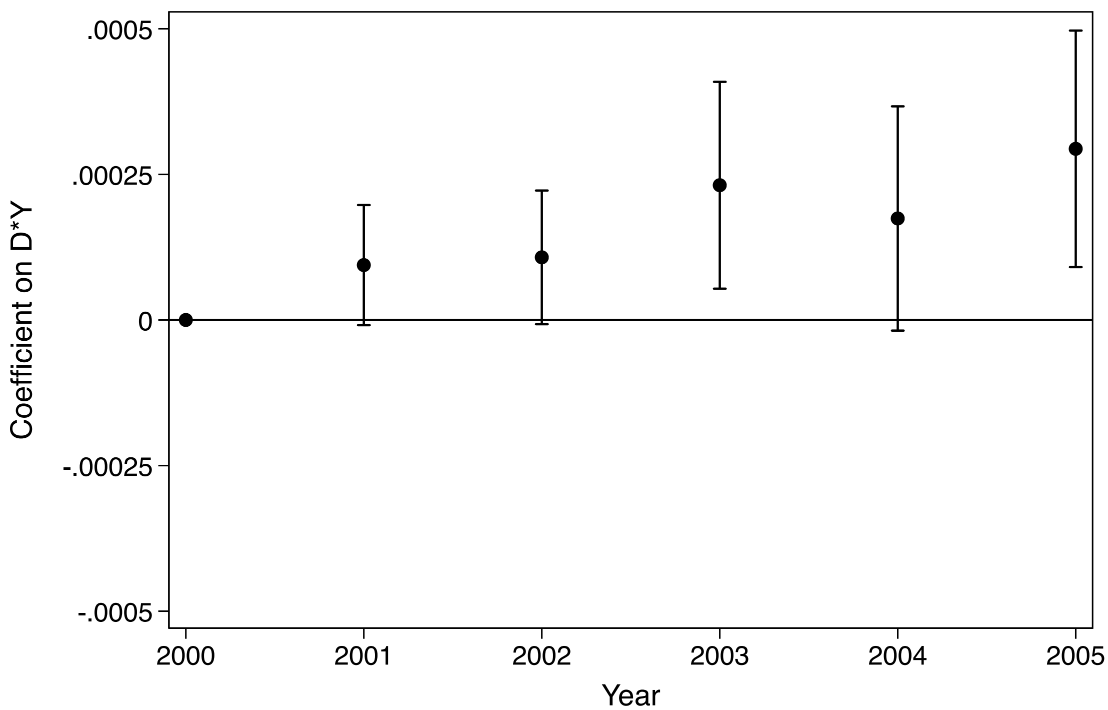

Figure 6: Coefficients on D*Year in the analysis of differences in changes in the number of opportunistic trades

This figure presents the coefficients on the interaction between the treatment variable D and year indicators in the analysis of changes in the natural logarithm of the number of opportunistic trades plus 1 or the number of routine trades plus 1. The regression model is as follows:

$$\mathit{Log(\#\ Opp\ Trades\ +\ 1)}_{ijt} = \alpha_j + \beta_1 \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} D_j * Y_{t+\tau} + \beta_2 \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} Y_{t+\tau} + \beta Control_{ijt} + \epsilon_{ijt}$$

For the analysis of changes in routine trades, the model is similar to the one above, but the dependent variable is the natural logarithm of the number of routine trades plus 1. Bandwidths of standard errors at a 10% significance level are shown.

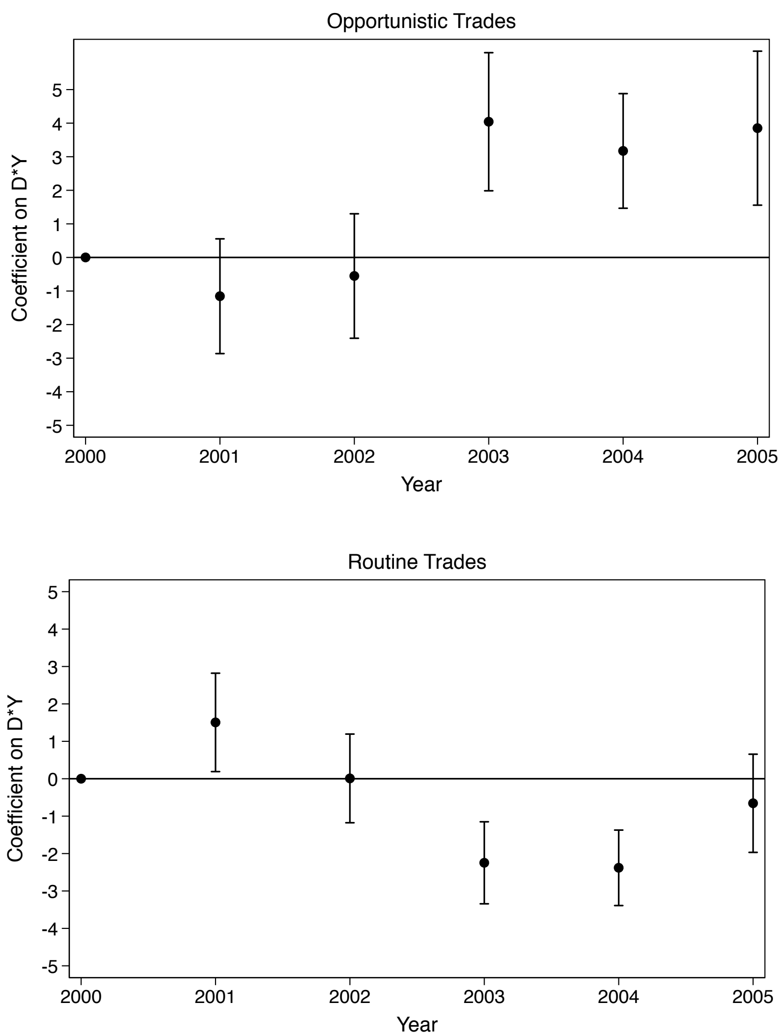

Table D1: Main outcome variables, units of analysis, and treatment variables used for the analyses

Variables	**Unit of Analysis**	**Data Source**	**Analysis of**	**Match FBI office**	**FBI office match**	**Treatment**
Cases referred	Judicial District	TRAC	diff in changes in # cases referred by the FBI	Yes	1 to 1-3 FBI offices	Weighted D of FBI offices
White-collar crime rates	County	NIBRS	diff in changes in white-collar crime rates	Yes	1 to 1	D of FBI office
Opp/Routine trade	Firm	Thomson Reuters Insider Filings	diff in changes in insider trading behavior	Yes	1 to 1	D of FBI office
Fraud-related suspicious activity reports filed by financial institutions	State	FinCEN SAR	diff in changes in state level SARs	Yes	1 to 1-4 offices	Weighted D of FBI offices
Indicator for options grant date timing	Event	Thomson Reuters Insider Filings	diff in changes in options grant date timing	Yes	1 to 1	D of FBI office

Table D2: Summary statistics for the analysis of changes in white-collar criminal cases referred for prosecution at federal judicial districts

This table reports the summary statistics for variables used in the analysis of changes in white-collar criminal cases referred for prosecution. The data apply to 90 judicial districts during the period 2000-2005. *White-Collar* is the number of white-collar criminal cases referred to judicial districts by the FBI. *Financial Inst.* is the number of financial institution fraud cases referred by the FBI to a given judicial district. *Securities* is the number of securities and investment fraud cases referred by the FBI to a given judicial district. The control variables are obtained at the county level from the U.S. Census Bureau and are aggregated at the district level. *High School Edu.* is the rate of high school education. *Divorce Rate* is the rate of divorce. *Pop Density* is the density of the population and is calculated as the total population divided by the total land area in square miles. *Pop in Poverty* is the percentage of the population living in poverty. *Median Income* is the mean of the median household income of all counties in a given judicial district. *Unemp Rate* is the unemployment rate. $D_{Weighted\ Muslim\ Density}$ is the treatment variable, and is the population-weighted average density of the Muslim population of the jurisdictions of FBI offices covering a given judicial district. $D_{Weighted\ Muslim}$ is the weighted number of Muslims in the jurisdictions of FBI offices covering a given judicial district.

	count	min	mean	max	sd
White-Collar	540	4.00	76.72	444.00	66.30
Financial Inst.	540	0.00	29.31	231.00	28.42
Securities	540	1.00	5.04	57.00	7.67
High School Edu.	540	0.12	0.20	0.31	0.04
Divorce Rate	540	0.05	0.08	0.12	0.01
Pop Density	540	1.11	362.67	9479.62	1142.50
Pop in Poverty	540	5.66	12.67	22.16	3.32
Median Income	540	25886.54	38641.34	62696.57	7111.68
Unemp Rate	540	0.02	0.05	0.09	0.01
$D_{Weighted\ Muslim\ Density}$	540	0.00	0.11	0.60	0.11
$D_{Weighted\ Muslim}$	540	609.00	26479.72	204010.98	35492.51

Table D3: Summary statistics for the analysis of changes in white-collar crime rates in U.S. counties

This table reports the summary statistics for variables used in the analysis of changes in the rates for white-collar crimes such as wire fraud, credit card fraud, and embezzlement in U.S. counties. The data are at the county level with all non-missing data for the time period 2000-2005 (3,105 counties for 2000-2004 and 3,098 for 2005). *Wire Fraud*, *Credit Fraud*, and *Embezzle* are, respectively, the total number of wire fraud, card fraud, and embezzlement cases reported in each county in a given year. *Wire Fraud R*, *Card Fraud R*, and *Embezzle R* are, respectively, the rate of wire fraud, card fraud, and embezzlement in each county in a given year and are calculated as the number of fraud incidents divided by the county population. $D_{Muslim\ Density}$ is the treatment variable and equals the Muslim population density in the jurisdiction of the FBI office that oversees a given county. D_{Muslim} equals the number of Muslims in the jurisdiction of the FBI office that covers a given county, and is another way of measuring the intensity of treatment. *Pop Density* is the density of the population. *Pop Poverty* is the percentage of the population living in poverty. *Med. Income* is the median household income. *Divorce* is calculated as the total number of divorced people divided by the total population. *High School* is the proportion of the population with a high school education. *Unemp* is the unemployment rate. *Bank Offices* is the number of banks and savings institutions' offices.

	count	min	mean	max	sd
Wire Fraud	18623	0	0.42	130	3.17
Credit Fraud	18623	0	6.73	1431	42.1
Embezzle	18623	0	4.33	1020	29.2
Wire Fraud R	18623	0	0.0000047	0.00098	0.000024
Card Fraud R	18623	0	0.000057	0.0031	0.00017
Embezzle R	18623	0	0.000042	0.0093	0.00019
$D_{Muslim\ Density}$	18623	0.00057	0.0098	0.042	0.0074
D_{Muslim}	18623	609	21878.0	204011.0	27273.1
Pop Density	18623	0.042	229.1	69959.7	1685.3
Pop Poverty	18623	1.70	13.9	51	5.65
Med. Income	18623	15025	36988.5	98245	9447.5
Divorce	18623	0.016	0.081	0.18	0.019
High School	18623	0.051	0.24	0.87	0.052
Unemp	18623	0.014	0.054	0.21	0.019
Bank Offices	18623	0	27.9	1611	66.0

Table D4: Correlation table of variables used in the analysis of changes in white-collar crime rates in U.S. counties

This table reports the correlations of variables used in the analysis of changes in white-collar crime rates such as wire fraud, credit card fraud, and embezzlement in U.S. counties. The data are for counties with all non-missing data for the time period 2000-2005 (3,105 counties for 2000-2004 and 3,098 for 2005). *Wire*, *Credit* and *Embezzle* are, respectively, the total numbers of wire fraud, card fraud, and embezzlement cases reported in each county in a given year. *Wire R*, *Card R* and *Embezzle R* are, respectively, the rates of wire fraud, card fraud, and embezzlement and are calculated as the total numbers of fraud incidents in each county divided by the total population. $D_{Muslim\ Density}$ is the treatment variable and equals the Muslim population density in the jurisdiction of the FBI office that oversees a given county. D_{Muslim} equals the number of Muslims in the jurisdiction of the FBI office that covers a given county. *Pop Density* is the density of the population. *Poverty* is the percentage of the population living in poverty. *Income* is the median household income. *Divorce* is calculated as the total number of divorced people divided by the total population. *High School* is the proportion of the population with a high school education. *Unemp* is the unemployment rate. *Bank Offices* is the number of banks and savings institutions' offices.

	Wire	Credit	Embezzle	Wire R	Card R	Embezzle R	$D_{Muslim\ Density}$	D_{Muslim}	Pop Density	Poverty	Income	Divorce	High School	Unemp	Bank Offices
Wire	1														
Credit	0.755	1													
Embezzle	0.535	0.731	1												
Wire R	0.441	0.203	0.163	1											
Card R	0.401	0.516	0.372	0.397	1										
Embezzle R	0.190	0.217	0.491	0.204	0.376	1									
$D_{Muslim\ Density}$	0.0375	0.0107	0.0452	0.0683	0.0707	0.0795	1								
D_{Muslim}	0.0781	0.0795	0.108	0.0827	0.0659	0.101	0.282	1							
Pop Density	0.0440	0.0583	0.0439	-0.00265	0.00226	-0.00195	0.0499	0.309	1						
Poverty	-0.0587	-0.0728	-0.0729	-0.0556	-0.0879	-0.0762	-0.0274	-0.147	-0.00115	1					
Income	0.144	0.173	0.146	0.0756	0.144	0.0752	0.106	0.297	0.105	-0.754	1				
Divorce	0.00862	0.0200	0.0200	0.0144	0.0474	0.0245	-0.101	-0.111	-0.0271	0.104	-0.0709	1			
High School	-0.111	-0.148	-0.105	-0.0223	-0.103	0.00193	-0.0775	-0.102	-0.143	-0.0420	-0.277	0.252	1		
Unemp	-0.00412	-0.0153	-0.0194	0.0201	-0.0141	-0.000837	-0.0552	-0.0259	0.00803	0.512	-0.358	0.214	0.0913	1	
Bank Offices	0.176	0.272	0.208	0.00279	0.0532	0.0205	-0.0129	0.315	0.345	-0.148	0.337	-0.00282	-0.286	-0.0515	1

Table D5: Summary statistics for the analysis of changes in insider trading

This table reports summary statistics for the regression analysis of changes in insider trading after 2002. The time period is 2000-2005. There are 2,373 unique firms in the sample. These are the firms for which trades can be classified into routine or opportunistic based on trading data in the previous consecutive three years starting in 1997 and are matched successfully to the jurisdictions of FBI offices. The observations are at the firm-month level. *Opp* is an indicator variable that takes the value of 1 if a firm has an opportunistic trade in a given month. *Routine* is an indicator variable that equals 1 if a firm has a routine trade in a given month. *Log(#Opp + 1)* is the natural logarithm of the number of opportunistic trades plus 1 in a given month. *Log(#Routine + 1)* is the natural logarithm of the number of routine trades plus 1 in a given month. *Size* is the natural logarithm of market equity. *Log(BM)* is the natural logarithm of book to market. *Lag return* is the previous month's returns. *SEC enforcement* is an indicator variable that is 1 if a firm in the same FBI office's jurisdiction receives an SEC enforcement action for illegal insider trading in the previous year. *Profit* is the total profits gained from opportunistic share purchases and losses avoided by opportunistic sales, in million dollars, at a given firm in a given month, calculated as the total value of opportunistic transactions multiplied by the excess returns in the following month. *Sale Profit* is the total losses avoided by all opportunistic insider sales, in million dollars, at a firm in a given month. *Buy Profit* is the total profits gained from all opportunistic insider buys, in million dollars, at a firm in a given month.

	count	min	mean	max	sd
After 2002					
Opp	17904	0.000	0.777	1.000	0.417
Routine	17904	0.000	0.324	1.000	0.468
Log(#Opp + 1)	17904	0.000	1.154	6.756	1.010
Log(#Routine + 1)	17904	0.000	0.412	6.683	0.828
Size	17904	14.814	20.417	26.725	1.991
Log(BM)	17904	-8.116	-0.906	1.619	0.713
Lag return	17904	-0.611	0.027	0.966	0.114
SEC enforcement	17904	0.000	0.163	1.000	0.370
$D_{Muslim\ Density}$	17904	0.001	0.006	0.040	0.009
D_{Muslim}	17904	609.000	43953.874	204010.984	57926.315
Profit	17904	-125.10	-0.05	99.68	2.26
Sale Profit	17904	-125.10	-0.07	41.40	1.76
Buy Profit	17904	-29.54	0.01	99.68	1.44
Before 2002					
Opp	15485	0.000	0.840	1.000	0.366
Routine	15485	0.000	0.234	1.000	0.423
Log(#Opp + 1)	15485	0.000	1.098	7.565	0.825
Log(#Routine + 1)	15485	0.000	0.277	6.201	0.662
Size	15485	13.705	19.936	27.046	2.331
Log(BM)	15485	-7.307	-0.759	3.781	0.952
Lag return	15485	-0.981	0.016	1.000	0.171
SEC enforcement	15485	0.000	0.356	1.000	0.479
$D_{Muslim\ Density}$	15485	0.001	0.007	0.040	0.009
D_{Muslim}	15485	609.000	45148.025	204010.984	58770.537
Profit	15485	-651.50	-0.20	235.79	9.73
Sale Profit	15485	-651.50	-0.23	169.17	9.16
Buy Profit	15485	-32.21	0.03	235.79	3.27
Total					
Opp	33389	0.000	0.806	1.000	0.395
Routine	33389	0.000	0.282	1.000	0.450
Log(#Opp + 1)	33389	0.000	1.128	7.565	0.929
Log(#Routine + 1)	33389	0.000	0.349	6.683	0.758
Size	33389	13.705	20.194	27.046	2.168
Log(BM)	33389	-8.116	-0.838	3.781	0.835
Lag return	33389	-0.981	0.022	1.000	0.143
SEC enforcement	33389	0.000	0.253	1.000	0.435
$D_{Muslim\ Density}$	33389	0.001	0.006	0.040	0.009
D_{Muslim}	33389	609.000	44507.692	204010.984	58321.529
Profit	33389	-651.50	-0.12	235.79	6.83
Sale Profit	33389	-651.50	-0.14	169.17	6.37
Buy Profit	33389	-32.21	0.02	235.79	2.46

Table D6: Summary statistics for the analysis of changes in fraud within financial institutions reported through the Suspicious Activity Reports

This table reports summary statistics for the analysis of changes in the prevalence of financial institution fraud reported by banks and financial institutions through FinCEN's Suspicious Activity Reports in 50 states from 2000 through 2005. *All SAR Cases* is the total number of reported fraud cases. *All SAR Cases Over Pop* is calculated as the total number of reported fraud cases divided by the state population. *High School Edu.* is the rate of high school education. *Divorce Rate* is the rate of divorce. *Pop Density* is the population density. *Pop in Poverty* is the percentage of the population living in poverty. *Median Income* is the median household income. *Unemp. Rate* is the unemployment rate. *Bank Save Offices* are the total number of banks and savings institutions' offices. $D_{Muslim\ Density}$ is the treatment variable and is the population-weighted average Muslim population density in the jurisdictions of the FBI offices that oversee a given state. D_{Muslim} is the population-weighted average number of Muslims in the jurisdictions of the FBI offices that cover a given state.

	count	min	mean	max	sd
All SAR cases	300	65	5954.8	132583	12592.0
All SAR Cases Over Pop	300	0.000065	0.0011	0.024	0.0021
High School Edu.	300	0.12	0.20	0.29	0.029
Divorce Rate	300	0.057	0.084	0.12	0.012
Pop Density	300	1.10	185.6	1164.1	252.0
Pop in Poverty	300	5.60	11.8	21	2.97
Median Income	300	30187	43135.2	61694	6486.8
Unemp. Rate	300	0.023	0.049	0.081	0.011
Bank Save Offices	300	129	1742.3	6620	1480.8
D_{Muslim}	300	609	35119.4	226232.1	50790.4
$D_{Muslim\ Density}$	300	0.00057	0.011	0.072	0.011

Table 1: Changes in cases referred for prosecution at judicial districts after 2002

This table reports the regression coefficient estimates for the analysis of differences in changes in the number of white-collar criminal cases referred by FBI offices to a given judicial district. The number of cases referred by the FBI for prosecution is regressed on the treatment variable D, the density of the Muslim population in the jurisdictions of FBI offices corresponding to a given district, the interaction between D and *After*, which equals 1 for years after 2002 and 0 otherwise, the variable *After*, and control variables. *White-Collar*, *Securities*, and *Financial Inst.* are, respectively, the number of white-collar criminal cases, securities and investment fraud cases, and financial institution fraud cases. The control variables are obtained at the county level from the U.S. Census Bureau and are aggregated at the district level. *High School Edu.* is the proportion of people with a high school education in a given district. *Divorce Rate* is the rate of divorce. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population that is living in poverty. *Median Income* is the mean of the median household income of counties in a given district. *Unemp Rate* is the rate of unemployment. *White-Collar 1999*, *Securities 1999*, and *Financial Inst. 1999* are, respectively, the number of white-collar criminal cases, securities and investment fraud cases, and financial institution fraud cases in 1999. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the district and year levels.

	(1) White-Collar	(2) White-Collar	(3) Securities	(4) Securities	(5) Financial Inst.	(6) Financial Inst.
D*After	-92.44***	-91.34***	-4.03*	-5.25*	-46.04***	-39.39***
	(-3.74)	(-2.79)	(-2.02)	(-1.77)	(-2.91)	(-3.60)
After	-21.62***	-30.57	-3.04***	-3.20**	-14.55***	-19.49***
	(-3.06)	(-1.51)	(-5.29)	(-2.05)	(-5.77)	(-3.17)
D	40.47		-0.76		50.83***	
	(1.14)		(-0.37)		(3.39)	
High School Edu.	-26.42	-82.68	-24.84***	-236.72***	54.10*	274.91
	(-0.33)	(-0.18)	(-4.75)	(-5.01)	(1.69)	(1.27)
Divorce Rate	2.80	2131.23*	63.54*	480.63***	179.84	793.99**
	(0.01)	(1.81)	(2.48)	(3.95)	(1.33)	(2.01)
Pop Density	0.00	-0.11	-0.00	-0.07*	0.00**	0.06
	(1.47)	(-0.50)	(-1.61)	(-1.65)	(1.99)	(0.48)
Pop in Poverty	0.66	-0.74	-0.15	0.06	0.04	-2.26*
	(0.49)	(-0.29)	(-1.86)	(0.29)	(0.10)	(-1.86)
Median Income	-0.00	-0.00*	0.00	-0.00	-0.00	-0.00*
	(-0.00)	(-1.92)	(1.65)	(-0.77)	(-0.65)	(-1.88)
Unemp Rate	-255.49	-209.29	51.93*	26.52	-214.24**	-286.90**
	(-0.86)	(-0.49)	(2.47)	(0.80)	(-2.51)	(-2.32)
White-Collar 1999	0.72***					
	(8.13)					
Securities 1999			0.62***			
			(5.36)			
Financial Inst. 1999					0.48***	
					(11.69)	
District F.E.	No	Yes	No	Yes	No	Yes
Observations	540	540	540	540	540	540
Adjusted R^2	0.696	0.834	0.664	0.765	0.437	0.705

Table 2: Changes in cases referred for prosecution by year

This table reports regression coefficient estimates for the analysis of differences in changes in the number of white-collar criminal cases referred by FBI offices to a given judicial district over the years from 2001 through 2005 compared with the baseline year of 2000 (t-2). The number of cases referred by the FBI for prosecution is regressed on the interaction between the treatment variable D, the density of the Muslim population in the jurisdiction of FBI offices corresponding to a given district, and year indicators. *White-Collar*, *Securities*, and *Financial Inst.* are, respectively, the number of white-collar criminal cases, securities and investment fraud cases, and financial institution fraud cases. The control variables are obtained at the county level from the U.S. Census Bureau and are aggregated at the district level. *High School Edu.* is the proportion of people with a high school education in a given district. *Divorce Rate* is the rate of divorce. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population that is living in poverty. *Median Income* is the mean of the median household income of counties in a given district. *Unemp Rate* is the rate of unemployment. *White-Collar 1999*, *Securities 1999*, and *Financial Inst. 1999* are, respectively, the number of white-collar criminal cases, securities and investment fraud cases, and financial institution fraud cases in 1999. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the district and year levels.

	(1) White-Collar	(2) White-Collar	(3) Financial Inst.	(4) Financial Inst.	(5) Securities	(6) Securities
$D * Y_{t-1}$	-27.86	-30.21	-1.18	-1.06	-7.56	-7.95
	(-0.54)	(-0.83)	(-0.04)	(-0.05)	(-1.22)	(-1.30)
$D * Y_t$	-15.94	-25.74	-17.70	-16.87	-5.40	-6.44
	(-0.30)	(-0.63)	(-0.57)	(-0.70)	(-0.83)	(-0.99)
$D * Y_{t+1}$	-68.47	-76.71*	-37.41	-32.93	-10.21	-12.01*
	(-1.43)	(-1.94)	(-1.38)	(-1.49)	(-1.31)	(-1.71)
$D * Y_{t+2}$	-122.98**	-134.63***	-57.20**	-52.69**	-7.58	-9.64
	(-2.35)	(-3.29)	(-2.10)	(-2.30)	(-1.18)	(-1.46)
$D * Y_{t+3}$	-127.61***	-141.93***	-63.16**	-59.10**	-7.37	-9.60
	(-2.61)	(-3.38)	(-2.45)	(-2.47)	(-1.22)	(-1.60)
D	60.53		59.16**		3.72	
	(1.45)		(2.47)		(0.83)	
Y_{t-1}	-8.23	-12.70**	-5.41	-4.96	-0.11	-0.46
	(-1.40)	(-2.57)	(-1.42)	(-1.54)	(-0.10)	(-0.48)
Y_t	-5.49	-11.36*	-4.29	-3.38	-0.09	-0.32
	(-0.81)	(-1.86)	(-1.07)	(-0.87)	(-0.08)	(-0.31)
Y_{t+1}	-17.78**	-42.63***	-14.59***	-23.87***	-2.40*	-1.18
	(-2.46)	(-3.38)	(-3.61)	(-3.50)	(-1.92)	(-0.66)
Y_{t+2}	-29.89***	-46.03***	-19.73***	-27.90***	-3.50***	-1.54
	(-4.17)	(-3.54)	(-4.67)	(-4.00)	(-3.16)	(-0.77)
Y_{t+3}	-39.21***	-47.12***	-22.56***	-29.32***	-3.73***	-1.08
	(-5.33)	(-3.14)	(-5.58)	(-3.81)	(-3.30)	(-0.46)
High School Edu.	-14.09	-51.15	61.09*	300.77	-24.31***	-74.27**
	(-0.28)	(-0.12)	(1.96)	(1.39)	(-4.06)	(-2.17)
Divorce Rate	36.14	1874.09**	188.20	675.39*	63.19**	61.08
	(0.15)	(2.33)	(1.40)	(1.74)	(2.52)	(0.68)
Pop Density	0.00	-0.06	0.00	0.07	-0.00	-0.05
	(1.14)	(-0.23)	(1.49)	(0.57)	(-1.27)	(-1.42)
Pop in Poverty	2.08**	2.93	0.52	-0.08	-0.10	0.10
	(2.49)	(1.09)	(1.37)	(-0.06)	(-0.77)	(0.27)
Median Income	0.00*	-0.00	0.00	-0.00	0.00*	-0.00
	(1.80)	(-1.24)	(0.56)	(-0.03)	(1.93)	(-1.32)
Unemp Rate	-392.20**	76.47	-221.60**	-203.02	51.53**	59.63
	(-2.12)	(0.28)	(-2.51)	(-1.31)	(2.33)	(1.41)
White-Collar 1999	0.71***					
	(18.06)					
Financial Inst. 1999			0.47***			
			(11.69)			
Securities 1999					0.62***	
					(9.66)	
District F.E.	No	Yes	No	Yes	No	Yes
Observations	540	540	540	540	540	540
Adjusted R^2	0.709	0.839	0.445	0.708	0.663	0.748

Table 3: Changes in county wire fraud rates after 2002

This table reports coefficient estimates for the analysis of changes in wire fraud rates after 2002 across counties located in the jurisdictions of FBI offices that vary in treatment intensity *D*, the Muslim population density. The coefficients on *D*After*, *D*, and *After* have been multiplied by 10^5 for ease of readability. The control variables are obtained at the county level from the U.S. Census Bureau. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population that is living in poverty. *Median Income* is the median household income. *Divorce Rate* is the rate of divorce. *High School Edu.* is the proportion of people with a high school education. *Bank Offices* is the number of banks and savings institutions' offices. *Unemp Rate* is the rate of unemployment in a given county. *Wire Fraud 1999* is the rate of wire fraud in 1999. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the county and year levels.

	(1) Wire Fraud	(2) Wire Fraud
D*After	16.56***	16.27***
	(3.43)	(3.09)
D	4.17	
	(1.04)	
After	0.19*	0.17**
	(1.84)	(2.10)
Pop Density	-0.00	-0.00
	(-0.90)	(-0.039)
Pop in Poverty	-0.00***	0.00
	(-3.09)	(0.51)
Median Income	0.00*	0.00***
	(1.94)	(3.12)
Divorce Rate	0.00	0.00
	(0.064)	(1.03)
High School Edu.	-0.00*	-0.00***
	(-1.88)	(-3.26)
Bank Offices	-0.00**	-0.00*
	(-2.54)	(-1.83)
Unemp Rate	0.00**	0.00
	(2.28)	(1.42)
Wire Fraud 1999	0.49***	
	(6.35)	
FBI Office F.E.	No	Yes
Observations	18623	18623
Adjusted R^2	0.061	0.144

Table 4: Changes in county wire fraud rates after 2002 for low and high treatment

This table reports coefficient estimates for the analysis of differences in changes in wire fraud rates after 2002 across counties located in the jurisdictions of FBI offices associated with low and high levels of treatment D, in models (1) and (2), respectively. The coefficients on *After* have been multiplied by 10^5 for ease of readability. *Wire Fraud* is a county's wire fraud rate. The control variables are obtained at the county level from the U.S. Census Bureau. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population that is living in poverty. *Median Income* is the median household income. *Divorce Rate* is the rate of divorce. *High School Edu.* is the proportion of people with a high school education. *Banks Offices* is the number of banks and savings institutions' offices. *Unemp Rate* is the rate of unemployment. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the county and year levels.

	(1) Low D	(2) High D
	Wire Fraud	Wire Fraud
After	0.25^{***}	0.43^{***}
	(5.11)	(6.69)
Pop Density	-0.00	0.00
	(-0.06)	(1.28)
Pop Poverty	0.00	0.00
	(0.45)	(0.14)
Median Income	0.00^{**}	0.00^{***}
	(2.39)	(4.40)
Divorce Rate	0.00^{*}	0.00
	(1.80)	(0.05)
High School Edu.	-0.00^{***}	-0.00^{***}
	(-3.22)	(-2.61)
Bank Offices	-0.00	-0.00^{***}
	(-0.17)	(-3.39)
Unemp Rate	0.00	0.00^{***}
	(0.96)	(2.96)
FBI Office F.E.	Yes	Yes
Observations	9966	8657
Adjusted R^2	0.077	0.191

Table 5: Changes in wire fraud rates over the years

This table reports coefficient estimates for the analysis of changes in wire fraud rates over the years from 2001 through 2005 compared with the baseline year of 2000 (t-2), which is set at 0. The coefficients on $D * Y$, D, and Y have been multiplied by 10^5 for ease of readability. The control variables are obtained at the county level from the U.S. Census Bureau. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population that is living in poverty. *Median Income* is the median household income. *Divorce Rate* is the rate of divorce. *High School Edu.* is the proportion of people with a high school education. *Bank Offices* is the number of banks and savings institutions' offices. *Unemp Rate* is the rate of unemployment. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the county level.

$$Wire\ Fraud_{ijt} = \alpha_j + \beta_1 \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} D_j * Y_{t+\tau} + \beta_2 \sum_{\tau=\Upsilon_{min}-2002}^{\tau=\Upsilon_{max}-2002} Y_{t+\tau} + \beta Control_{ijt} + \epsilon_{ijt}$$

	(1) Wire Fraud	(2) Wire Fraud	(3) Wire Fraud
$D * Y_{t-1}$	9.73	9.73	9.43
	(1.56)	(1.55)	(1.50)
$D * Y_t$	11.33	11.33	10.75
	(1.61)	(1.61)	(1.54)
$D * Y_{t+1}$	22.99**	22.99**	23.14**
	(2.13)	(2.13)	(2.14)
$D * Y_{t+2}$	17.50	17.50	17.43
	(1.50)	(1.50)	(1.49)
$D * Y_{t+3}$	30.55**	30.52**	29.39**
	(2.48)	(2.48)	(2.38)
D	6.84		
	(1.47)		
Y_{t-1}	-0.01	-0.01	-0.02
	(-0.09)	(-0.09)	(-0.32)
Y_t	-0.00	-0.00	-0.05
	(-0.02)	(-0.02)	(-0.62)
Y_{t+1}	0.02	0.02	-0.04
	(0.20)	(0.20)	(-0.34)
Y_{t+2}	0.26**	0.26**	0.22*
	(2.08)	(2.07)	(1.75)
Y_{t+3}	0.35***	0.35***	0.34***
	(2.84)	(2.83)	(2.74)
Pop Density			-0.00
			(-0.11)
Pop in Poverty			-0.00
			(-1.56)
Median Income			0.00*
			(1.66)
Divorce Rate			0.00
			(1.14)
High School Edu.			-0.00***
			(-3.64)
Bank Offices			-0.00
			(-1.40)
Unemp Rate			0.00***
			(2.71)
FBI Office F.E.	No	Yes	Yes
Observations	18623	18623	18623
Adjusted R^2	0.014	0.141	0.146

Table 6: Changes in insider trading activities

This table reports difference-in-differences coefficient estimates for the analysis of differences in changes in insider trading activities at firms located in the jurisdictions of FBI field offices exposed to varying treatment levels D, the density of the Muslim population. The time period of the sample is 2000-2005. The regression model is as follows:

$$Opportunistic\ Insider\ Trades_{ijt} = \alpha + \beta_1 D_j * After + \beta_2 After + \beta_3 D_j + \beta Control_{ijt} + \epsilon_{ijt}$$

where *Opportunistic Insider Trades*$_{ijt}$ in column (1) is an indicator of whether there is an opportunistic trade at firm i located in the jurisdiction of FBI office j in month-year t. In column (3), the dependent variable is the natural logarithm of the number of opportunistic trades plus 1. *After* is an after-treatment indicator that equals 1 for the years after the treatment. The regression model for routine trades is similar to the model above and is as follows:

$$Routine\ Insider\ Trades_{ijt} = \alpha + \beta_1 D_j * After + \beta_2 After + \beta_3 D_j + \beta Control_{ijt} + \epsilon_{ijt}$$

Opp is an indicator variable that equals 1 if a firm has an opportunistic trade in a given month. *Routine* is an indicator variable that equals 1 if a firm has a routine trade in a given month. *Log(#Opp + 1)* is the natural logarithm of the number of opportunistic trades plus 1. *Log(#Routine + 1)* is the natural logarithm of the number of routine trades plus 1. *Size* is the natural logarithm of market equity. *Log(BM)* is the natural logarithm of book to market. *Lag return* is the previous month's return. *SEC enforcement* is an indicator variable that equals 1 if a firm in the same FBI office's jurisdiction was investigated for illegal insider trading by the SEC in the previous year. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the firm and month levels.

	(1) Opp	(2) Routine	(3) Log(#Opp + 1)	(4) Log(#Routine + 1)
D*After	1.12**	-2.05***	4.46***	-4.13***
	(2.32)	(-3.64)	(3.39)	(-4.98)
After	-0.08***	0.11***	-0.02	0.16***
	(-6.67)	(8.34)	(-0.78)	(8.93)
D	-0.39	1.00***	1.28	1.86***
	(-1.31)	(2.73)	(1.57)	(3.28)
Size	0.01***	-0.00	0.04***	-0.00
	(3.81)	(-0.16)	(6.64)	(-0.06)
Log(BM)	0.01	-0.01**	-0.06***	-0.06***
	(1.38)	(-1.99)	(-4.04)	(-6.24)
Lag return	0.02	-0.02	0.12	-0.03
	(0.69)	(-0.61)	(1.29)	(-0.67)
SEC enforcement	-0.00	-0.01	-0.03	-0.01
	(-0.27)	(-0.75)	(-1.57)	(-0.91)
Observations	33389	33389	33389	33389
Adjusted R^2	0.009	0.011	0.022	0.013

Table 7: Changes in insider trading activities – FBI office fixed effects

This table reports difference-in-differences coefficient estimates for the analysis of differences in changes in insider trading activities at firms located in the jurisdictions of FBI field offices exposed to varying treatment levels D, the density of the Muslim population, with FBI office fixed effects. The time period of the sample is 2000-2005. The regression model is as follows:

$$Opportunistic\ Insider\ Trades_{ijt} = \alpha_j + \beta_1 D_j * After + \beta_2 After + \beta Control_{ijt} + \epsilon_{ijt}$$

where *Opportunistic Insider Trades*$_{ijt}$ in column (1) is an indicator of whether there is an opportunistic trade at firm i located in the jurisdiction of FBI office j in month-year t. In column (3), the dependent variable is the natural logarithm of the number of opportunistic trades plus 1. *After* is an after-treatment indicator that equals 1 for the years after the treatment. α_j are FBI fixed effects. The regression model for routine trades is similar to the model above and is as follows:

$$Routine\ Insider\ Trades_{ijt} = \alpha_j + \beta_1 D_j * After + \beta_2 After + \beta Control_{ijt} + \epsilon_{ijt}$$

Opp is an indicator variable that equals 1 if a firm has an opportunistic trade in a given month. *Routine* is an indicator variable that equals 1 if a firm has a routine trade in a given month. *Log(#Opp + 1)* is the natural logarithm of the number of opportunistic trades plus 1. *Log(#Routine + 1)* is the natural logarithm of the number of routine trades plus 1. *Size* is the natural logarithm of market equity. *Log(BM)* is the natural logarithm of book to market. *Lag return* is the previous month's return. *SEC enforcement* is an indicator variable that equals 1 if a firm in the same FBI office's jurisdiction was investigated for illegal insider trading by the SEC in the previous year. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the firm and month levels.

	(1) Opp	(2) Routine	(3) Log(#Opp + 1)	(4) Log(#Routine + 1)
D*After	0.98***	-1.28***	4.95***	-2.73***
	(2.94)	(-3.56)	(4.98)	(-4.90)
After	-0.09***	0.12***	-0.03	0.17***
	(-8.16)	(10.30)	(-1.20)	(9.76)
Size	0.01***	0.01**	0.03***	0.00
	(3.57)	(2.53)	(6.58)	(1.06)
Log(BM)	-0.00	0.01	-0.06***	-0.03***
	(-0.52)	(1.03)	(-4.06)	(-3.30)
Lag return	0.02	-0.02	0.11	-0.01
	(0.62)	(-0.47)	(1.24)	(-0.30)
SEC enforcement	-0.01	0.00	-0.02	-0.01
	(-1.08)	(0.33)	(-0.76)	(-0.59)
FBI Office F.E.	Yes	Yes	Yes	Yes
Observations	33389	33389	33389	33389
Adjusted R^2	0.057	0.083	0.050	0.059

Table 8: Changes in insider trading activities over the years

This table reports coefficient estimates for the analysis of differences in changes in insider trading activities across firms located in the jurisdictions of differentially treated FBI offices, over the years from 2001 through 2005, compared with the baseline year of 2000 (t-2), which is set at 0. Indicators for opportunistic or routine insider trades or the natural logarithm of the number of opportunistic or routine insider trades plus 1, are regressed on the interaction of the treatment variable and year indicators. *Opp* is an indicator variable that equals 1 if a firm has an opportunistic trade in a given month. *Routine* is an indicator variable that equals 1 if a firm has a routine trade in a given month. *Log(#Opp + 1)* is the natural logarithm of the number of opportunistic trades plus 1 at a given firm in a given month. *Log(#Routine + 1)* is the natural logarithm of the number of routine trades plus 1 at a given firm in a given month. *D* is the treatment variable, and is the Muslim population density in the corresponding FBI field office's jurisdiction. *SEC enforcement* is an indicator variable that equals 1 if a firm in the same FBI office's jurisdiction was investigated for illegal insider trading by the SEC in the previous year. *Size* is the natural logarithm of market equity. *Log(BM)* is the natural logarithm of book to market. *Lag return* is the previous month's return. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the firm and month levels.

	(1) Opp	(2) Routine	(3) Log(#Opp + 1)	(4) Log(#Routine + 1)
$D * Y_{t-1}$	-0.95	1.44	-1.16	1.51
	(-1.07)	(1.50)	(-1.11)	(0.93)
$D * Y_t$	-0.33	-0.02	-0.55	0.01
	(-0.34)	(-0.02)	(-0.49)	(0.01)
$D * Y_{t+1}$	0.91	-1.44	4.04^{***}	-2.25
	(1.15)	(-1.54)	(3.23)	(-1.39)
$D * Y_{t+2}$	0.93^{*}	-1.28^{*}	3.17^{***}	-2.38^{**}
	(1.65)	(-1.95)	(3.06)	(-2.40)
$D * Y_{t+3}$	0.27	-0.05	3.85^{***}	-0.66
	(0.31)	(-0.05)	(2.76)	(-0.32)
Y_{t-1}	0.01	-0.00	-0.03	0.01
	(0.20)	(-0.05)	(-1.00)	(0.25)
Y_t	-0.03	0.04	0.06	0.05
	(-1.11)	(1.26)	(1.44)	(1.11)
Y_{t+1}	-0.10^{***}	0.14^{***}	-0.05	0.18^{***}
	(-3.34)	(3.44)	(-1.30)	(3.24)
Y_{t+2}	-0.11^{***}	0.14^{***}	0.01	0.19^{***}
	(-3.96)	(4.45)	(0.30)	(4.23)
Y_{t+3}	-0.10^{***}	0.12^{***}	-0.00	0.18^{***}
	(-3.59)	(3.87)	(-0.11)	(3.62)
SEC enforcement	-0.01	0.00	-0.01	-0.01
	(-0.49)	(0.05)	(-0.43)	(-0.36)
Size	0.01^{**}	0.01	0.03^{***}	0.00
	(2.02)	(1.44)	(6.60)	(0.54)
Log(BM)	-0.00	0.01	-0.06^{***}	-0.03
	(-0.25)	(0.51)	(-4.09)	(-1.54)
Lag return	0.02	-0.02	0.13	-0.01
	(0.71)	(-0.55)	(1.44)	(-0.31)
FBI Office F.E.	Yes	Yes	Yes	Yes
Observations	33389	33389	33389	33389
Adjusted R^2	0.058	0.084	0.051	0.059

Table 9: Changes in profits from opportunistic insider trading

This table reports coefficient estimates for the analysis of differences in changes in profits from opportunistic insider trades at firms located in the jurisdictions of FBI offices with varying levels of treatment D, the Muslim population density in the corresponding FBI field offices' jurisdictions. The regression model is as follows:

$$Profit_{ijt+1} = \alpha_j + \beta_1 D_j * After + \beta_2 After + \beta Control_{ijt} + \epsilon_{ijt}$$

where $Profit_{ijt+1}$ is the profits gained (for buys) or losses avoided (by sales) at firm i located in the jurisdiction of FBI office j in month-year t+1. D_j is the treatment variable and equals the Muslim population density in the corresponding FBI field office's jurisdiction. a_j are FBI field office fixed effects. $Control_{ijt}$ is a vector of control variables associated with firm i located in the jurisdiction of FBI office j in month-year t.
Profit is the total profits gained from opportunistic share purchases and losses avoided by opportunistic sales, in million dollars, at a given firm in a given month, calculated as the total value of opportunistic transactions multiplied by the excess returns in the following month. *Sale Profit* is the losses avoided by opportunistic insider sales at a firm in a given month and is calculated as the negative value of all opportunistic sale transactions multiplied by the excess returns in the following month. *Buy Profit* is the gains from opportunistic insider stock purchases at a firm in a given month and is calculated as the value of all opportunistic buy transactions multiplied by the excess returns in the following month. *After* equals 1 if the observation's year is after the treatment year and 0 otherwise. *Size* is the natural logarithm of market equity. *Log(BM)* is the natural logarithm of book to market. *Lag return* is the previous month's return. *SEC enforcement* is an indicator variable that equals 1 if a firm in the same FBI office's jurisdiction was investigated for illegal insider trading by the SEC in the previous year. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the firm and month levels.

	(1) Profit	(2) Profit	(3) Sale Profit	(4) Sale Profit	(5) Buy Profit	(6) Buy Profit
D*After	29.08*	27.66*	23.19***	26.21**	5.89	1.46
	(1.66)	(1.92)	(3.08)	(2.06)	(0.49)	(0.20)
After	0.05	0.07	0.12	0.11	-0.08	-0.04
	(0.24)	(0.38)	(0.93)	(0.63)	(-0.68)	(-0.52)
D	-20.80		-11.15		-9.65	
	(-1.20)		(-0.92)		(-0.82)	
Size	-0.04	-0.05	-0.03	-0.03	-0.01	-0.01
	(-0.96)	(-1.07)	(-0.90)	(-0.80)	(-0.91)	(-0.98)
Log(BM)	0.24	0.26	0.32**	0.34*	-0.08	-0.08
	(1.30)	(1.31)	(2.08)	(1.85)	(-1.22)	(-1.20)
SEC Enforcement	0.09	0.13	0.12**	0.17	-0.03	-0.03
	(1.06)	(0.90)	(2.06)	(1.12)	(-1.13)	(-1.32)
Lag return	0.28	0.27	0.73**	0.75*	-0.45	-0.47
	(0.49)	(0.48)	(2.02)	(1.91)	(-1.15)	(-1.17)
FBI Office F.E.	No	Yes	No	Yes	No	Yes
Observations	33389	33389	33389	33389	33389	33389
Adjusted R^2	0.001	0.002	0.003	0.002	0.001	0.011

Table 10: Changes in profits from routine insider trading

This table reports coefficient estimates for the analysis of differences in changes in profits from routine insider trades at firms located in the jurisdictions of FBI offices with varying levels of treatment D, the Muslim population density in the corresponding FBI field offices' jurisdiction. The regression model is as follows:

$$Profit_{ijt+1} = \alpha_j + \beta_1 D_j * After + \beta_2 After + \beta Control_{ijt} + \epsilon_{ijt}$$

where $Profit_{ijt+1}$ is the profits gained (for buys) or losses avoided (by sales) at firm i located in the jurisdiction of FBI office j in month-year t+1. D_j is the treatment variable and equals the Muslim population density in the corresponding FBI field office's jurisdiction. a_j are FBI field office fixed effects. $Control_{ijt}$ is a vector of control variables associated with firm i located in the jurisdiction of FBI office j in month-year t.
Profit is the total profits gained from routine share purchases and losses avoided by routine sales, in million dollars, at a given firm in a given month, calculated as the total value of routine transactions multiplied by the excess returns in the following month. *Sale Profit* is the losses avoided by routine insider sales at a firm in a given month and is calculated as the negative value of all routine sale transactions multiplied by the excess returns in the following month. *Buy Profit* is the gains from routine insider stock purchases at a firm in a given month and is calculated as the value of all routine buy transactions multiplied by the excess returns in the following month. *After* equals 1 if the observation's year is after the treatment year and 0 otherwise. *Size* is the natural logarithm of market equity. *Log(BM)* is the natural logarithm of book to market. *Lag return* is the previous month's return. *SEC enforcement* is an indicator variable that equals 1 if a firm in the same FBI office's jurisdiction is investigated for illegal insider trading by the SEC in the previous year. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the firm and month levels.

	(1) Profit	(2) Profit	(3) Sale Profit	(4) Sale Profit	(5) Buy Profit	(6) Buy Profit
D*After	-0.37	1.36	-3.73	-2.29	3.36	3.65
	(-0.03)	(0.21)	(-0.32)	(-0.38)	(1.27)	(1.40)
After	0.13	0.12	0.14	0.14*	-0.02	-0.02
	(1.39)	(1.54)	(1.58)	(1.87)	(-1.21)	(-0.93)
D	8.87		8.60		0.27	
	(0.75)		(0.72)		(0.58)	
Size	-0.02**	-0.03**	-0.02**	-0.03**	-0.00	-0.00
	(-2.07)	(-2.41)	(-1.98)	(-2.37)	(-0.55)	(-0.32)
Log(BM)	0.11**	0.10**	0.12**	0.11**	-0.01	-0.01
	(2.23)	(2.12)	(2.45)	(2.37)	(-1.18)	(-1.62)
SEC Enforcement	0.02	-0.03	0.02	-0.01	-0.00	-0.03**
	(0.59)	(-0.64)	(0.64)	(-0.14)	(-0.26)	(-2.08)
Lag return	0.25*	0.24	0.26*	0.25*	-0.01	-0.01
	(1.73)	(1.64)	(1.79)	(1.70)	(-0.24)	(-0.25)
FBI Office F.E.	No	Yes	No	Yes	No	Yes
Observations	33389	33389	33389	33389	33389	33389
Adjusted R^2	0.002	0.002	0.003	0.003	0.000	-0.000

Table 11: Financial Institutions Fraud from FinCEN data around 2002

This table reports coefficient estimates for the analysis of differences in changes in the rates of fraud reported by financial institutions in states overseen by differentially treated FBI offices. $D_{Muslim\ Density}$ is the population-weighted average Muslim population density in the FBI field offices whose jurisdictions cover a given state. D_{Muslim} is the population-weighted average number of Muslims in the FBI field offices whose jurisdictions cover a given state. *All SAR Cases Over Pop* is calculated as the total number of suspicious activity cases reported divided by the state population. The control variables are obtained at the county level from the U.S. Census Bureau and are aggregated to the state level. *High School Edu.* is the proportion of the population with a high school education. *Divorce Rate* is calculated as the total number of people divorced in a state divided by the total state population. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population that is living in poverty. *Median Income* is the mean of the median household income of all counties within a given state. *Unemp. Rate* is the unemployment rate in a given state. *Bank Save Offices* is the total number of banks and savings institutions' offices in a given state. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the state and year levels.

	(1) All SAR Cases Over Pop	(2) All SAR Cases Over Pop
$D_{Muslim\ Density}$*After	0.03*	
	(1.77)	
$D_{Muslim\ Density}$	-0.00	
	(-0.03)	
D_{Muslim}*After		0.14*10^{-7**}
		(2.47)
D_{Muslim}		0.14*10^{-7*}
		(1.69)
After	0.00	0.00
	(0.53)	(0.76)
High School Edu.	0.00	-0.00
	(0.54)	(-0.34)
Divorce Rate	-0.01	0.01
	(-0.39)	(0.30)
Pop Density	-0.00	-0.00**
	(-0.99)	(-2.01)
Pop in Poverty	0.00***	0.00*
	(3.01)	(1.91)
Median Income	0.00***	0.00**
	(2.63)	(2.27)
Unemp. Rate	-0.03*	-0.02
	(-1.82)	(-1.40)
Bank Save Offices	-0.00	-0.00
	(-1.07)	(-1.46)
Observations	300	300
Adjusted R^2	0.104	0.295

Table R1: Placebo Test – Changes in cases referred for prosecution 1995-2000

This table reports regression coefficient estimates for the analysis of differences in changes in the number of cases referred for prosecution after the pseudo-treatment year 1997 across judicial districts located in the jurisdictions of FBI offices that vary in treatment, proxied by the population-weighted Muslim population density. The placebo period is from 1995 through 2000. The regression model is as follows:

$$Cases\ Referred_{it} = \alpha + \beta_1 D_i * After_{1997} + \beta_2 D_i + \beta_3 After_{1997} + \beta Control_{it} + \epsilon_{it}$$

where $Cases\ Referred_{it}$ is the number of cases referred for prosecution in district i in year t. D_i is the population-weighted average Muslim density of FBI offices overseeing district i. $After_{1997}$ is an indicator variable that equals 1 for the years after 1997 and 0 otherwise. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the district and year levels.

	(1) White-Collar	(2) Securities	(3) Financial Inst.
D*After$_{1997}$	19.70	1.75	28.31
	(0.28)	(0.25)	(1.06)
After$_{1997}$	-26.08***	-0.94	-16.00***
	(-3.00)	(-1.05)	(-3.66)
D	231.31***	11.83***	84.32***
	(4.36)	(3.07)	(4.13)
High School Edu.	-118.26*	-12.40*	-7.18
	(-1.69)	(-1.66)	(-0.19)
Divorce Rate	786.96***	45.08	473.46***
	(3.38)	(1.37)	(3.90)
Pop Density	-0.01***	-0.00*	-0.00***
	(-3.58)	(-1.81)	(-4.20)
Pop in Poverty	8.66***	1.42***	2.07**
	(5.50)	(4.66)	(2.55)
Median Income	0.01***	0.00***	0.00***
	(9.10)	(5.54)	(5.66)
Unemp Rate	-95.59	-59.82*	8.61
	(-0.35)	(-1.95)	(0.06)
Observations	540	540	540
Adjusted R^2	0.326	0.295	0.150

Table R2: Changes in economic conditions across districts after 2002

This table tests for whether there are significant differences in changes in variables that capture economic conditions such as the unemployment rate, the natural logarithm of the median household income, the percentage of the population that is living in poverty, the natural logarithm of bank deposits, and the natural logarithm of the number of banks and savings institutions' offices. The regression model is as follows:

$$Outcome\ Variable_{it} = \alpha + \beta_1 D_i * After + \beta_2 D_i + \beta_3 After + \beta Control_{it} + \epsilon_{it}$$

where *Outcome Variable*$_{it}$ is the unemployment rate, the natural logarithm of the median household income, the percentage of the population that is living in poverty, the natural logarithm of bank deposits, or the number of banks and savings institutions' offices in district i in year t. D_i is the weighted average Muslim population density of FBI offices overseeing district i. *After* is an indicator variable that equals 1 for the years after 2002 and 0 otherwise. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the district and year levels.

	(1) Unemp Rate	(2) Log Med. House. Income	(3) Pop in Poverty	(4) Log Bank Deposits	(5) Log Bank Office
D*After	0.01	-0.04	1.45	0.05	0.03
	(1.40)	(-0.27)	(0.56)	(0.06)	(0.05)
After	0.01***	0.06***	0.95**	0.20*	0.04
	(3.93)	(2.91)	(2.49)	(1.73)	(0.37)
D	-0.01*	0.20*	-5.88***	3.07***	3.20***
	(-1.79)	(1.89)	(-3.01)	(5.23)	(6.49)
Observations	540	540	540	540	540
Adjusted R^2	0.085	0.033	0.050	0.112	0.182

Table R3: Estimation of expected wire fraud rates after 2002

This table reports coefficient estimates for the analysis of differences in changes in wire fraud rates after 2002 across counties located in the jurisdictions of FBI offices with varying levels of treatment D, the Muslim population density. Column (1) shows the coefficients for the estimation regression, which is a regression of wire fraud rates on the predicting variables for the years from 2000 through 2002. Columns (2) and (3) show the coefficients obtained by regressing differences between the real and predicted wire fraud rates for the years from 2002 through 2005 on the treatment variable D. The regression model for column (1) is as follows:

$$\begin{aligned}\textit{Wire Fraud Rate}_{ijt} &= \alpha_{+}\beta_1 PopDensity_{ijt} + \beta_2 Poverty_{ijt} + \beta_3 MedianIncome_{ijt} \\ &+ \beta_4 DivorceRate_{ijt} + \beta_5 HighSchoolEdu_{ijt} + \beta_6 BankOffices_{ijt} + \beta_7 UnempRate_{ijt} + \epsilon_{ijt}\end{aligned}$$

The regression model for column (3) is as follows:

$$\begin{aligned}\Delta\textit{Wire Fraud Rate}_{ijt} &= \alpha_{+}\beta_0 D + \beta_1 PopDensity_{ijt} + \beta_2 Poverty_{ijt} + \beta_3 MedianIncome_{ijt} \\ &+ \beta_4 DivorceRate_{ijt} + \beta_5 HighSchoolEdu_{ijt} + \beta_6 BankOffices_{ijt} + \beta_7 UnempRate_{ijt} + \epsilon_{ijt}\end{aligned}$$

where $\Delta\textit{Wire Fraud Rate}_{ijt} = \textit{Real Wire Fraud Rate}_{ijt} - E[\textit{Wire Fraud Rate}_{ijt}]$, and $E[\textit{Wire Fraud Rate}_{ijt}]$ is estimated from the coefficients obtained in column (1). The control variables are obtained at the county level from the U.S. Census Bureau. *Pop Density* is the density of the population. *Poverty* is the percentage of the population that is living in poverty. *Median Income* is the median household income. *Divorce Rate* is the rate of divorce. *High School Edu.* is the proportion of people with a high school education in a given county. *Bank Offices* is the number of banks and savings institutions' offices. *Unemp Rate* is the rate of unemployment. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the county and year levels.

	(1) Wire Fraud (WF)	(2) Real-Predicted WF	(3) Real-Predicted WF
D		0.00030***	0.00028***
		(3.21)	(3.14)
Pop Density	-0.00000		-0.00000
	(-0.86)		(-1.12)
Poverty	-0.00000***		-0.00000
	(-4.58)		(-1.10)
Median Income	-0.00000		0.00000*
	(-0.08)		(1.90)
Divorce Rate	0.00001		-0.00001
	(0.76)		(-0.37)
High School Edu.	-0.00002***		-0.00001
	(-3.35)		(-0.68)
Bank Offices	-0.00000***		-0.00000
	(-3.45)		(-0.84)
Unemp Rate	0.00005***		0.00004*
	(3.81)		(1.82)
Observations	9315	9308	9308
Adjusted R^2	0.006	0.006	0.007

Table R4: Changes in wire fraud rates after 2002 – Propensity score matching

This table reports the coefficient estimates for the analysis of differences in changes in wire fraud rates after 2002 between counties located in the jurisdictions of FBI offices in the treatment group, which consists of counties whose Muslim population densities are in the upper 50 percentile, and matched counties located in the jurisdictions of FBI offices in the control group, which consists of counties whose Muslim population densities are in the lower 50 percentile. Treatment counties are matched with control counties based on propensity score matching of the covariates. County-level wire fraud rates are regressed on the interaction of the treatment variable *Treat* and the variable *After*, which is an indicator variable that equals 1 for the years after 2002 and 0 otherwise. The coefficients on *Treat*After*, *Treat*, and *After* have been multiplied by 10^5 for ease of readability. *Wire Fraud* is a county's rate of wire fraud. The regression model for the coefficient estimates are as follows:

$$\textit{Wire Fraud}_{ijt} = \alpha + \beta_1 Treat_i * After + \beta_2 After + \beta_3 Treat_i + \beta Control_{ijt} + \epsilon_{ijt}$$

where *Wire Fraud*$_{ijt}$ is the rate of wire fraud in county i in the jurisdiction of FBI office j in year t. *Treat*$_i$ equals 1 if county i is in the treatment group and 0 otherwise. *After* is an indicator variable that equals 1 for the years after 2002 and 0 otherwise. The control variables are obtained at the county level from the U.S. Census Bureau. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population that is living in poverty. *Median Income* is the median household income. *Divorce Rate* is the rate of divorce. *High School Edu.* is the proportion of people with a high school education. *Bank Offices* is the number of banks and savings institutions' offices. *Unemp Rate* is the rate of unemployment. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the county and year levels.

	(1) Wire Fraud	(2) Wire Fraud
Treat*After	0.19***	0.18**
	(2.65)	(2.53)
Treat	-0.03	-0.02
	(-0.73)	(-0.50)
After	0.25***	0.25***
	(5.34)	(4.39)
Pop Density		0.00
		(0.17)
Pop Poverty		-0.00***
		(-3.40)
Median Income		0.00
		(0.80)
Divorce Rate		0.00
		(0.65)
High School Edu.		-0.00***
		(-3.38)
Bank Offices		-0.00
		(-0.69)
Unemp Rate		0.00***
		(2.90)
Observations	14407	14407
Adjusted R^2	0.007	0.014

Table R5: Placebo Test – Changes in unemployment, income, poverty, bank offices, and bank deposits across counties

This table tests whether there are any differences in changes in variables that capture economic conditions in counties located in the jurisdictions of FBI offices that vary in treatment levels. *Unemp Rate* is the rate of unemployment. *Log Median House Inc.* is the natural logarithm of the median household income. *Pop in Poverty* is the percentage of the population that is living in poverty. *Log Bank Offices* is the natural logarithm of the number of banks and savings institutions' offices. *Log Bank Deposits* is the natural logarithm of total bank deposits. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the county and year levels.

	(1) Unemp Rate	(2) Log Median House Inc.	(3) Pop in Poverty	(4) Log Bank Offices	(5) Log Bank Deposits
D*After	0.06	-0.01	16.51	-0.65	0.45
	(1.46)	(-0.01)	(1.38)	(-0.28)	(0.16)
D	-0.17***	2.63***	-29.35***	3.62**	5.61***
	(-6.09)	(6.22)	(-3.37)	(2.15)	(2.71)
After	0.01***	0.05***	0.38***	0.03	0.11***
	(12.48)	(9.22)	(2.73)	(0.87)	(2.96)
Observations	18623	18623	18623	18474	18474
Adjusted R^2	0.032	0.020	0.003	0.000	0.002

Table R6: Placebo Test – Changes in the rates of statutory crimes over which other local law enforcement agencies have more prominent investigative roles.
This table reports the coefficient estimates for the analysis of changes in credit card fraud, embezzlement, and robbery after 2002 for counties overseen by FBI offices with varying levels of treatment. The coefficients on *D*After*, *D*, and *After* have been multiplied by 10^5 for ease of readability. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population that is living in poverty. *Median Income* is the median household income. *Divorce Rate* is the rate of divorce. *High School Edu.* is the proportion of people with a high school education in a given county. *Banks Offices* is the number of banks and savings institutions' offices. *Unemp Rate* is the rate of unemployment. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the county and year levels.

	(1) Card Fraud	(2) Card Fraud	(3) Embezzle	(4) Embezzle	(5) Robberies	(6) Robberies
D*After	44.23	44.22	49.25	49.62	-71.70	-37.73
	(1.24)	(1.32)	(1.49)	(1.45)	(-1.28)	(-0.30)
D	38.19*		121.02***		4.42	
	(1.77)		(4.20)		(0.11)	
After	2.90***	2.64***	-1.52***	-1.22***	-0.24	-0.95
	(7.34)	(6.77)	(-3.29)	(-2.79)	(-0.40)	(-0.73)
Pop Density	-0.00***	-0.00**	-0.00***	-0.00***	0.00	0.00**
	(-2.76)	(-2.38)	(-3.79)	(-3.13)	(0.90)	(2.25)
Pop in Poverty	-0.00	0.00	-0.00***	-0.00	-0.00**	0.00**
	(-0.09)	(1.29)	(-4.19)	(-0.25)	(-2.38)	(2.07)
Median Income	0.00***	0.00***	0.00***	0.00***	0.00*	-0.00***
	(4.51)	(9.15)	(2.95)	(4.40)	(1.83)	(-5.75)
Divorce Rate	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(3.29)	(7.84)	(4.21)	(4.85)	(3.81)	(18.38)
High School Edu.	-0.00***	-0.00***	0.00	-0.00***	-0.00***	-0.00***
	(-7.95)	(-15.56)	(0.11)	(-5.94)	(-5.41)	(-20.61)
Banks Offices	-0.00	0.00***	0.00	-0.00	0.00***	0.00***
	(-0.26)	(2.68)	(0.78)	(-0.57)	(6.95)	(14.40)
Unemp Rate	0.00	0.00	0.00***	-0.00**	0.00***	0.00***
	(0.57)	(1.03)	(2.78)	(-2.42)	(3.79)	(3.29)
Credit Fraud 1999	1.25***					
	(28.37)					
Embezzle 1999			0.53***			
			(5.02)			
Robberies 1999					0.70***	
					(21.03)	
FBI Office F.E.	No	Yes	No	Yes	No	Yes
Observations	18623	18623	18623	18623	18623	18623
Adjusted R^2	0.315	0.311	0.178	0.171	0.838	0.432

Table R7: Placebo Test – Changes in wire fraud 1995-2000

This table tests whether there are any differences in changes in the rates of wire fraud after the pseudo-treatment year of 1997 across counties located in the jurisdictions of FBI offices that vary in treatment intensity D, the same Muslim population density used for the main analysis. After_{1997} is an indicator variable that equals 1 for the years after 1997 and 0 otherwise. The coefficients on D*After_{1997}, After_{1997}, and D have been multiplied by 10^5 for ease of readability. *Unemp Rate* is the rate of unemployment. *Banks Offices* is the number of banks and savings institutions' offices. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population that is living in poverty. *Med. Income* is the median household income. *Divorce Rate* is the rate of divorce. *High School Edu.* is the proportion of people with a high school education. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1) Wire Fraud	(2) Wire Fraud
D*After_{1997}	8.16	10.35
	(1.25)	(1.36)
D	-1.69	-1.83
	(-0.44)	(-0.44)
After_{1997}	-0.02	-0.03
	(-0.20)	(-0.37)
Unemp Rate		0.00^{**}
		(2.09)
Banks Offices		-0.00^{**}
		(-2.40)
Pop Density		-0.00
		(-1.61)
Pop in Poverty		-0.00^{***}
		(-3.62)
Med. Income		-0.00^{**}
		(-2.37)
Divorce Rate		0.00
		(1.29)
High School Rate		-0.00^{***}
		(-2.90)
Observations	18840	18626
Adjusted R^2	0.002	0.005

Table R8: Placebo test – Changes in insider trading activities 1995-2000

This table tests whether there are any differences in changes in insider trading activities at firms located in the jurisdictions of FBI field offices exposed to varying levels of pseudo-treatment D after the pseudo-treatment year of 1997. The regression model is as follows:

$$\textit{Opportunistic Insider Trades}_{ijt} = \alpha + \beta_1 D_j * After_{1997} + \beta_2 After_{1997} + \beta_3 D_j + \beta Control_{ijt} + \epsilon_{ijt}$$

where *Opportunistic Insider Trades*$_{ijt}$ in column (1) is an indicator of whether there is an opportunistic trade at firm i located in the jurisdiction of FBI office j in month-year t. In column (2), the dependent variable is the natural logarithm of the number of opportunistic trades plus 1. *After* is an indicator variable that equals 1 for the years after 1997 and 0 otherwise. The regression model for routine trades is similar to the model above and is as follows:

$$\textit{Routine Insider Trades}_{ijt} = \alpha + \beta_1 D_j * After_{1997} + \beta_2 After_{1997} + \beta_3 D_j + \beta Control_{ijt} + \epsilon_{ijt}$$

D has the same value as the real treatment for the main analysis. The time period of the sample is from 1995 through 2000, immediately preceding the original analysis' sample period. *Opp* is an indicator variable that equals 1 if a firm has an opportunistic trade in a given month. *Routine* is an indicator variable that equals 1 if a firm has a routine trade in a given month. *Log(#Opp + 1)* is the natural logarithm of the number of opportunistic trades plus 1. *Log(#Routine + 1)* is the natural logarithm of the number of routine trades plus 1. *Size* is the natural logarithm of market equity. *Log(BM)* is the natural logarithm of book to market. *Lag return* is the previous month's return. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the firm and month levels.

	(1)	(2)	(3)	(4)
	Opp	Log(#Opp + 1)	Routine	Log(#Routine + 1)
D*After$_{1997}$	-0.29	1.39	0.37	0.71
	(-0.39)	(1.27)	(0.39)	(0.58)
D	1.19*	-0.36	-1.26	-2.78**
	(1.69)	(-0.39)	(-1.52)	(-2.51)
After$_{1997}$	-0.01	0.01	0.04**	0.05
	(-0.71)	(0.24)	(2.09)	(1.56)
Size	-0.01**	-0.01**	0.03***	0.03***
	(-2.49)	(-2.19)	(5.85)	(3.76)
Log(BM)	-0.01	-0.10***	-0.00	-0.03*
	(-1.20)	(-6.21)	(-0.46)	(-1.92)
Lag return	0.05**	0.16***	-0.05**	-0.10***
	(2.42)	(3.69)	(-2.22)	(-2.89)
Observations	25943	25943	25943	25943
Adjusted R^2	0.003	0.013	0.022	0.016

Table R9: Changes in insider trading – No Internet firms

This table reports coefficient estimates for the analysis of differences in changes in insider trading activities across firms located in the jurisdictions of FBI field offices that vary in treatment levels, excluding Internet firms. Internet firms, as identified in Ljungqvist and Wilhelm (2003), are removed from the sample that was used in the main analysis. Indicators for opportunistic or routine trades, or the natural logarithm of the number of opportunistic or routine insider trades plus 1 are regressed on the interaction of the treatment variable and an indicator for whether a given year is after the treatment year, and other variables. *D* is the density of the Muslim population in the corresponding FBI offices' jurisdictions. *Opp* is an indicator variable that equals 1 if a firm has an opportunistic trade in a given month. *Routine* is an indicator variable that equals 1 if a firm has a routine trade in a given month. *Log(#Opp + 1)* is the natural logarithm of the number of opportunistic trades at a given firm plus 1 in a given month. *Log(#Routine + 1)* is the natural logarithm of the number of routine trades at a given firm plus 1 in a given month. *After* equals 1 if the observation's year is after 2002 and 0 otherwise. *Size* is the natural logarithm of market equity. *Log(BM)* is the natural logarithm of book to market. *Lag return* is the previous month's return. *SEC enforcement* is an indicator variable that equals 1 if a firm in the same FBI office's jurisdiction is investigated for illegal insider trading by the SEC in the previous year. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the firm and month levels.

	(1) Opp	(2) Routine	(3) Log(#Opp + 1)	(4) Log(#Routine + 1)
D*After	1.30***	-2.22***	5.14***	-4.36***
	(2.58)	(-3.96)	(4.24)	(-5.10)
After	-0.08***	0.11***	-0.04	0.18***
	(-6.60)	(8.44)	(-1.43)	(9.36)
D	-0.46	1.02***	1.06	1.94***
	(-1.46)	(2.76)	(1.27)	(3.47)
Size	0.01***	-0.00	0.04***	-0.00
	(3.99)	(-0.60)	(6.17)	(-0.40)
Log(BM)	0.01	-0.02**	-0.06***	-0.06***
	(1.39)	(-2.34)	(-3.52)	(-5.88)
Lag return	0.02	-0.02	0.10	-0.02
	(0.49)	(-0.41)	(0.99)	(-0.42)
SEC enforcement	-0.00	-0.01	-0.03	-0.01
	(-0.06)	(-0.78)	(-1.18)	(-1.02)
Observations	30928	30928	30928	30928
Adjusted R^2	0.010	0.012	0.023	0.014

Table R10: Changes in opportunistic stock options grant date timing around 2002

This table reports coefficient estimates for the analysis of changes in opportunistic stock options grant timing. The sample is from 2000 through 2005. The observation is at the options grant event level. The regression model is as follows:

$$Opportunistic\ Options\ Timing_{ijt} = \alpha + \beta_1 D_j * After + \beta_2 After + \beta_3 D_j + \beta Control_{ijt} + \epsilon_{ijt}$$

where *Opportunistic Optioms Timing*$_{ijt}$ is an indicator variable that equals 1 if the grant date of a given grant event i falls on the day of the lowest stock price of the month for a firm located in the jurisdiction of FBI office j in year t. D_j is the treatment variable and equals the density of the Muslim population in the jurisdiction of FBI office j. *After* is an indicator variable that equals 1 if the year is after 2002 and 0 otherwise. *Opportunistic Options Timing* is 1 if options were given at the lowest price of the month. D is the density of the Muslim population in the corresponding FBI field office. *After* is an indicator variable and equals 1 for the years after 2002 and 0 otherwise. *Size* is the natural logarithm of market equity. *Log(BM)* is the natural logarithm of book to market. *Lag return* is the previous month's return. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the firm and year levels.

	(1) Opportunistic Options Timing	(2) Opportunistic Options Timing
D*After	0.250	0.326
	(0.520)	(0.667)
After	-0.017**	-0.018**
	(-2.016)	(-2.080)
D	-0.128	
	(-0.254)	
Log(BM)	-0.002	-0.002
	(-0.996)	(-0.990)
Size	0.001	0.001
	(0.945)	(0.878)
Lag return	-0.636***	-0.634***
	(-11.535)	(-11.961)
FBI Office F.E.	No	Yes
Observations	57548	57548

Summary Statistics

	count	min	mean	max	sd
Opportunistic Options Timing	57548	0.000	0.060	1.000	0.238
D	57548	0.001	0.006	0.040	0.008
Size	57548	15.842	19.640	24.616	1.925
Log(BM)	57548	-9.403	-0.800	3.557	0.920
Lag return	57548	-0.548	0.000	1.000	0.049

Table R11: Effects of changes in the number of agents utilized for financial crime on wire fraud rates in the jurisdictions of seven FBI field offices

This table reports coefficient estimates for the analysis of differences in changes in wire fraud in areas that were affected differentially by the reduction in agent utilization for financial crime investigations in the jurisdictions of seven FBI field offices. The coefficients on *Decrease in Agent Use*After*, *Decrease in Agent Use* and *After* have been multiplied by 10^5 for ease of readability. *Wire Fraud* is the rate of wire fraud. *Pop Density* is the density of the population. *Pop in Poverty* is the percentage of the population living in poverty. *Median Income* is the median household income. *Divorce Rate* is calculated as the total number of divorced people divided by the total population. *High School Edu.* is the proportion of the population with a high school education. *Bank Offices* is the number of banks and savings institutions' offices. *Unemp Rate* is the rate of unemployment. t-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the FBI office and year levels.

	(1) Wire Fraud
Decrease in Agent Use*After	0.004^{**}
	(2.070)
Decrease in Agent Use	0.000
	(1.530)
After	-0.061^{*}
	(-1.860)
Pop Density	0.000^{**}
	(2.042)
Pop in Poverty	0.000
	(1.228)
Median Income	0.000^{*}
	(1.911)
Divorce Rate	0.000^{*}
	(1.860)
High School Edu.	0.000^{*}
	(1.894)
Banks Offices	-0.000
	(-0.780)
Unemp Rate	-0.000^{***}
	(-3.136)
Observations	839
Adjusted R^2	0.022

Summary Statistics

	count	min	mean	max	sd
Wire Fraud	839	0	0.00000032	0.000078	0.0000040
Decrease in Agent Use	839	-4	23.0	50	14.0
Pop Density	839	3.95	1682.5	69959.7	7305.7
Pop in Poverty	839	3.10	15.8	45.4	6.83
Median Income	839	18931	39927.6	80242	13350.2
Divorce Rate	839	0.042	0.079	0.14	0.017
High School Edu.	839	0.092	0.21	0.32	0.054
Banks Offices	839	2	100.6	1611	204.3
Unemp Rate	839	0.027	0.062	0.17	0.019