Do Financial Misconduct Experiences Spur White-Collar Crime? *

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Abstract:

We use individual police records on criminal activity to investigate whether personal experiences with financial misconduct spur white-collar crime. Experiences with financial misconduct derives from individuals holding accounts at distressed banks where executives are prosecuted for misconduct. We show that individuals with such experiences are two to three times more likely to be convicted of white-collar crime themselves, compared to similar customers of distressed banks where the financial supervisory authority did not press charges. Our results are driven by the extensive margin: the increase in white-collar crime is caused almost exclusively by customers who had no prior history of criminal activity.

JEL Classifications: K42, D03, D14, G11,

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1. **Introduction**

In recent years several major newspapers and news outlets discussed a dramatic increase in white-collar crimes linked to the financial crisis and the subsequent economic recession.[1] The public's interest in white-collar crime is not surprising: financial misconduct is an economically significant source of losses for governments and businesses. Employees in the financial sector have been estimated to have stolen more than ten times the amount stolen by bank robbers (Lipman and McGraw, 1988). Dyck, Morse, and Zingales (2014) estimate the cost of fraud among large financial U.S. companies to be more than $380 billion *per year*, likely an underestimate given that most fraud, as they suggest, goes undetected. At the same time, the years surrounding the financial crisis have been marked by some of the largest and most salient cases of financial misconduct.[2] Therefore, it seems timely to examine whether the recent financial crisis indeed spurred an increase in white-collar crime, and through which mechanisms.

Measuring the prevalence of crime and its correlation with the business cycle can be computed using aggregate data to understand how crime generally moves with economic conditions.[3] However, to understand the underlying causes of white-collar crime and how white-collar crime may disseminate, detailed individual-level data on criminal activity is necessary. While the literature has considered both theoretically and empirically the determinants of general criminal activity, most studies have focused on lower-income households, or previous criminals with data that are self-reported and aggregated at the state or county level. As such, even relatively simple questions about which individual characteristics predict financial crime, and through which mechanisms white-collar crime may spread, remain unanswered.

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[1] In 2009, a headline from The Guardian published "Recession pushes white-collar crime to new highs," in May 2009, the New York Times reported an article titled. "The Recession Made Them Do It," in August 2012, "First Recession, Then Crime and Fear," and in November 2009, National Public Radio asked "Is Recession Causing Rise In Financial Crimes?"

[2] For example the revelation of Worldcom's accounting scandal in 2001, Enron and Arthur Anderson's accounting scandals in 2001-2002, Bernie Maddoff's Ponzi scheme in 2008, arguably the 2015 Volkswagen emissions scandal, were several public incidences of fraud and were surrounded by many less public but equally brazen corporate crimes.

[3] For example Cook and Zarkin, (1985); Mocan and Bali, (2010); Bushway, Phillips, and Cook, (2012).

In this paper we attempt to fill this void. We present a detailed view into the determinants of white-collar crime, and investigate the mechanism for its dissemination following the financial crisis using a novel research design. We use micro-data from the universe of police records in Denmark containing individual-level criminal charges and convictions linked to administrative data on demographic and financial characteristics. We map the Danish criminal codes into United States Federal Bureau of Investigation (FBI) definitions of crime and more specifically, white-collar crimes. We first investigate the determinants of white-collar crime in the aftermath of the global financial crisis. Crime may increase as a result of the financial crisis, indeed Denmark experienced a 40 percent increase in white-collar crime from 2007 to 2012. Economic recessions are likely to have adverse effects on labor market conditions. A rational model of crime would predict that lower wages and higher unemployment increase an individual's economic motive for crime. At the same time, increased policing and punishments can reduce the returns to criminal activity. In addition to these channels, as we test in this paper, significant and formative experiences with financial misconduct may be so powerful, that they potentially change individuals' perceptions about white-collar crime in society.

Considering these plausible mechanisms, we start with a simple econometric model to make an out of sample prediction of the prevalence of white-collar crime in the aftermath of the financial crisis using standard individual characteristics such as job loss, changes in financial well-being, and the rate of policing. The prediction using the differences of these observable characteristics from pre- to post-crisis periods does an inadequate job at explaining the growth in observed financial crime following the crisis. This attempt to capture the rational motives for crime under-predicts the observed rate of white-collar convictions by more than 60 percent. This simple exercise suggests that the increase in financial crime may be driven by other factors, and motivates a more careful analysis of whether individuals' experiences made during the crisis were significant enough to affect their own future criminal activity.

To investigate whether financial misconduct experiences affect how individuals' perceive financial crime, we turn to a unique setting affecting the retail banking sector in Denmark. We hypothesize that financial misconduct amongst retail banking institutions created substantial negative spillovers, and exposure to fraud allegations increased the propensity for directly affected individuals to commit and be convicted of their own white-collar crimes. In our setting, individual experiences derive from investments in retail banks that defaulted in the aftermath of the financial crisis. According to the Danish Financial Supervisory Authority (2009), several institutions which defaulted were found to have violated marketing regulations and their respective senior-executives were charged with market manipulation, financial misconduct, fraud, and of breaching trust with banking customers.

We find strong evidence that first-hand experiences with this negative banking shock had significant implications on the rate of convicted white-collar crimes for those directly affected. Our results suggest that negative experiences with financial misconduct significantly increased the number of white-collar criminal charges and convictions after a bank's default by more than two to three times.[4] These new white-collar crime convictions were primarily driven by individuals without prior criminal histories. Furthermore, these convictions constitute serious economic crime. More than 60% of the convictions identified in our empirical setting result in prison sentencing – a rather rare occurrence in Denmark.

To understand the underlying mechanism of why misconduct spillovers may cause white-collar crime in the general population, we perform a powerful difference-in-differences test. Specifically, we compare the probability of conviction for vested customers of banks which defaulted after the financial crisis and were subsequently charged criminally with financial misconduct, with investors of non-criminally charged banks which also defaulted during the

[4] We remove individuals working in the financial sector to avoid a spurious relationship between the misconduct cases and individuals' own criminal activity.

financial crisis. Our experiment allows us to disentangle between three potential mechanisms. White-collar crime may occur as a result of spillovers because exposed investors are harmed financially, and the pecuniary effect of losing substantial investments increases their propensity to engage in fraud. Additionally there are two *non-pecuniary* factors relevant in our setting - white collar crime may increase as a result of the transmission of *information* content or due to *social utility* - as investigated in transmission of peer effects in financial decision making (Bursztyn, Ederer, Ferman, and Yuchtman, 2014). Exposure to financial misconduct may spread information about penalties and benefits of crime, and about white-collar crime in general. On the other hand, personally experiencing misconduct could change how individuals view what is morally just in a society – a social utility based mechanism. In this scenario, individuals may partake in criminal activity because they view the norms of society differently, or they feel cheated and seek some form of retribution.[5] We argue that our setting allows us to abstract from the first two proposed mechanisms. The wealth effects are held constant across investors experiencing defaults exposed to financial losses, regardless if the bank was charged with misconduct or not, and as the defaults and misconduct cases were significantly large, the informational content about crime was dispersed nationally and absorbed by the time fixed effects in our specifications. Our results therefore suggest that personally experiencing misconduct may loosen a 'moral constraint' individuals hold, which allows them to partake in behavior they may have previously perceived as wrong.

In our setting, changes to the moral utility channel is likely to have been significantly large and salient. Retail banks charged with financial misconduct were given a focal point in national media. Many media organizations in Denmark reported how senior level executives contributed to their bank's demise, costing tax payers and shareholders billions of Danish Kroner, yet were retiring

[5] Both Guiso, Sapienza, and Zingales (2013) and Brown, Schmitz, and Zehnder (2017) investigate the non-pecuniary channels of strategic mortgage default and suggest that changed views about fairness and morality may be an important factor.

with generous pension packages.[6] The saliency of these events are likely to have contributed to a feeling of hypocrisy or unjustness in affected shareholders.

A second strength of our research design is that it allows us to remove a source of potential selection bias. Unobservable characteristics - which may be correlated with both investment in troubled banks prior to the financial crisis and future criminal activity - could bias our naïve estimation. However, whether or not the Danish government decided to formally charge a bank for misconduct after its default should be unrelated to pre-crisis investment (or holding deposits) in a troubled bank. Across specifications and samples we find that investors of criminally-prosecuted intuitions are more than two times as likely to be convicted of a future financial fraud, even when controlling for investment style, demographic characteristics, differences in regional enforcement, and quantitatively similar changes in financial well-being throughout the crisis. As we use the difference between individual investors in prosecuted versus non-prosecuted banks and present the findings in an event-study approach with no statistical differences in pre-trend rates of crime, we can rule out that the increase in observed crime is driven by individual or regional factors. Furthermore, we show that cross-sectional rates of policing and enforcement do not differ between affected and unaffected municipalities.

Our results suggest that first-hand experience with financial misconduct affected primarily the extensive margin, as the effects are almost completely driven by investors who had no prior history of criminal activity. In addition, we find that these experiences have no significant effects on other types of crime such as property theft or violent crime. Individuals exposed to financial misconduct are more likely to engage in fraud-related white-collar crime such as tax, credit card, check, or unemployment related frauds. Some of these economic crimes are particularly severe, and we note that more than 60% of the new convictions resulted in prison sentencing. This

[6] For example, Exstra Bladet "Afdød bankdirektør fik 15 millioner" October 9, 2009; Exstra Bladet "Millioner til Roskilde Bank-direktør" November 17, 2008; Berlingske Business "Roskilde Bank-direktører scorede 55 mio. kr." July 11th, 2008.

supports our hypothesis that exposure to misconduct has a spillover effect, affecting one's perceptions about what is morally 'right' as suggested by our title: 'experience is the best teacher.'

The fact that our findings appear to be driven by a moral channel speaks to the external validity of our results. In the United States for example, there is ample evidence of executives receiving golden parachutes even after sizeable scandals within their firms (Fiss, 2016). Put simply, "what is unique is not the magnitude of fraud [in the financial sector], but the fact that most people committing it seem to have got away with it, leaving shareholders to bear the cost (Zingales, 2015)." As such, we believe our results extrapolate to experiences with misconduct in a general sense. On the other hand, crime in Denmark is significantly lower than in other OECD countries, and therefore, the magnitude of our results likely estimate a lower bound for the effect of spillovers from the financial sector to households.

The existing literature which intersects white-collar crime and the economic choices of households is surprisingly sparse, but growing. Our paper is related to Garmaise and Moskowitz (2006) who find that counties in the United States that experience more bank mergers see an influx of poorer households (due to higher interest rates, reduced construction, and lower property prices) and experience higher property crime in the following years. Other researchers have examined how incidence of fraud may affect trust in financial markets. For example, Giannetti and Wang (2016) show that corporate fraud has negative and lasting spillovers affecting household stock market participation and risk taking. Similarly, Guran, Stoffman, and Yonker (2017) show that individuals living in areas with higher concentration of victims from a large Ponzi scheme withdraw assets from independent financial advisors and increase savings at banks in safe assets. Foley (2011) uses the daily reported rates of financial motivated crimes and welfare payment systems in major cities in the United States to show that financially motivated crimes are increasing in the elapsed time since welfare payment distribution. Our paper is also closely related to Guiso, Sapienza, and Zingales (2013) who investigate households' motives for strategically defaulting on mortgages.

They find that exposure to other people who strategically defaulted increases the propensity to default, and non-pecuniary factors such as ideals about fairness and morality play a strong role in individuals' decisions. Similarly, Brown, Schmitz, and Zehnder (2017) investigate strategic default in the laboratory and find that weak economic conditions soften debtors' moral constraints. Our study adds to this literature by using a unique empirical strategy to separate between informational and moral non-pecuniary channels, and to show more generally, that white-collar crime is partially an artefact of experiences, and these personal experiences - not necessarily economic conditions - are what changes perceptions about morality and criminal behavior.

We also contribute to a growing literature in corporate finance examining the incentives to commit financial misconduct. Bhattacharya and Marshall (2012) investigate the economic rationality of white-collar crime in top management executives indicted for illegal insider trading in publicly traded firms in the United States. The authors hypothesize that lower net worth executives should have a higher economic incentive to commit fraud, however find the opposite to be true in their sample, and therefore rule out the economic motive for white-collar crime. Conversely, in a novel setting, Dimmock, Gerkin, and Alfen (2018) find that financial advisors increase misconduct after experiencing large declines in the value of their personal real estate. Their focus is on if financial pressure can explain increased misconduct in an exhaustive sample of advisors, whereas we focus rather on how spillovers from public misconduct cases affect non-financial employees from the general public. Our paper is also connected to Dimmock, Gerkin, and Graham (2018) who find that for financial advisors, the propensity to engage in fraud is increased when a new coworker has a history of fraud, complementing our analysis on spillovers in financial misconduct.

Prior studies have shown negative career consequences for perpetrators of financial misconduct, including Fich and Shivdasani (2007) for corporate directors, Karpoff, Lee, and Martin (2008) for accounting fraud, and Egan, Matvos and Seru (2017a, 2017b) for financial advisors. Agarwal and Cooper (2015) provide suggestive evidence that some managers trade even during misstated earnings periods to earn higher returns, indicating that insider trading is rather widespread. Wang, Winton and Yu (2010) find that the propensity of corporate fraud increases with investor beliefs about the industry, suggesting that regulators and auditors should be 'especially vigilant for fraud during booms.' Finally, similar to our result, Parsons, Sulaeman, and Titman (2018) provide evidence that regional differences in social norms, rather than enforcement, explain cross-sectional differences in financial misconduct. Our results add to this stream of the literature by showing that financial misconduct can have far-reaching non-pecuniary ramifications, including on individual motives for crime.

Our study proceeds as follows: we first describe in detail the construction and sources of our dataset. In Section 3, we discuss white-collar crime and our approaching to measuring it. In Section 4 we describe the institutional setting in Denmark with respect to banks and criminal activity, and the deceptive statistics of the individual investors in our sample. We then consider the effect of first-hand experiences with financial misconduct on criminal activity. We discuss the interpretation of our findings and provide additional specifications and robustness checks in Sections 6 and 7; we then conclude.

2. Data

We assemble a dataset from the universe of the Danish population - focusing on adults aged between 20 and 60 in 2006.[7] In addition to criminal records, we exploit information on economic, financial, and demographic information about the individuals, as well as their close family members. The dataset is constructed based on several different administrative registers made available from Statistics Denmark.

[7] The age of criminal responsibility is 15 years in Denmark. As we focus on the effect of personal experiences during the financial crisis and its effect on white-collar crime, we restrict the sample to individuals who are aged 20 or above in 2006.

Data on criminal offences is obtained from the Danish Central Crime Register (*Det Centrale Kriminalregister*) at the Danish National Police (*Rigspolitiet*). The data contain records of all criminal offences, legal charges, convictions and fines (if larger than DKK 1,500). All records are registered at the individual by personal identification number *(CPR)* and contain information about the nature of the crime, the police district, and the associated legal outcome.

Within the Danish Crime Registers there are several datasets which we exploit in our analysis: *Kriminalstatistik sigtelser* (criminal charges) gives us all individuals charged with a crime, the date of the crime they are being charged with and a 7 digit code which describes the criminal activity. Each crime register dataset contains a 16 digit journal number imputed at the time of the criminal charge by the police district. This code along with the *CPR* allows us to link between crime datasets, e.g. linking charged crimes to convictions, and between datasets, e.g. between crimes committed and financial and demographic characteristics. *Kriminalstatistik afgørelser* (criminal decisions), informs us of the legal decisions of the criminal activity. We refer to this database as convictions and use it not only to define our main variables of interest, but also for considering both the individual's and their family's past history of criminal offenses. From this database we also exclude individuals whose charges were subsequently dropped, withdrawn, were acquitted, or received a written warning. Finally, we obtain aggregate crime statistics at the municipality level from *Kriminalstatistik*.

Income, wealth, and asset allocations are from the official records at the Danish Tax and Customs Administration (*SKAT*). This dataset contains personal income and wealth information by *CPR* numbers on the Danish population. *SKAT* receives this information directly from the relevant sources; financial institutions supply information to *SKAT* on their customers' deposits and holdings of security investments. Employers similarly supply statements of wages paid to their employees. Through Statistics Denmark, we obtain access to personal income and wealth data from 1990 to 2012. From 2005 to 2012, we additionally have information on individuals' stock and mutual fund holdings by ISIN number at the end of the year. For simplicity, we refer to the joint holdings of stocks and mutual funds as stocks. In addition, we obtain the bank registration number of each individuals' primary bank account. These bank registration numbers come directly from the tax authorities, as they are the account associated with each individuals' tax records.

Data on individual employment and unemployment spells are from a matched employer-employee panel dataset drawn from the Integrated Database for Labor Market Research in Denmark (IDA). Employment and unemployment spells are identified from the statement of wages paid to employees that employers are obliged to submit to the Danish Tax Authorities.

Educational records are from the Danish Ministry of Education. All completed (formal and informal) education levels are registered on a yearly basis and made available through Statistics Denmark. We use these data both to measure an individual's education level and to identify measures of financial literacy.

Finally, demographic and family data originate from the official Danish Civil Registration System. These records include the personal identification number (*CPR*), gender, date of birth, *CPR* numbers of family members (legal parents, children, and thus siblings), and their marital histories (number of marriages, divorces, and widowhoods).

All datasets provides an unique identification across individuals, households, generations, and time – allowing us to identify incidents and history of white-collar crime.[8]

3. Defining white-collar crime

The term 'white-collar crime' was first used in 1939 by Edwin H. Sutherland in his presidential address at the American Sociological Meeting. He described his concerns over the academic community's focus on lower-status offenders and 'street crimes' and their inattention on

[8] We create a final sample dataset from 1995 to 2012. This allows us to be confident that the criminal charges we include in our sample led to completed convictions or dropped cases. Since convictions often take longer times to process, we note a large drop off in reported criminal activity in the years after 2012 due to cases which have not yet been fully processed. As such, ending our sample following the financial crisis therefore provides a more conservative view of the results.

occupational crime committed by people with higher status occupations (Barnett, 2000). The FBI chose to define white-collar crime as "...those illegal acts which are characterized by deceit, concealment, or violation of trust and which are not dependent upon the application or threat of physical force or violence. Individuals and organizations commit these acts to obtain money, property, or services; to avoid the payment or loss of money or services; or to secure personal or business advantage (United States Department of Justice, 1989)."[9] We follow Barnett (2000), and map the Danish criminal codes into definitions of white-collar crime: broad white-collar crime, fraud-specific crime, corporate crime, and legal crimes.[10]

In Figure 1, we show how overall incidence and rates of crime and white-collar crime have been decreasing over time with the trend seemingly reversing around 2009.[11] Overall crime in Denmark is relatively low; the homicide rate is 0.8 per 100.000, lower than the OECD average of 4.1 (OECD, 2015) and survey data reveals that 80% of people feel safe walking alone at night, compared to the OECD average of 69% (OECD, 2015). At a recent low, in 2007 there were 3,409 white-collar criminal convictions, the bulk of which were financial fraud related cases including tax and unemployment fraud, forgery, embezzlement, or corporate crimes. Corporate crimes include different types of violations of business regulations such as hiring and firing practices, environmental or construction violations, as well as marketing and accounting fraud. By 2012, the number of convicted white-collar crimes which resulted in a *conviction* had increased by more than

[9] Following this directive, Barnett (2000) outlines how the FBI can map Uniform Crime Reporting data (UCR) of criminal activity into a definition of white-collar crime. The classification put forth by Barnett (2000) is reproduced in Appendix F for convenience.

[10] In the United States, criminal activities are defined in four broad categories: Crimes against Persons, Crimes against Property, Crimes against Society, and Other. We firstly map the Danish criminal codes into these four broad definitions. A quick scan of the categories and criminal activities reveal that financially motivated crimes could overlap between the broad categories. For example Tax Fraud and Perjury related offences are characterized as 'Other Crimes' while Check Fraud and Embezzlement are considered 'Crimes against Property,' therefore it is necessary to further classify the crimes which we denote as white-collar crimes. In Appendix G we define all white-collar criminal definitions, codes, descriptions and their translations, and the number of respective convictions in our sample.

[11] In Appendix A we provide an exact tabulation of the number of individuals charged, and convicted by type of criminal activity in Denmark during the period 2003-2012, the period covering shortly before, during, and after the financial crisis.

40% to 4,825, setting the level of white-collar crime back to the level of the 1990's. As tabulated in Appendix A, the majority of this increase came directly from fraud related white-collar crimes. These crimes increased by 55% over the same time period and were particularly driven by an increase in general fraud crimes (credit card fraud and employment fraud) as well as tax related frauds.

As in other European countries, the global financial crisis had significant effects on the socioeconomic situation of many households in Denmark. The unemployment rate increased from 2.5% in 2008, to over 6% in 2010. Individuals lost significant financial wealth via their personal investments and pension holdings, and the average households' expectations about macroeconomic growth deteriorated.[12] In the following section we investigate how these mechanisms are linked to the increase in white-collar crime. Our findings suggest that economic conditions were not necessarily a sole driver of the increase, and therefore we hypothesize that the incidents were in part, driven by experiences made with fraud.

4. Determinants of white-collar crime

The starting point of the analysis is to characterize the individuals in our sample. Table 1 reveals that individuals with any type of contemporaneous criminal conviction compared to non-criminals are significantly younger, more likely to be male, and are less likely to be married.[13] Criminals are also more likely to be immigrants, hold less years of formal education, and less likely to be employed in the financial sector. Criminals also have lower net wealth, lower income, and are less likely to own property. In Columns 3 and 4 we contrast between white-collar criminals and criminals of other types of crime. Interestingly, white-collar criminals are significantly more wealthy,

[12] Wealth loses are documented in Andersen, Hanspal and Nielsen (2018), while unemployment and expectation data is from "Statistikbanken" at Statistics Denmark.

[13] We disregard a number of minor crimes from our analysis: violations of dog 'leash-laws,' failure to pay the state television tax, various traffic violations, and for failing vehicle inspections. We do however include more serious traffic related convictions such as driving under the influence of alcohol or drugs.

educated, more likely to work in the financial sector and to hold stock market investments compared to other types of criminals.

While these characteristics of white-collar criminals contrasted to 'street' criminals may match the descriptions portrayed in the popular press and media, there is limited empirical research at the individual-level which we can compare our results to. For example, we note that only about 1.7% of the white-collar criminals in our sample are employed in the financial sector compared to about 1.1% of all other types of criminals, an economically insignificant difference however often portrayed differently. Interestingly, almost 9% of white-collar criminals in 2005 were self-employed business owners, a substantial difference from other types of criminals. This is partially due to the nature of white-collar offenses: almost half of the convictions for business owners were for various employer related offenses i.e., violations of regulations in regards to proper insurance, working hours, and wages paid to employees. The remaining crimes are distributed across white-collar offenses such as forgery, fraud, and breaking tax laws, suggesting potentially that the selection into entrepreneurship is correlated with some level of illicit behavior as noted by Levine and Rubinstein (2017).

Panel B of Table 1 reveals that in the cross-section, criminal activity seems to be a family affair: at the mean, 73% of criminals have a parent with a prior criminal history. Interestingly, 25% of white-collar criminals have a parent who was also convicted of a white-collar crime.

In Table 2 we characterize individuals in our sample by the odds ratios for their propensity to commit (to be charged with and convicted of) a crime *prior* to the financial crisis in 2005 using a simple logistic regression. The crime incidence probability of individual i at time t can be written as:

$$Pr(y_{it} = 1 \mid \boldsymbol{x}) = \Lambda(\alpha_0 + \boldsymbol{x_i}\beta) \tag{1}$$

where the dependent variable, y_{it}, consists of a an indicator taking the value of one if an individual was convicted of a crime committed in year 2005, and x_i is the individual characteristics in 2005 and Λ is the logistic link function. Column 1 focuses on all white-collar crimes while Columns 2-4 analyze the determinants of the specific types of white-collar crime with indicator variables for fraud, corporate, or legal crimes. Fraud related crimes consist of offenses such as embezzlement, credit card or check fraud, tax, unemployment or public benefits fraud, counterfeiting or money laundering, usury and extortion, etc. Legal based white-collar crimes are offenses related to perjury and breaching confidentiality regulations. Corporate white-collar crimes are business related offenses in marketing or accounting practices, and also employer violations of employee benefits, wages, or labor laws. The specific offenses by type of crime are detailed further in Appendix H. Across columns corresponding to the different types of white-collar crimes we note important differences particularly in gender and small business ownership. Finally, perhaps unsurprisingly, the role of previous convictions seems to be an important characteristic of all contemporaneous crimes.[14]

A rational model of crime would suggest that an individual "commits an offense if the expected utility to him exceeds the utility he could get by using his time and other resources at other activities (Becker, 1968, p. 176)." In this framework, the link between observed criminal behavior would largely be driven by predictors of crime such as socioeconomic status, history of criminal behavior (both individually and within an individual's network) or by changes in returns to crime, namely if: *i*) returns from legal employment changes; *ii*) returns from illicit activity changes; *iii*) costs of penalty changes; or *iv*) probability of being detected changes.

We proxy for these *cost* and *return* measures in order to understand their relative importance in explaining the observed increase in white-collar criminal activity.[15] We test how well changes in

[14] Until recently, the literature has been undecided on the effects of penalty such as incarceration on criminal recidivism. Nagin et al., (2009) state that "remarkably little is known about the effects of imprisonment on reoffending." Schnepel (2018) finds that increases in labor market opportunities at the time of release are associated with significant reductions in recidivism, and in a unique setting, Bhuller et al., (2016) use random assignment of judges to show that time spent in prison with a focus on rehabilitation have preventive effects on future crime.

[15] Existing research on the economics of crime has indeed focused on integrating measures of these *costs* and *returns* to criminal activity into empirical analyses, which we follow. For example see Witte (1980); Myers (1983) Cornwall and Trumball (1994); Machin and Meghir (2004) among others.

individual and community characteristics explain the rise in white-collar crime in Table 3. The first column (Column 1) provides pre-crisis descriptive statistics of the sample in 2005. In Column 2, we examine the predictive power of the characteristics in Column 1 on the probability of white-collar crime conviction.[16] We estimate a pre-crisis model on panel data from year 1995 through to 2007 with the following estimation equation:

$$Pr(y_{it} = 1 \mid \boldsymbol{x}) = \Lambda(\boldsymbol{x}\beta + \boldsymbol{z}\eta) \tag{2}$$

where y_{it} is conviction of a white-collar crime, $\boldsymbol{x}_i$ are the individual and community characteristics stated in Column 1 for each year, and Λ is the logistic link function. In this estimation, we also include municipality fixed effects and ten industry dummies in matrix $\boldsymbol{z}$ to control for differences in crime and enforcement across communities, and industry specific employment trends. We omit year-fixed effects or time related trends to see how well the predicted crime level fits the observed level in each year. Using the fitted values from this model in the years prior to the crisis, we plot the dashed line relative to observed white-collar crimes (solid line) in Figure 2. The fitted values provide a close mapping to the overall downward trend of white-collar crime using standard demographic characteristics as well as measures attempting to proxy for the associated *costs* and *returns* associated with the rationale to commit crime. Following the literature, we include such 'cost' variables as the changes in household status in terms of having children, purchasing a home, and becoming married/divorced, as well as the local policing rate. Increases in these variables across the sample, are expected to decrease overall financial crime. Similarly, we include changes in local wages, unemployment rates and changes in individual wealth and employment status to capture economic 'returns' to committing a financial crime. We would expect that increases in the sample of these characteristics, would yield an increase in overall crime.

Column 3 therefore states the post-crisis (2012) mean values of our observable individual and local characteristics across our sample. Column 4 states a *t*-test of the differences. We note

[16] The model coefficents from Column 2 are scaled as values per 1,000 individuals for legibility.

that, as expected, in the post-crisis period we observe decreases in income, wealth, local average wages, and increases in unemployment, i.e., the rational model's *returns* to criminal activity. We would expect to see this contribute to the overall increase in white-collar crime. On the other hand, we also observe increases in the rate of policing,[17] or an increase to the *costs* of rational crime.

In Column 5, we quantify the contribution of the changes in observable characteristics (income, wealth, unemployment, etc.) to the overall level of post-crisis white-collar crime. Specifically, we extrapolate the model coefficient from Column 2 relative to the difference in covariates from 2005 and 2015 (Column 4) for the number of individuals in 2012. The value therefore represents the additional white-collar crimes expected in 2012 relative to 2005, assuming that the econometric model in Equation 2 captures all the relevant predictors of financial crime. The bottom of Column 5 shows that the sum of these expected crimes totals to 347 additional white-collar crimes, relative to the observed increase in crime between the two years of 904, suggesting that the observable components in our model predict less than 40% of the observed growth in white-collar crime. This result is depicted visually as well in Figure 2. As described, the rate of observed white-collar crime (solid line) decreases until 2007, where it then reverses trend. The fitted values (dashed line) from the model map closely to the observed rate of white-collar crime. Post-crisis we show the model prediction for the rate of white-collar crime (dotted line) based on the observable components in the model, and note that the predication significantly under-predicts the observed rate of white-collar crime.

In summary Figure 2 and Table 3, show a strong under-prediction in the rate of white-collar crime for convictions relative to the observed level of crime in our microdata. The large number of excess crimes during the post-financial crisis period suggests that a model of 'smoking gun' observable characteristics does an inadequate job at predicting the rates of white-collar crime. In

[17] We proxy the rate of policing by measuring a municipality's rate of criminal charges relative to reported crime.

the following section we propose an alternative mechanism as to why white-collar crime may have increased during the financial crisis.

5. The effect of financial misconduct experiences on white-collar crime

As the financial crisis evolved in Denmark it resulted in several retail bank defaults. Many of these institutions were investigated for financial misconduct. Excessive exposure to real estate developers and farm land, led to severe write-offs and liquidity needs in many banks in the period 2007-2012. As a result of write-offs on non-performing loans, eight publicly traded retail banks defaulted between 2008 and 2012.[18] These defaults affected more than 10,000 shareholders (close to 10% of all Danes holding stocks in 2006) who suffered significant personal investment losses. On average, shareholders lost 36,270 DKK (4,800 EUR), or approximately 15% of their portfolios. Furthermore, 75% of investors were also customers; the defaulted bank acted as their primary bank.

In a report issued after the first wave of bank defaults, the Danish Financial Supervisory Authority concluded that investments in the bank's stocks were often encouraged by direct marketing campaigns with a one-sided focus on benefits such as capital gains, dividends and banking privileges, with little attention to the inherent risks. Depositors were contacted directly by their bankers and offered to participate in equity issues, and in some cases offered a loan to finance the purchase (Danish Financial Supervisory Authority, 2009). Many depositors seemed to have placed a great deal of trust in this investment advice and purchased stock in their banks without adequately considering the potential risks or their portfolios' lack of diversification. Investors' portfolios were highly skewed towards the stocks of their own banking institution: more than half of all stock market participants held stocks in their banks (51.8%), and 29.4% of all participants held portfolios *solely* consisting of their bank's stock.

[18] Collectively, the 8 defaulted banks held assets worth 141 billion DKK (EUR 18.9 billion EUR), see Appendix A for more information. Andersen, Hanspal, and Nielsen (2018) describes how the 2007-9 financial crisis had a significant impact on financial institutions in Denmark.

The crisis resulted in significantly lower stock prices of financial institutions and triggered a wave of bankruptcies across the financial sector. Customers' deposits were insured by the Danish government, but any investments in retail bank's stock were not.[19] Shareholders were exposed to large financial losses.[20] These investment experiences were portrayed as violations of advisors' and local retail savings banks' fiduciary duty, and in some cases they resulted in criminal charges for bank executives.

Seventeen retail banking institutions were investigated by either the Danish Financial Supervisory Authority (FSA) or the Danish Serious Economic and International Crime (SØIK).[21] In total, eight retail banks were charged and prosecuted for fraud, embezzlement, market manipulation, financial misconduct, and excessive risk taking.[22] Of these eight, six were in publically traded retail institutions. In contrast to consumer fraud which results in a conviction or reversal relatively quickly after the initial charge, these investigations were made over many years and in many cases the results and verdicts were only made public well after the banks' default.[23] The locations of the banks across Denmark are shown in Figure 4.

We hypothesize that the resulting negative experiences with negligent and criminally prosecuted financial institutions changed individuals perceptions about financial crime and triggered an increase in white-collar crime. By directly experiencing financial misconduct, investors were exposed to financial losses. In addition, as experiences made during the financial crisis may

[19] Depositor insurance in Denmark provided by The Guarantee Fund for Depositors and Investors guarantees 100% of deposits up to 750,000 DKK (100,000 EUR). From October 5, 2008 to September 30, 2010, the Danish government decided to provide unlimited guarantees to depositors.
[20] Rather than reproducing detailed portfolios loss figures we refer the reader to Andersen, Hanspal, and Nielsen, 2018; Table 4.
[21] Appendix C outlines the troubled banks around the financial crisis and documents whether the bank consolidated in private merger and acquisitions or if it resulted in default.
[22] For example, the chief executive officer, senior-executives, and members of the board of directors of were suggested to be charged for breach of trust, violations of section 54 of the Danish Public Companies Act and section 71 of the Danish Financial Business Act by a legal consul (Summary, 2009). For EBH Bank, The CEO was charged with market manipulation and a number of lawsuits during the financial crisis (Borsen.dk).
[23] As an illustrative example, Amagerbanken defaulted in February 2011 and its senior board members were finally acquitted from wrongdoing in June 2017. In several of the cases, senior management was ultimately acquitted or not found to be liable.

have been particularly severe, we hypothesize that information about crime, and potentially the norms of society may also have been transferred as a result of the banking defaults. We argue that customers of affected banks were more closely affected and may be more likely to engage in future crime through one of these proposed mechanisms.

To test these hypotheses we begin by investigating the effect of different types of experiences with financial institutions on the propensity to commit white-collar crime. Our first analysis is to consider the propensity of white-collar crime amongst deposit customers exposed to the financial crisis.

In Table 4, we estimate the following equation:

$$Pr(y_{it} = 1 \mid \boldsymbol{x}) = \Lambda(\boldsymbol{x\beta} + \boldsymbol{z\eta}) \tag{X}$$

Columns 1-3 of Table 4 include a sample of all deposit customers from 2003-2012. In the first column we define *any bank depositor experience* as a variable which captures the effect of holding savings deposits in a retail bank which defaults in the aftermath of the financial crisis. The variable takes the value of one in post-default years, and zero otherwise. Across deposit customers, exposure to a default retail banking institution increases the propensity to be convicted of collar-crime significantly.

To avoid spurious correlation we exclude several types of individuals from our sample. We exclude very wealthy individuals (individuals with annual income greater than 1 million DKK or net wealth greater than 4 million DKK) as well as individuals employed in the financial sector as an attempt to remove individuals who may have been top executives or board members of any federally prosecuted retail banks. In addition we exclude individuals who have ever been convicted of a previous white-collar crime. [24]

[24] To be specific, an individual is excluded if at time t, he or she has prior convictions in any period prior from 1980 until t-1.

The coefficients of Table 4 are odds-ratios and therefore state that default bank depositors are approximately 15% more likely to be convicted of a white-collar crime in the years following the default. Across specifications in this table and subsequent tables we control for year fixed-effects, age, age-squared, indicator variables for male, married, living with children in the home, being an immigrant, home-ownership, completed high school education, completed a masters-level or greater education, employment in the financial sector and being a small business owner. We also control for the natural logarithm of total income from all sources, net wealth, and indicator variables for the different regions of the country in order to control for any potentially differences in local enforcement or legal process.

In Column 2, we distinguish between different types of retail banking experience. A *criminal bank depositor experience* indicates the post-default period for deposit customers of retail banks which were charged for criminal financial misconduct following the financial crisis. As mentioned previously, in some cases these misconduct charges resulted in acquittals. Our source of variation however, is simply in the charging of criminal wrongdoing, as *non-criminal bank depositor experience* indicates exposure to retail banks which were initially investigated by the Danish FSA who then concluded that the management cannot be held liable for the subsequent bankruptcy. Criminal banks on the other hand were formally prosecuted after the FSA and SOIK charged executive management with financial misconduct and excessive risk taking. The prosecution resulted in increased media attention and awareness for many people living in Denmark. We note in Column 2 that a *non-criminal depositor bank experience* has no statistical or economic significance on the propensity to be charged with a white-collar crime, however *criminal bank depositor experience* is significant at the 5% confidence level and suggests that the exposure increased the probability of a charge by approximately 16%. In Column 3 we then exclude all individuals with any previous criminal history and note that the coefficients on our primary variable of interest, *criminal bank depositor experience,* remains positive and statistically significant, implying that white-collar crime convictions are being driven by individuals with experiences with criminally-prosecuted retail banks, who have had no prior criminal experience.

While these initial results suggest that there is a strong correlation between exposure to criminally-prosecuted retail banking institutions and white-collar crime, even for individuals with no previous crime history, it remains unclear as to which types of customers may be driving this effect. We therefore focus the sample in Columns 4-6 to individuals who invested in the share offerings of retail banking institutions prior to the financial crisis. To understand the different types of experiences individuals make with retail banks, we examine two groups of customers: we consider individuals who held stock market investments in retail banks but were not deposit customers, and deposit customers who also hold investments in their own retail bank. Holding investments in an individuals' retail bank was relatively common prior to the financial crisis, as many investors followed the advice of their financial advisors as described in Andersen, Hanspal, and Nielsen (2018). These customers were financially invested in their banks, lost significant holdings in the corresponding bankruptcies, and in some cases were associated with post-bankruptcy lawsuits and financial claims. If personal experiences are an important determinant of white-collar crime, we expect our results to be driven by this segment of consumer. The two groups are denoted across Columns 4-6 as *bank investor experience*, and *bank depositor and investor experience.*

In Column 4 we first investigate *any bank experience* for investors and deposit customers and investors and note that investors who are also deposit customers are approximately 26% more likely to be convicted of a white-collar crime after experiencing their bank default whereas investment without being a customer has a negligible and insignificant effect. Columns 5 and 6 decompose *any bank experience* for the two groups by investigating whether the default bank was criminal prosecuted by the state or not. Across specifications, we note that the coefficient on *criminal bank depositor and investor experience* remains economically and statistically significant: investors exposed to financial misconduct are approximately 33% more likely to be convicted of a white-collar crime, particularly if they were vested customers of the bank. At the same time, non-criminal bank experiences, and non-customer and investor experiences have an effect on future criminal activity which is statistically indistinguishable from zero. Our results appear to be primarily driven by this group of customers that were exposed to their deposit bank's default while holding investments in that institution, as such, we continue to focus on these deposit customers who were also investors of their retail bank in the following analyses.

Depositors or investors who made experiences with retail banks which were charged for financial misconduct may also have had a higher likelihood to commit white-collar crimes prior to the bank's default. To mitigate such concerns we turn to a differences-in-differences (DD) estimation design. Specifically, we estimate the model:

$$Pr(y_{it} = 1 \mid \boldsymbol{x}) = \Lambda(\beta_1 Exposed_i + \beta_2 Post_t + \beta_3 (Exposed_i \times Post_t) + \gamma \boldsymbol{x}) \quad (3)$$

The sample consists of own-bank investors who work outside of the financial sector and have no prior white-collar crime convictions. *Exposed* is an indicator which takes the value of one for individuals who invested in a bank which defaults and was subsequently prosecuted for financial misconduct following the financial crisis. *Post* takes the value of one in post-crisis time periods, in the years 2008-2012, the variable takes a zero value in years 2003-2007. To account for serial-correlation in errors that could cause bias often found in DD models we collapse the dataset into two pre- and post- time periods (Bertrand, Duflo, and Mullainathan, 2004). The vector $\boldsymbol{x}_i$ contains individual pre-crisis characteristics.[25]

In Table 5 we estimate the econometric model in equation (3) with various dependent variables indicating different types of criminal convictions. We first note that in Column 1 investors

[25] As shown in Ai and Norton (2003) the coefficients of interaction terms in non-linear models do not translate directly to differences-in-differences estimates as in linear models. Instead, in non-linear estimations, differences-in-differences should be evaluated using the full underlying model. To account for this, we compute each coefficient as described based on the conditional probability including all covariates held at their mean values. We report the standard coefficients and note that the computed coefficients are generally larger with smaller standard errors, therefore we take a more conservative approach.

who held stocks of retail banks which defaulted and were subsequently criminally-prosecuted, *investors in criminal banks,* were no more likely to be convicted of a fraud related crime prior to the financial crisis. The second variable, *after default*, captures the post-crisis period, and as we have shown graphically white-collar crime convictions increase significantly. The interaction of the two variables gives us β_3 from equation (3) and captures the difference-in-differences effect. Across Columns 1-3 we differentiate between the type of white-collar crime. Difference-in-differences estimates for fraud convictions suggests that after experiencing a retail banking default, investors of criminally prosecuted banks, relative to bank customers of solvent banks with a similar investment style, are 2.7 times more likely to be convicted of a fraud-related white-collar crime. Furthermore, in Columns 4-5, our results suggest that these individuals are no more likely to be convicted of non-white-collar crimes. In fact, the coefficient of interest, $\beta_{3,}$ suggests that these individuals are less likely to be convicted of property crimes and crimes against persons (crimes of a violent nature) compared to similar investors unexposed to experiences with criminally-charged financial institutions.

A deterioration of financial well-being could be an important mechanism predicting an increase in financially motivated fraud-related crime. It is also reasonable to suspect retail banks which defaulted and were criminally-prosecuted for financial misconduct had investors who may have been more exposed from the financial crisis, either mechanically from the banking shock, or due to unrelated characteristics correlated with investment in troubled banks. We address the potential omission of changes in financial well-being during the crisis period in Table 6 by matching exposed individuals with unexposed investors in the sample.

We create matched samples using five nearest-neighbors of investors in criminally-prosecuted banks. For each treated investor we match on age, gender, marital status, higher education, previous while-collar crime convictions, self-employment, home ownership, and 50-quantiles of net wealth. In Columns 3 (4) (5) matching is based on the nearest five neighbors from the covariate list and the pre- to post-crisis change in financial wealth (net wealth) (total debt) rounded to the nearest 10^{th} percentile bin. We note that in the first column, the pre-crisis rate of fraud convictions is not significantly different for investors with experiences in criminally-charged banks compared to individuals with investments in different banks. However, after experiencing the default of the criminal bank, investors are more than twice as likely to be convicted of a fraud related crime.

To rule out spurious correlation due to differences in local enforcement, we additionally match on the region of the country by matching exposed investors to unexposed investors who live in the same municipality. Column 2 presents this results and suggests that potential cross-sectional differences in policing is not a factor: exposed investors are 2.4 times more likely to be convicted of a white-collar crime after experiencing financial misconduct first hand relative to individuals living in the same local area – who presumably would be exposed to heightened enforcement, were it a factor.

In Column 3 we also account for the change in financial, or liquid wealth by matching treated to untreated investors experiencing a similar wealth contraction. Again, we find no evidence of pre-crisis effects for exposed investors and a two-fold increase in the probability of fraud conviction after exposure. Columns 4 and 5 tell a similar story when we control for the pre- to post-crisis changes in net wealth and total sources of financial debt. In total, Table 6 confirms that the increase in the probability of fraud convictions is not driven by observable characteristics, including relative changes in financial wealth.

Our identification strategy assumes parallel pre-trends in rates of criminal activity prior to the banking defaults. We test this formally in Figure 4 by creating a year-by-year sample of the collapsed DD sample and regressing the interaction term of dummy variables for the years since the bank default and our 'treatment' indicator on fraud convictions. The econometric model therefore takes the form of:

$$y_{imt} = \beta_1 \boldsymbol{\Omega}_t + \beta_2(Exposed_i \times \boldsymbol{\Omega}_t) + \gamma \boldsymbol{X}_i + a\boldsymbol{\delta}_i + u_{it} \tag{4}$$

In this model, $\boldsymbol{\Omega}_t$ is a vector of years since default-dummies, and $\boldsymbol{\delta}$, an individual-fixed effect accounting for time-invariant characteristics. The left panel presents the results of this test while excluding individuals with previous white-collar crime convictions, while the right panel excludes individuals with any previous criminal history. The figure shows pre-default interaction terms to be statistically and economically insignificant with signs often changing directions, providing satisfactory evidence of parallel pre-trends prior to the financial crisis. In the time periods after experiencing the bank charged with financial misconduct however, the rate of fraud convictions increases significantly by approximately an additional 75 convictions per 100,000 individuals.

6. Why do misconduct experiences affect crime?

As the financial crisis evolved, eight publically traded retail banks in Denmark defaulted, and in the aftermath five were criminally-charged while three were not held liable for their bankruptcy. We therefore can compare the differences in probability of criminal activities between investors in criminally-prosecuted retail banks and banks which were not indicted, conditional on the individual investing in a troubled retail banking institution. In this analysis, if there is a latent selection effect into a certain type of investment, it is by construction held constant between investors in these troubled banks. Pre-crisis demographic and socioeconomic control should rule out any differences between the type of troubled retail bank that the investor held assets in.

Furthermore, this powerful test allows us to shed light on the mechanism behind our results. Financial misconduct spillovers may cause an increase in white-collar crime in the general population for a number of reasons. Exposure to misconduct can have direct, pecuniary effects on customers and shareholders by lost savings or investments. A rational model of crime, as we noted in a previous analysis, should cause an increase in observed crime. As suggested by recent literature (Guiso, Sapienza, and Zingales (2013), Brown, Schmitz, and Zehnder (2017)), non-pecuniary factors may also be of particularly importance, especially during times of financial crisis. White-collar crime may increase as a result of the transmission of informational content to potentially new criminal entrants. Individuals unfamiliar with the risks and returns of white-collar crime could learn about the pitfalls and rewards associated with it through exposure to financial misconduct. Separately, individuals may be affected by a channel unrelated to learning or information (Bursztyn, Ederer, Ferman, and Yuchtman, 2014). Exposure to financial misconduct could change how individuals view what is morally just in a society - after exposure they now view the norms of society differently, or they feel cheated and want some form of retribution.

Our setting allows us to disentangle between these three potential mechanisms. Firstly, the pecuniary effect is held constant across investors experiencing defaults regardless if the bank was charged with misconduct or not. Furthermore we have shown in Table 6, using matched samples, that the propensity to be convicted of a white-collar crime is particularly large for exposed investors even after taking into account quantitate changes in financial well-being.

Secondly, the informational content about crime transmitted to potentially new entrants was dispersed nationally and in our specification should be constant across individuals and effectively absorbed by the time fixed effects included in our specification. This therefore suggests, that the increase in individuals' propensity to engage in facially motivated white-collar crime following direct exposure to financial misconduct, may have been driven by a loosening of individuals' 'moral constraint.' These individuals made experiences with misconduct so powerful, that view the norms of society in a new light.

In Table 7, we present the results of this powerful test. In Column 1, we begin by removing investors with previous white-collar crime convictions. By focusing on individuals with limited criminal history we note that the effect of having an experience with a criminally-charged retail bank increases the probability of being convicted of a fraud by 3.2 times and is significant at the 5% level. In Column 2, we additional exclude individuals who worked pre-crisis in the financial industry to ensure we do not capture any spurious correlation from charged employees of the retail banks in our sample. The effect on the interaction term reduces slightly but remains highly significant. In the final column, we exclude individuals with *any* previous criminal history. The effect on the interaction term of interest increases to 3.0 times and remains significant at the 5% level. Table 7 suggests that experiences with retail banks charged with financial misconduct has a large effect on the extensive margin of criminal activity, these experiences provoked *new*-criminals into fraud convictions rather than individuals with extensive white-collar crime histories.

7. **Are differences in post-crisis crime driven by heterogeneity in policing and enforcement?**

A potential concern is that our results may be driven by cross-sectional differences in enforcement. In Figure 5 we provide evidence suggesting that rates of policing and enforcement does not differ between affected and unaffected municipalities enough to be an alternative explanation to our results. We plot the differences in pre and post-crisis measures of reported crime and policing by municipalities where the headquarters of a retail bank defaulted compared to municipalities which have at least one retail bank, and experienced no defaults. The upper-left (-right) quadrant displays the rate of municipality-level total crime reported relative to crimes charged (convicted) by the police. The bottom-left quadrant is the rate of reported white-collar crime relative to white-collar convictions within a municipality. The bottom-right quadrant is the fraction of white-collar crime relative to total reported crime in a municipality. Each plot states the difference in pre- to post-crisis measures between the two groups of municipalities. The values represent coefficients from a linear regression controlling for municipality-level household income, wealth, and average wages and unemployment rates. In total, Figure 5 shows that on average, across municipalities the rates of policing and enforcement increased slightly from pre to post-crisis periods, however there is no statistical differences between municipalities exposed to retail bank defaults and unexposed municipalities.

In the next test, we map municipalities into police jurisdictions across Denmark…. In Table 8 we include police-jurisdiction fixed effects to our main specifications presented across prior tables…..

8. Conclusion

In this study we investigate the rise in financial and white-collar crime in the aftermath of the financial crisis and in the subsequent economic recession. As opposed to the existing literature, our analysis exploits individual-level administrative data on criminal activity and focuses on higher wealth individuals with limited criminal histories. We show that a dramatic negative experience in the banking sector had a causal effect on the propensity to commit and be convicted of a white-collar crime. Individuals exposed to banks prosecuted for financial misconduct by the federal authorities are more than twice as likely to subsequently be convicted of a financial fraud related crime.

Our findings suggest that having close experiences with financial misconduct and breaches of trust within the retail banking sector has a strong effect on future decisions over criminal activity. Furthermore our findings are almost entirely driven by individuals with no previous criminal history. We compare exposed investors to observably similar investors holding assets in banks which were not prosecuted by the state for misconduct in order to shed light on the mechanism behind our results. Ruling out pecuniary factors, and information-based learning channels, we suggest that formative experiences with financial misconduct are powerful enough to change the moral views individuals hold about society – the spillovers in our setting are likely to be large enough that they allow new entrants to participate in white-collar crime.

The results from this study combined with the findings from Andersen, Hanspal, and Nielsen (2018) show that financial misconduct and misallocation from financial institutions can have strong negative externalities on customers and shareholders. Not only do first-hand experiences with troubled banks have real effects on wealth and risk taking behavior, such shocks can also seemingly alter the perceptions individuals hold about the costs and returns to engaging in financially motivated white-collar crime.

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Table 1: Individual characteristics and criminal activity

We report descriptive statistics: mean and standard deviation for all individuals in Denmark aged 2-60 in 2005, the year prior to the financial crisis. For each individual, we observe financial, household, and demographic characteristics detailed below. We compare the mean characteristics of individuals who in Column 1 have no criminal conviction in 2005, and in Column 2 have been convicted of any crime. The next column tests whether these differences are significantly different from zero. In Columns 4 and 5 we compare criminals who are convicted of white-collar crimes compared to any other crime. The next column tests whether these differences are significantly different from zero. Corresponding *t*-statistics are reported in square brackets. All amounts are in thousands year-2010 DKK. Standard deviations are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Sample	**All crimes**			**White-collar crimes**		
	No conviction	**Criminal conviction**	**Difference**	**Other conviction**	**White-collar crime**	**Difference**
	(1)	**(2)**	**(2)-(1)**	**(3)**	**(4)**	**(4)-(3)**
Panel A: Individual Characteristics						
Age	40.67	34.66	-6.01***	34.40	35.94	1.54***
	(11.47)	(10.62)	[-79.26]	(10.63)	(10.48)	[8.31]
Male	50.26	79.95	29.69***	79.95	79.95	0.00
	(50.00)	(40.04)	[89.90]	(40.04)	(40.04)	[0.00]
Married	52.00	23.45	-28.55***	20.77	36.50	15.73***
	(49.96)	(42.37)	[-86.49]	(40.57)	(48.15)	[21.38]
Have children in household	42.00	25.77	-16.23***	23.40	37.31	13.92***
	(49.36)	(43.74)	[-49.77]	(42.34)	(48.37)	[18.28]
Immigrant	8.88	19.49	10.61***	19.21	20.86	1.65**
	(28.45)	(39.61)	[56.19]	(39.40)	(40.64)	[2.38]
Net wealth	240.42	3.65	-236.77***	-2.17	32.01	34.18***
	(705.18)	(465.01)	[-50.87]	(388.96)	(729.36)	[4.19]
Total income	307.86	198.65	-109.21***	187.88	251.15	63.27***
	(168.55)	(139.66)	[-98.08]	(120.28)	(201.88)	[26.22]
Own property	0.23	0.08	-0.15***	0.06	0.17	0.11***
	(0.42)	(0.27)	[-55.14]	(0.23)	(0.38)	[24.53]
Stock market participation	22.92	7.59	-15.33***	6.60	12.42	5.82***
	(42.03)	(26.48)	[-55.28]	(24.82)	(32.99)	[12.59]
Length of Education	12.13	9.82	-2.30***	9.72	10.33	0.62***
	(3.33)	(3.35)	[-104.51]	(3.35)	(3.29)	[10.50]
Employed financial industry	3.29	0.90	-2.38***	0.87	1.07	0.20
	(17.83)	(9.46)	[-20.28]	(9.28)	(10.30)	[1.22]
Self-employed	1.97	2.34	0.37***	0.99	8.93	7.94***
	(13.90)	(15.12)	[4.01]	(9.89)	(28.52)	[30.55]
Unemployment (% of year)	4.92	9.96	5.04***	9.86	10.44	0.58
	(15.58)	(21.66)	[48.77]	(21.46)	(22.58)	[1.52]
Panel B: Criminal Background						
Previous any crime conviction	11.48	68.07	56.59***	71.16	53.00	-18.16***
	(31.88)	(46.62)	[267.26]	(45.30)	(49.92)	[-22.46]
Previous white-collar crime conviction	2.93	23.63	20.71***	23.00	26.73	3.73***
	(16.86)	(42.48)	[182.03]	(42.08)	(44.26)	[5.01]
Previous imprisonment	1.94	32.59	30.66***	35.04	20.66	-14.38***
	(13.78)	(46.87)	[323.59]	(47.71)	(40.49)	[-17.62]
Parent criminal conviction	8.17	7.59	-0.57***	7.54	7.84	0.29
	(27.38)	(26.49)	[-3.11]	(26.41)	(26.88)	[0.62]
Parent criminal imprisonment	1.45	1.96	0.51***	1.98	1.89	-0.09
	(11.96)	(13.87)	[6.45]	(13.92)	(13.61)	[-0.37]
N	3,003,278	23,035	-	19,114	3,921	-

Table 2: Determinants of white-collar crime

This table presents the results from the economic model in Equation 2 presented as odds-ratios:

$$Pr(y_{it} = 1 \mid \boldsymbol{x}) = \Lambda(\alpha_0 + \boldsymbol{x}\boldsymbol{\beta})$$

The dependent variable is an indicator variable for being convicted with a specific type of white-collar crime in 2005. The sample includes all individuals in Denmark aged 20-60 in 2005. In the first column the dependent variable takes the value of one if an individual is convicted with any white-collar crime. Column 2 focuses on fraud-activity based white-collar crimes, while Columns 3 and 4 focus on corporate and legal crimes respectively. Coefficients present Odds Ratios estimated after a logistic regression. Standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	**Type of white-collar crime**			
	All	**Fraud**	**Corporate**	**Legal**
	(1)	**(2)**	**(3)**	**($)**
Age	1.023*	1.081***	0.996	0.996
	(0.012)	(0.018)	(0.022)	(0.027)
Age^2	0.999***	0.999***	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)
Male	3.026***	2.124***	5.564***	3.924***
	(0.125)	(0.112)	(0.519)	(0.411)
Married (%)	0.861***	0.797***	1.166**	0.595***
	(0.035)	(0.046)	(0.085)	(0.064)
Have children in household (%)	0.955	0.954	1.107	0.751***
	(0.038)	(0.052)	(0.079)	(0.073)
Immigrant (%)	1.881***	1.801***	2.641***	1.238*
	(0.080)	(0.105)	(0.198)	(0.136)
Log net wealth	0.876***	0.818***	0.950***	0.853***
	(0.007)	(0.010)	(0.011)	(0.017)
Log net income	0.843***	0.842***	0.826***	0.871***
	(0.010)	(0.014)	(0.015)	(0.025)
Own a house	1.699***	1.329***	2.143***	1.240
	(0.089)	(0.120)	(0.170)	(0.189)
Stock market participation	0.855***	0.685***	1.163**	0.568***
	(0.044)	(0.060)	(0.087)	(0.085)
High school education or less	2.296***	2.339***	1.980***	2.969***
	(0.151)	(0.219)	(0.212)	(0.551)
Post graduate education	0.976	0.801	1.005	1.158
	(0.119)	(0.157)	(0.178)	(0.394)
Employed in financial sector	0.514***	0.581**	0.654*	0.073***
	(0.080)	(0.128)	(0.149)	(0.073)
Small business owner	4.260***	1.325*	8.180***	2.055***
	(0.264)	(0.202)	(0.634)	(0.455)
Unemployment dummy	1.793***	2.114***	0.994	1.899***
	(0.066)	(0.101)	(0.086)	(0.154)
Previous WCC conviction	6.465***	7.211***	4.631***	6.608***
	(0.251)	(0.380)	(0.350)	(0.586)
Pseudo R^2	0.11	0.12	0.12	0.12
N	3,026,313	3,026,313	3,026,313	3,026,313

Table 3: Model prediction of white-collar crime after the financial crisis

This table reports descriptive statistics of proxies for *cost* and *benefits* of white-collar crime for the pre-crisis period (2005) in Column 1 and post crisis period (2012) in Column 3. The coefficients of the econometric model of incidence of white-collar crime convictions (Equation 2) over the period 1995-2007 is presented in Column 2. We test whether the level of the proxies are different from pre- to post-crisis periods in Column 4, and in Column 5 we predict the change in the number of white-collar crimes in the post-crisis period due to changes in proxies. *Total white-collar crimes* is the observed number of crimes in Columns 1 and 3, and the difference in Column 4. In Column 5, it is the *predicted* difference in white-collar crime convictions from pre to post-crisis based on the model in Column 2. Corresponding *t*-statistics are reported in square brackets. All amounts are in thousands year-2010 DKK. Standard deviations are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Pre-crisis	**Model**	**Post-crisis**	**Differences**	**Prediction**
	(1)	**(2)**	**(3)**	**(3)-(1)**	**(2)*((3)-(1))*N**
Age	40.621	-0.051***	40.453	-0.169***	25.8
	(11.472)	[-90.972]	(11.570)	[-17.920]	
Male	0.505	1.481***	0.504	-0.001***	-6.2
	(0.500)	[116.365]	(0.500)	[-3.443]	
High school education or less	0.737	0.975***	0.700	-0.036***	-117.5
	(0.440)	[70.582]	(0.458)	[-99.368]	
Graduate education	0.066	0.161***	0.085	0.012***	20.9
	(0.247)	[7.982]	(0.279)	[90.714]	
Employed in financial sector	0.033	-0.193***	0.035	0.003***	-1.5
	(0.178)	[-4.316]	(0.184)	[17.361]	
Small business owner	0.020	3.295***	0.014	-0.005***	-52.6
	(0.139)	[79.386]	(0.119)	[-50.674]	
Unemployment (% of year)	4.955	0.026***	3.254	-1.701***	-132.7
	(15.640)	[69.533]	(12.070)	[-149.039]	
Previous WCC conviction	0.031	11.537***	0.033	0.002***	58.4
	(0.173)	[321.720]	(0.178)	[11.888]	
Immigrant	0.090	0.769***	0.128	0.038***	86.7
	(0.286)	[33.181]	(0.334)	[149.445]	
Stock market participation	0.228	-0.021	0.220	-0.009***	0.6
	(0.420)	[-1.360]	(0.414)	[-25.491]	
Log net income	5.513	-0.307***	5.471	-0.042***	9.9
	(0.914)	[-47.968]	(1.055)	[-52.519]	
Log net wealth	2.973	-0.113***	2.544	-0.428***	144.8
	(2.964)	[-48.132]	(2.861)	[-180.293]	
Child at home	-0.003	-0.381***	-0.007	-0.004***	5.0
	(0.229)	[-14.878]	(0.236)	[-22.337]	
Homeowner	0.055	-0.029	-0.003	-0.059***	5.1
	(0.260)	[-0.982]	(0.164)	[-328.933]	
Marriage	0.012	-0.455***	0.007	-0.005***	6.5
	(0.180)	[-13.427]	(0.161)	[-34.174]	
Change in unemployment status	-0.010	0.011	0.002	0.012***	0.4
	(0.332)	[0.635]	(0.290)	[46.504]	
Change in local avg. wages	0.074	-0.450**	0.013	-0.060***	82.3
	(0.036)	[-2.459]	(0.035)	[0.000]	
Change in local unemployment rate	-0.008	-0.619	0.001	0.009***	-17.4
	(0.010)	[-1.275]	(0.006)	[1326.067]	
Change in local policing rate	0.064	10.831***	0.074	0.010***	331.1
	(0.030)	[12.509]	(0.027)	[417.281]	
Industry and municipality FE	-	-	-	-	-57.5
Total white-collar crimes	3,921	-	4,825	904	392.1
N	3,026,313	33,508,382	2,979,535	-	

Table 4: Financial misconduct and white-collar crime

This table presents the effect of financial misconduct experiences on white-collar crime from the following econometric model:

$$\textit{Fraud convictions per 1,000 individuals} = \beta_1 Exposed_i + \beta_2 Post_t + \beta_3(Exposed_i \times Post_t) + \gamma\boldsymbol{x} + a\boldsymbol{\varphi} + u_i$$

The dependent variable is an indicator variable equal to one if an individual is convicted of a white-collar crime in year *t*. In Columns 1-3 the sample consists of all individuals with a bank deposit account. Columns 4-6 include individuals who invest in publically traded bank stocks prior to the financial crisis. All individuals are between the ages of 20 and 60. The variable *any bank experience* is an indicator for individuals who experienced the default of a retail bank in the post crisis period. (*Non-)criminal bank experience* is an indicator variable for individuals who experienced their own bank default and the bank was (not) investigated for negligence during the financial crisis. In Columns 4-6 we decompose the experiences based on if individuals were both deposit customers *and* investors of a retail bank compared to if individuals were solely investors. Individuals who were employed in the financial industry prior to the financial crisis, very high net wealth individuals, and individuals with previous white-collar crime convictions are excluded. Columns 3 and 6 further restrict the sample to exclude investors with any criminal conviction history after the year 2000. Coefficients state the odds ratio after a logistic regression. Additional control variables include the pre-crisis values of control variables shown in previous tables. Standard errors are reported in parentheses and clustered at the pre-crisis bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Deposit customers			Bank investors		
Dependent variable:	White-collar crime conviction					
	(1)	(2)	(3)	(4)	(5)	(6)
Any bank depositor experience	0.142**					
	(0.060)					
Criminal bank depositor experience		0.136**	0.108*			
		(0.063)	(0.060)			
Non-criminal bank depositor experience		0.126	0.149			
		(0.154)	(0.147)			
Any bank depositor & investor experience				0.328***		
				(0.096)		
Any bank investor experience				0.079		
				(0.088)		
Criminal bank depositor & investor experience					0.309***	0.300***
					(0.106)	(0.103)
Criminal bank investor experience					-0.039	-0.113
					(0.172)	(0.167)
Non-criminal bank depositor & investor experience					0.302	0.260
					(0.236)	(0.230)
Non-criminal bank investor experience					0.103	0.129
					(0.131)	(0.127)
Additional controls, Municipality-Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.08	0.08	0.07	0.07	0.07	0.07
N	19,489,897	19,489,897	19,489,897	4,075,929	4,075,830	4,027,341

Table 5: The effect of financial misconduct experiences on criminal activity

This table presents the effect of financial misconduct experiences on types of white-collar crime from the following the econometric model stated in equation 3:

$$\textit{Fraud convictions per 1,000 individuals} = \beta_1 Exposed_i + \beta_2 Post_t + \beta_3(Exposed_i \times Post_t) + \gamma \mathbf{x} + a\boldsymbol{\varphi} + u_i$$

The dependent variable is an indicator variable equal to one if an individual is convicted with a crime in year *t*. The data is collapsed down to pre-crisis (years 2003-2007) and a post-crisis (years 2008-2012) periods. *Investors in criminal bank*s is an indicator for individuals who experienced the default of their own bank and the bank was investigated for financial fraud, the variable *After default* indicates the post-crisis period, and the interaction term *Investors in criminal banks*After default* captures the difference-in-differences estimate of the probability of being charged with a crime in the post-default period. Columns 1-5 represent the different types of crimes as the dependent variable in each specification. Across the columns the sample includes individuals invested in their own retail bank stocks prior to the financial crisis. Individuals with previous white-collar crime convictions and individuals who previously worked in the financial industry are excluded. Additional control variables include the pre-crisis values of control variables shown in previous tables. Coefficients state odds ratios after a logistic regression. Standard errors are reported in parentheses and clustered at the pre-crisis bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Type of crime				
	Fraud	**Legal**	**Corporate**	**Property**	**Violence and assault**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Investors in criminal banks	0.695	1.276	1.152	1.264***	1.022
	(0.164)	(0.220)	(0.311)	(0.056)	(0.088)
After default	2.591***	1.695***	3.043***	0.807***	0.762***
	(0.433)	(0.163)	(0.237)	(0.025)	(0.049)
Investors in criminal banks* After default	2.907***	0.669	0.971	0.923	1.039
	(0.702)	(0.212)	(0.251)	(0.071)	(0.121)
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.11	0.09	0.10	0.19	0.23
N	777,336	777,336	777,336	777,336	777,336

Table 6: The effect of financial misconduct experiences on white-collar crime

This table presents the effect of financial misconduct experiences on white-collar crime from the following the econometric model stated in equation 3:

$$\textit{Fraud convictions per 1,000 individuals} = \beta_1 Exposed_i + \beta_2 Post_t + \beta_3 (Exposed_i \times Post_t) + \gamma \boldsymbol{x} + a\boldsymbol{\varphi} + u_i$$

The dependent variable is an indicator variable equal to one if an individual is convicted of a fraud related white-collar crime in year *t*. The data is collapsed down to pre-crisis (years 2003-2007) and a post-crisis (years 2008-2012) periods. *Investors in criminal bank*s is an indicator for individuals who experienced the default of their own bank and the bank was investigated for financial fraud, the variable *After default* indicates the post-crisis period, and the interaction term *Investors in criminal banks***After default* captures the difference-in-differences estimate of the probability of being charged with a crime in the post-default period. This analysis uses a matched sample based on exact matching and five nearest neighbors. In Columns 1 through 5 the exposed investors are matched to unexposed investors based on the following demographic variables: *age, gender, marital status, higher education, previous while-collar crime convictions, self-employment, home owner,* and 50-quantiles of *net wealth.* In Column 2, we additionally match on the region by matching exposed investors to unexposed investors who live in the same municipality. In Columns 3 (4) (5) matching is based on the previous list of covariates and the pre- to post-crisis change in *financial wealth (net wealth) (total debt).* The sample includes individuals invested in their own retail bank stocks prior to the financial crisis, individuals with previous white-collar crime convictions and individuals who previously worked in the financial industry are also excluded. Additional control variables include the pre-crisis values of control variables shown in previous tables. Coefficients state odds ratios after a logistic regression. Standard errors are reported in parentheses and clustered at the pre-crisis bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	**Fraud crime**				
	Own-bank investors without previous white-collar convictions and non-financial employees				
Matched sample:	**Demo**	**Municipality**	**Δ Fin. wealth**	**Δ Net wealth**	**Δ Total debt**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Investors in criminal banks	-0.153***	-0.027	-0.009	-0.047	-0.112**
	(0.050)	(0.035)	(0.038)	(0.045)	(0.048)
After default	0.122**	0.147***	0.194**	0.013	0.045
	(0.053)	(0.029)	(0.086)	(0.061)	(0.051)
Investors in criminal banks * After default	0.303***	0.309***	0.239*	0.419***	0.371***
	(0.094)	(0.089)	(0.124)	(0.107)	(0.100)
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.00	0.00	0.00	0.00	0.00
N	82,682	67,452	77,531	77,356	76,768

Table 7: Controlling for investment style and wealth losses: Customers of distressed banks

This table presents the effect of financial misconduct experiences on white-collar crime from the following the econometric model stated in equation 3:

$$\textit{Fraud convictions per 1,000 individuals} = \beta_1 Exposed_i + \beta_2 Post_t + \beta_3 (Exposed_i \times Post_t) + \gamma \mathbf{x} + a\boldsymbol{\varphi} + u_i$$

The dependent variable is an indicator variable equal to one if an individual is convicted with a crime in year *t*. The data is collapsed down to pre-crisis (years 2003-2007) and a post-crisis (years 2008-2012) periods. The sample consists of investors who invested in their own bank prior to the financial crisis and the bank defaulted during the years 2008-2012. *Investors in criminal bank*s is an indicator for individuals who experienced the default of their own bank and the bank was investigated for financial fraud, the variable *After default* indicates the post-crisis period, and the interaction term *Investors in criminal banks*After default* captures the difference-in-differences estimate of the probability of being charged with a crime in the post-default period. In Column 2 investors with no previous White-collar crimes are excluded, Column 3 also excludes investors with prior employment history in the financial sector, Column 4 excludes investors who ever had *any* criminal conviction. Additional control variables include the pre-crisis values of control variables shown in previous tables. Coefficients state odds ratios after a logistic regression. Standard errors are reported in parentheses and clustered at the pre-crisis bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Default-bank investors		
	No previous wcc	**No previous wcc and finance employment**	**No criminal convictions and finance employment**
	(1)	**(2)**	**(3)**
Investors in criminal banks	-0.033	-0.078	-0.079
	(0.079)	(0.087)	(0.098)
After default	0.191**	0.211**	0.195*
	(0.094)	(0.102)	(0.100)
Investors in criminal banks* After default	0.275**	0.263**	0.273**
	(0.106)	(0.111)	(0.121)
Municipality fixed effects	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
R^2	0.00	0.00	0.00
N	74,658	68,796	62,622

Table 8: Controlling for differences in policing and enforcement

This table presents the effect of financial misconduct experiences on white-collar crime from the following the econometric model stated in equation 3:

$$\textit{Fraud convictions per 1,000 individuals} = \beta_1 Exposed_i + \beta_2 Post_t + \beta_3 (Exposed_i \times Post_t) + \gamma \boldsymbol{x} + a\boldsymbol{\varphi} + u_i$$

The dependent variable is an indicator variable equal to one if an individual is convicted of a fraud related white-collar crime in year *t*. The data is collapsed down to pre-crisis (years 2003-2007) and a post-crisis (years 2008-2012) periods. *Investors in criminal bank*s is an indicator for individuals who experienced the default of their own bank and the bank was investigated for financial fraud, the variable *After default* indicates the post-crisis period, and the interaction term *Investors in criminal banks***After default* captures the difference-in-differences estimate of the probability of being charged with a crime in the post-default period. This analysis uses a matched sample based on exact matching and five nearest neighbors. In Columns 1 through 5 the exposed investors are matched to unexposed investors based on the following demographic variables: *age, gender, marital status, higher education, previous while-collar crime convictions, self-employment, home owner,* and 50-quantiles of *net wealth.* In Column 2, we additionally match on the region by matching exposed investors to unexposed investors who live in the same municipality. In Columns 3 (4) (5) matching is based on the previous list of covariates and the pre- to post-crisis change in *financial wealth (net wealth) (total debt).* The sample includes individuals invested in their own retail bank stocks prior to the financial crisis, individuals with previous white-collar crime convictions and individuals who previously worked in the financial industry are also excluded. Additional control variables include the pre-crisis values of control variables shown in previous tables. Coefficients state odds ratios after a logistic regression. Standard errors are reported in parentheses and clustered at the pre-crisis bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	**Fraud crime**				
	Own-bank investors without previous white-collar convictions and non-financial employees				
Matched sample:	**Baseline**	**Δ Fin. wealth**	**Δ Net wealth**	**Δ Total debt**	**Distressed banks**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Investors in criminal banks	-0.076***	-0.082	-0.037	-0.094**	-0.082
	(0.027)	(0.086)	(0.036)	(0.047)	(0.086)
After default	0.105***	0.193*	0.194**	0.013	0.193*
	(0.016)	(0.100)	(0.086)	(0.061)	(0.100)
Investors in criminal banks * After default	0.364***	0.274**	0.239*	0.419***	0.274**
	(0.083)	(0.121)	(0.124)	(0.107)	(0.121)
Police jurisdiction fixed effects	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes
R^2	0.00	0.00	0.00	0.00	0.00
N	775,567	61,456	77,531	77,356	61,456

Table 9: Alternative specifications: Rare events in binary outcomes

This table presents the effect of financial misconduct experiences on white-collar crime from the following the econometric model stated in equation 3:

$$\textit{Fraud convictions per 1,000 individuals} = \beta_1 Exposed_i + \beta_2 Post_t + \beta_3 (Exposed_i \times Post_t) + \gamma \mathbf{x} + a\boldsymbol{\varphi} + u_i$$

The dependent variable is an indicator variable equal to one if an individual is convicted of a fraud related white-collar crime in year *t*. The data is collapsed down to pre-crisis (years 2003-2007) and a post-crisis (years 2008-2012) periods. *Investors in criminal bank*s is an indicator for individuals who experienced the default of their own bank and the bank was investigated for financial fraud, the variable *After default* indicates the post-crisis period, and the interaction term *Investors in criminal banks*After default* captures the difference-in-differences estimate of the probability of being charged with a crime in the post-default period. This analysis uses a matched sample based on exact matching and five nearest neighbors. In Columns 1 through 5 the exposed investors are matched to unexposed investors based on the following demographic variables: *age, gender, marital status, higher education, previous while-collar crime convictions, self-employment, home owner,* and 50-quantiles of *net wealth.* In Column 2, we additionally match on the region by matching exposed investors to unexposed investors who live in the same municipality. In Columns 3 (4) (5) matching is based on the previous list of covariates and the pre- to post-crisis change in *financial wealth (net wealth) (total debt).* The sample includes individuals invested in their own retail bank stocks prior to the financial crisis, individuals with previous white-collar crime convictions and individuals who previously worked in the financial industry are also excluded. Additional control variables include the pre-crisis values of control variables shown in previous tables. Coefficients state odds ratios after a logistic regression. Standard errors are reported in parentheses and clustered at the pre-crisis bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	**Fraud crime**				
	Own-bank investors without previous white-collar convictions and non-financial employees				
Matched sample:					
Investors in criminal banks					
After default					
Investors in criminal banks * After default					
Police jurisdiction fixed effects					
Additional controls					
R^2	0.00	0.00	0.00	0.00	0.00
N	775,567	61,456	77,531	77,356	76,768

Figure 1: Incidence of crime

This figure reports the total number of white-collar convictions (right axis) and all other criminal convictions (left axis) and for the period 1995 to 2012

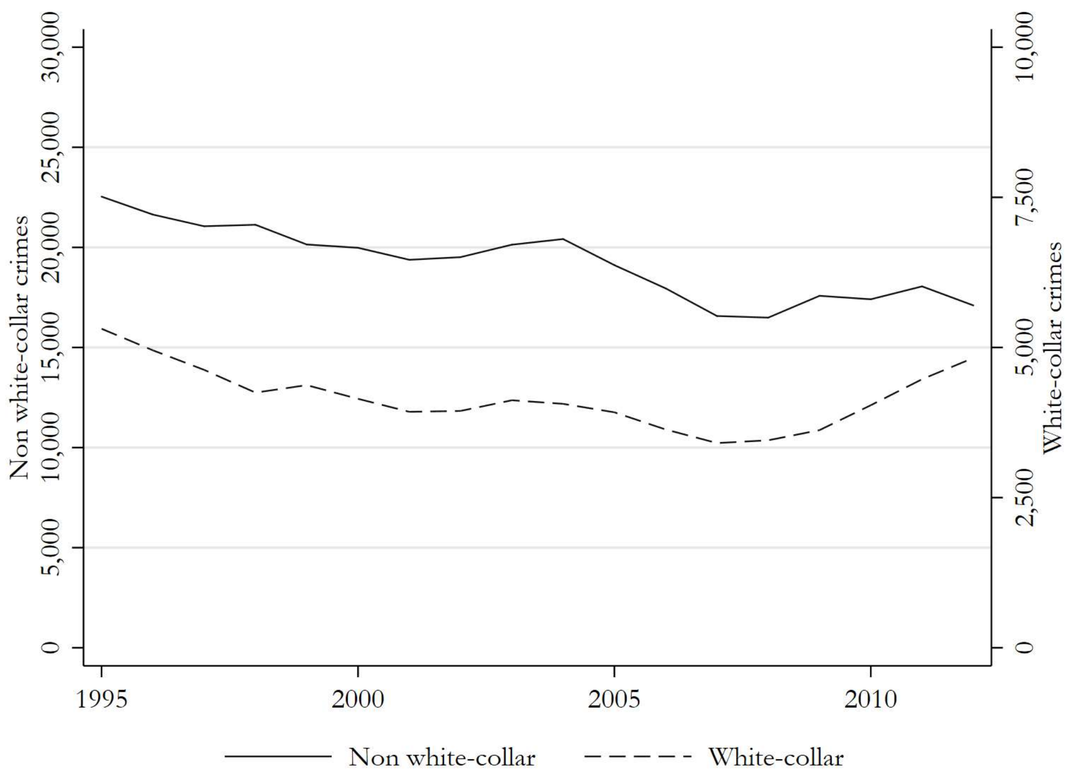


Figure 2: Observed, fitted, and predicted incidence of white-collar crime

This figure plots the observed rate of white-collar crime, the econometrically fitted rate of white-collar crime for the period 1995-2005, and the econometric predicted rate of white-collar crime in the period 2009-12. The gray are between 2007 and 2008 represent the financial crisis period.

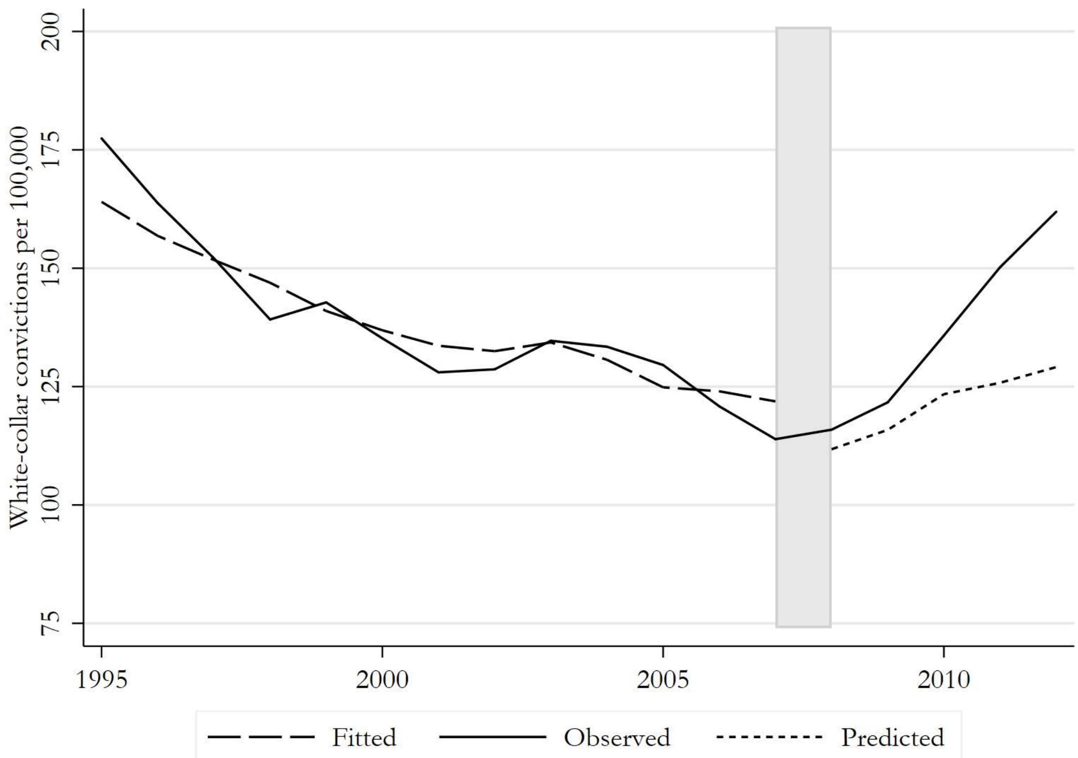


Figure 3: Location of local banks and incidences of bank defaults in Denmark

This map shows the location of publicly trading retail banks and incidences of bank defaults across municipalities in Denmark from 1990 to 2012 based on bank headquarters. Municipalities with a surviving publicly listed bank are displayed in grey. Municipalities in which a retail bank defaulted between 2008 and 2012 and was subsequently investigated and found not guilty of fraud are displayed in the darker gray shade. Municipalities in which a retail bank defaulted between 2008 and 2012 and was subsequently investigated and cited for financial fraud are displayed in black. Municipalities without a publicly listed retail bank are shown in white.

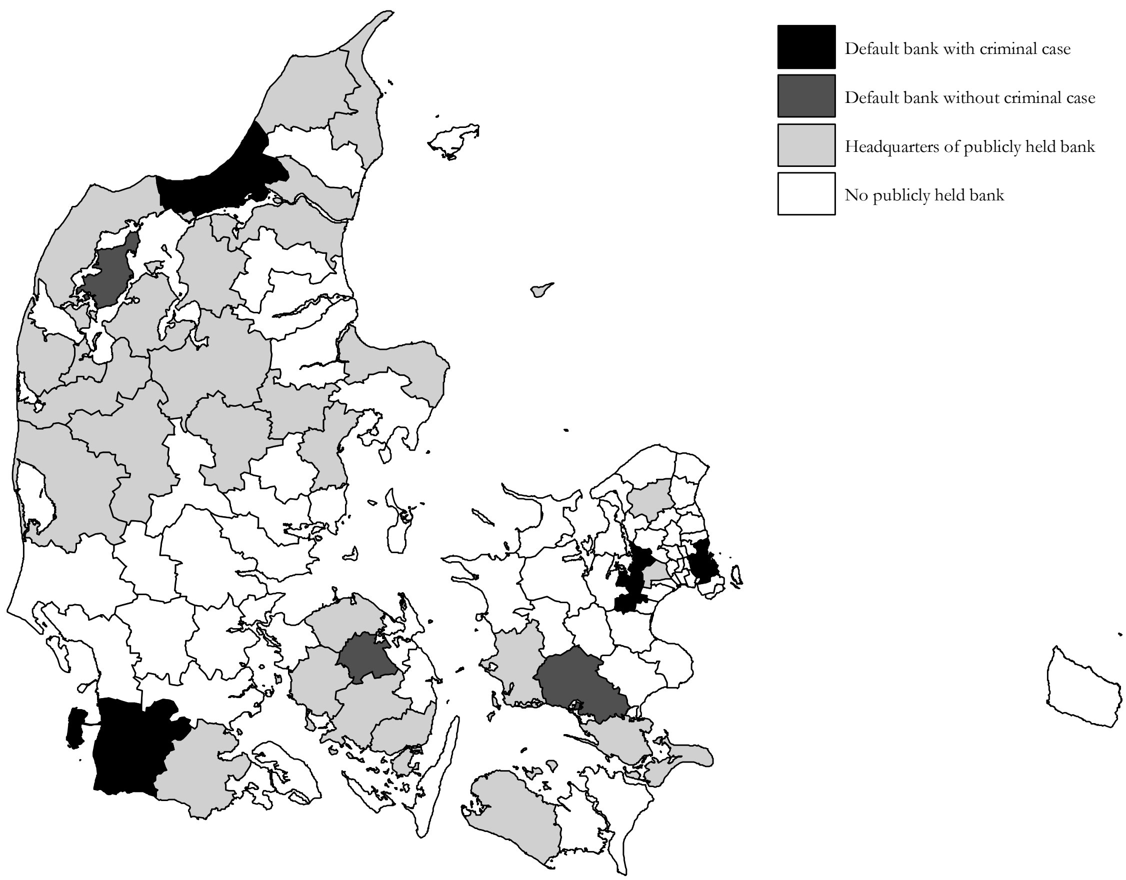


Figure 4: Financial misconduct experience and white-collar crime

This figure plots a dynamic version of the difference-in-differences model from Table 5 as specified in Equation (4). The *y*-axis presents the difference in the white-collar crime rate per 100,000 individuals while the *x*-axis states the years from bank default. The scatter points represents the difference in the conviction rates from the baseline to the sample of investors who were exposed to their own retail bank defaulting and being criminally investigated. The entire sample includes all individuals who invest in their own retail bank prior to the financial crisis. Individuals with very high wealth and who previously worked in the financial industry are excluded, as are individuals with previous white-collar crimes. The right-hand panel further excludes individuals with *any* prior criminal conviction. 90% Confidence bands are displayed.

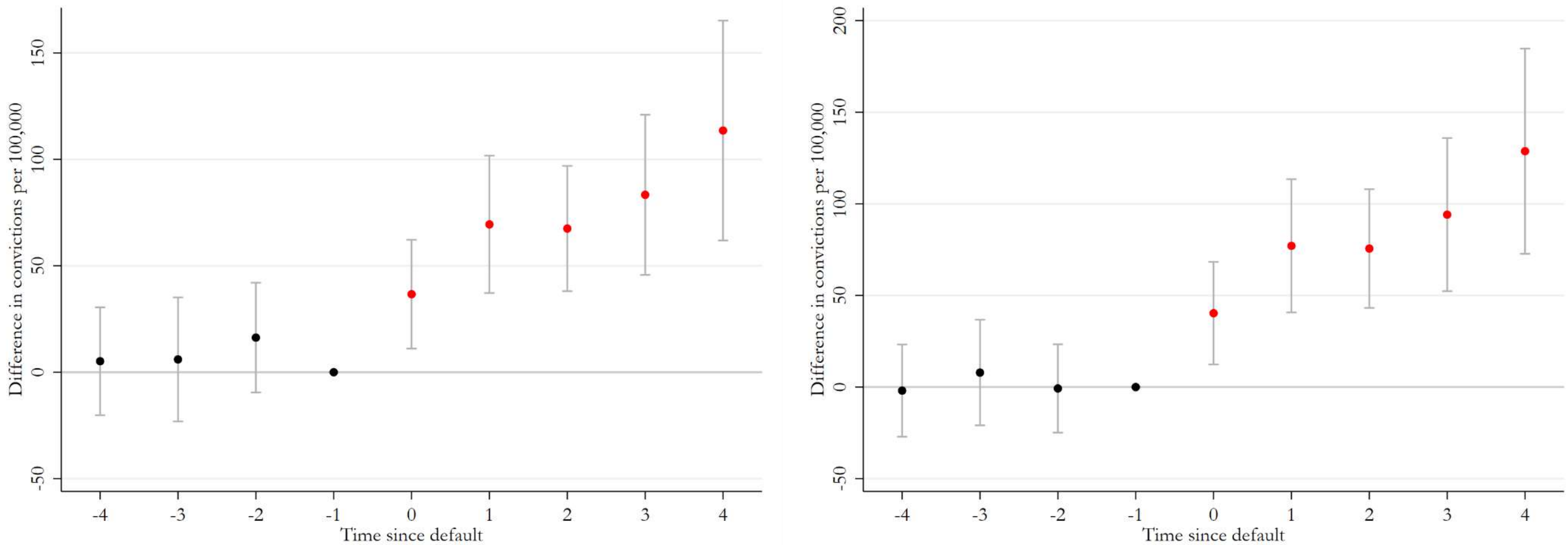
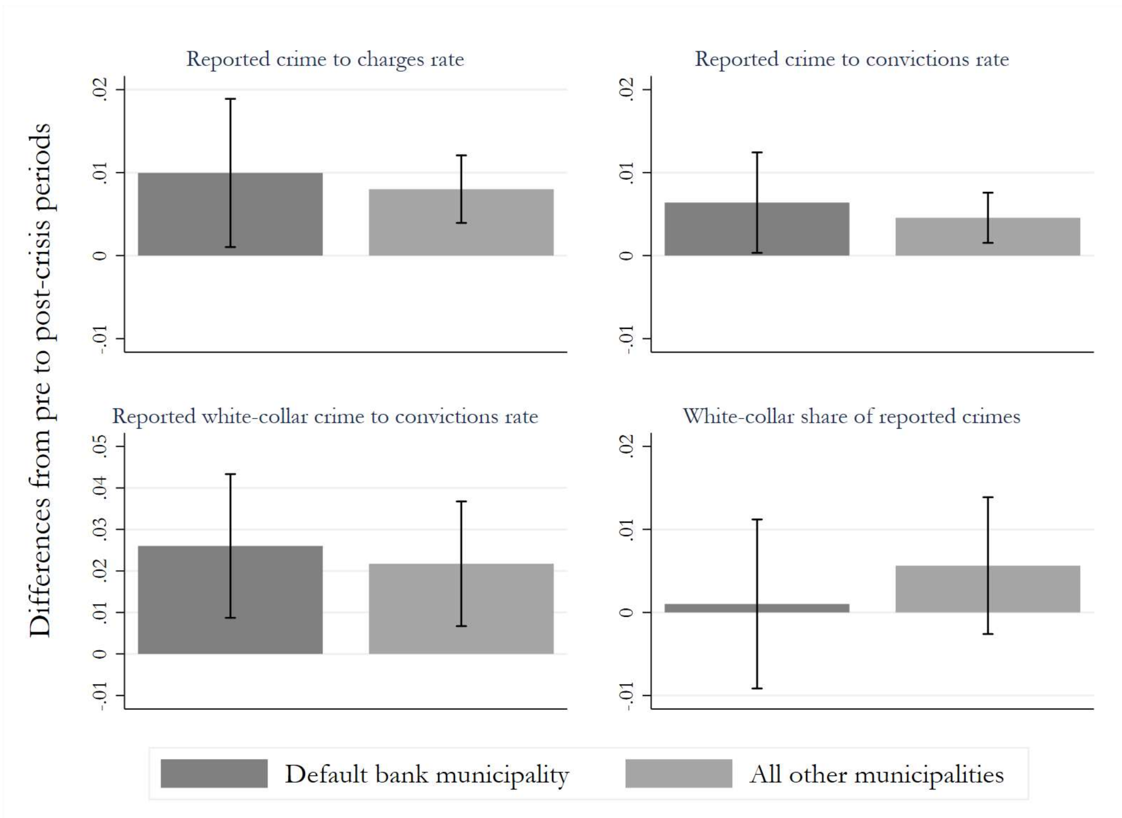


Figure 5: Regional reported crime and enforcement

This figure displays the differences between pre and post-crisis measures of reported crime and enforcement by municipalities where the headquarters of a retail bank defaulted compared to municipalities which have at least one retail bank, and experienced no defaults. The upper-left (-right) quadrant displays the rate of municipality-level total crime reported relative to crimes charged (convicted) by the police. The bottom-left quadrant is the rate of reported white-collar crime relative to white-collar convictions within a municipality. The bottom-right quadrant is the fraction of white-collar crime relative to total reported crime in a municipality. The values represent coefficients from a linear regression controlling for municipality-level household income, wealth, and average wages and unemployment rates.



Online Appendix for
"Experience is the Best Teacher:
Financial Misconduct and White-Collar Crime"

By

Steffen Andersen, Tobin Hanspal, and Kasper Meisner Nielsen

The following tables and figures are included in this appendix:

- **Appendix A: Sample statistics - incidence of crime**

- **Appendix B: List of default banks 2008-2012.**
  This table shows the chronology of bank defaults in Denmark in the aftermath of the financial crisis.

- **Appendix C: Bank investigations in Denmark**

- **Appendix D: Variable definitions**

- **Appendix E: FBI NIBRS classification of crimes**
  This table shows the FBI and international classification of criminal activity, we map Danish criminal codes into this international framework.

- **Appendix F: Mapping Danish criminal codes into FBI definition**
  This table shows the mapping of Danish criminal codes into FBI NIBRS Offenses.

- **Appendix G: FBI NIBRS classification of white-collar offenses**
  This table shows the listing FBI white-collar offenses.

- **Appendix H: Detailed white-collar convictions by type of crime**

- **Appendix I: Financial misconduct experience and criminal activity – deposit customers**

Appendix A: Sample statistics - incidence of crime

This table summarizes counts of individuals for incidence of crime across select years in our sample 2003-2012. Panel A reports the number of individuals with criminal charges by the year of the crime, as well as the number of resulting convictions from the crimes. We exclude minor traffic violations such as speeding tickets, but include more serious felonies such as driving under the influence. Panel B reports the number of individuals convicted by the type of criminal activity. Panels C shows the number of individuals convicted of white-collar crime. White-collar crime is defined by using the FBI criminal code definitions. Appendix G maps Danish crime codes into the FBI crime classifications. Because individuals can be convicted of multiple crimes, the total number of individuals in Panel B and C exceeds the number of individuals with criminal convictions and the number of individuals with white-collar crime convictions, respectively.

Year	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Panel A: Incidence of crime										
Number of individuals with criminal charges	36,102	35,939	34,306	34,053	31,997	32,047	32,439	32,591	34,166	33,008
Number of individuals with criminal convictions	24,256	24,480	23,035	21,588	19,981	19,947	21,205	21,448	22,525	21,927
Number of individuals without criminal charges	3,023,756	3,008,373	2,992,007	2,974,094	2,960,947	2,948,756	2,945,900	2,941,869	2,942,851	2,946,527
Panel B: Type of criminal conviction										
Crime against person	5,764	5,763	5,858	5,847	5,488	5,275	5,289	5,031	5,238	4,937
Crime against society	2,201	2,366	2,272	2,478	2,106	2,259	2,174	2,068	2,170	2,123
Crime against property	15,402	15,084	13,571	11,776	10,919	10,930	11,992	12,212	13,077	12,478
Other crime	2,055	2,419	2,441	2,466	2,371	2,381	2,713	3,182	3,273	3,542
White-collar crime	4,121	4,062	3,921	3,635	3,409	3,455	3,624	4,039	4,472	4,825
Panel C: Type of white-collar conviction										
Fraud	2,494	2,172	2,022	1,751	1,662	1,615	1,700	1,954	2,134	2,569
Corporate	915	1,118	1,192	1,214	1,065	1,307	1,381	1,507	1,694	1,624
Legal	735	786	720	688	697	547	559	604	672	666
Number of individuals in sample	3,059,858	3,044,312	3,026,313	3,008,147	2,992,944	2,980,803	2,978,339	2,974,460	2,977,017	2,979,535

Appendix B: List of default banks 2008-2012

This table lists the chronological order of defaults of publicly listed banks from 2008 to 2012. *Location of headquarters* is the city of the bank's headquarters. *Assets* are in DKK billions at the end of the year in the year before the default. *Number of shareholders* is the number of individual shareholders in our data at the beginning of the year of default.

Bank	Location of headquarters	Date of default	Assets DKK bn.	Number of shareholders
Roskilde Bank	Roskilde	24-08-2008	42.0	18,550
EBH Bank	Fjerritslev	28-11-2008	10.4	6,315
Fionia Bank	Odense	23-02-2009	32.8	18,716
Capinordic Bank	Hellerup	11-02-2010	1.7	2,108
Amagerbanken	Copenhagen	06-02-2011	28.3	40,649
Fjordbank Mors	Nykøbing Mors	24-06-2011	13.2	8,540
Max Bank	Næstved	09-11-2011	9.8	13,047
Tønder Bank	Tønder	04-11-2012	2.8	3,650

Source: Danish Financial Supervisory Authority and authors' own calculations.

Appendix C: Financial misconduct in Denmark

This table lists information about federal criminal investigations of banking institutions in Denmark following the financial crisis. The table includes banks which merged and defaulted listed in chronological order. The column *Public*, states whether a bank was publically traded (Y/N). The column *Criminal*, states whether the banking intuition was investigated and found to be negligent for financial misconduct (Y/N). The final column details the outcome of the investigation. Data is from the Danish FSA and the authors' own research.

Troubled bank	Year	Outcome	Public	Criminal	Investigation outcome
bankTrelleborg	2008	Merged	N	N	
Roskilde Bank	2008	Failed	Y	Y	Bank managers were investigated by SOIK but then dismissed. But the guarantor scheme was similar to Lokken case - found liable in terms of pushing sales to customers and ignoring risk warnings
Bonusbanken	2008	Merged	Y	N	Danish FSA concludes that the management and board members cannot be held liable for the bankruptcy
Sparekassen Spar Mors	2008	Merged	N	Y	Bank CEO charged with embezzlement, and convicted.
EBH Bank	2008	Failed	Y	Y	8 Bank managers were investigated by SOIK for market manipulation, but the case was dropped because of a post error.
Lokalbanken I Nordsjælland	2008	Merged	Y	N	
Forstædernes Bank	2008	Merged	Y	N	
Ringkjøbing Bank	2008	Merged	Y	N	
Løkken Sparekasse	2009	Failed	N	Y	Danish FSA has charged management and board members for financial misconduct and excessive risk taking
Gudme Raaschou	2009	Failed	N	N	Danish FSA concludes that the management and board members cannot be held liable for the bankruptcy
Fionia Bank	2009	Failed	Y	N	Danish FSA concludes that the management and board members cannot be held liable for the bankruptcy
Capinordic	2010	Failed	Y	Y	Danish FSA has charged management and board members for financial misconduct and excessive risk taking. 3 managers were found guilty in 2015 and ordered to pay compensation.
Finansbanken A/S	2010	Merged	N	N	
EIK	2010	Failed	Y	Y	Danish FSA has charged management and board members for financial misconduct and excessive risk taking
Skælskør Bank	2010	Merged	Y	N	Danish FSA concludes that the management and board members cannot be held liable for the bankruptcy
Amagaerbanken	2011	Failed	Y	Y	11 persons associated with the bankruptcy of Amagerbanken are charged
Sparekassen Midtfjord	2011	Merged	N	N	

Fjordbank Mors	2011	Failed	Y	N	Danish FSA concludes that the management and board members cannot be held liable for the bankruptcy
Max Bank	2011	Failed	Y	N	Danish FSA concludes that the management and board members cannot be held liable for the bankruptcy
Sparekassen Limfjorden	2011	Merged	N	N	
Sparekassen Farsø	2012	Merged	N	N	
Sparekassen Østjylland	2012	Failed	N	N	Danish FSA concludes that the management and board members cannot be held liable for the bankruptcy
Aarhus Lokalbank	2012	Merged	Y	N	Manager charged for insider trading, but not convicted
Spar Salling Sparekasse	2012	Failed	N	N	Danish FSA concludes that the management and board members cannot be held liable for the bankruptcy
Tonder Bank	2012	Failed	Y	Y	Mogens Mortensen, former director of Tonder Bank, is charged with financial misconduct and excessive risk takin. Found guilty in the Court of Sønderborg. Only fined 5,000 DKK.

Appendix D: List of variable definitions

All variables are expressed in DKK year 2010.

Variable	Description
Net wealth	Net wealth in 1,000DKK
Total income	Total individual income from wages and government benefits in 1,000 DKK
Bank savings	Total amount held in bank deposits at end of calendar year, in 1,000 DKK
Financial wealth	Financial wealth is the sum of stocks, bonds, and bank savings at the end of the year in 1,000 DKK
Value of debt	Total value of debt in 1,000 DKK
Total value of property	Total value of real estate assets in 1,000 DKK
Stock participant	Indicator variable which takes the value of 1 if an individual participates in the stock market by holding stocks in a given year
Age	Age in years
Length of Education	Education is measured in years 1-13
Employed financial industry	An individual is employed in the financial industry if his or her primary occupation is in the finance or real estate sector
Self-employed	Indicator for primary occupation is self-employed in tax reporting
Male	Indicator variable for male
Married	Indicator variable for married
Have children in household	Indicator variable for having any number of children in the household in current year
Immigrant	Indicator variable for being an immigrant to Denmark
Previous criminal conviction	Indicator variable takes the value of one if individual was convicted of any crime after 1980
Parent criminal record	Indicator variable takes the value of one if either of the individual's parents have a previous criminal conviction record
Family criminal record	Indicator variable takes the value of one if anyone in the individual's family (spouse, parents, siblings, children, and in-laws) has a previous criminal conviction record
Family white-collar criminal record	Indicator variable takes the value of one if anyone in the individual's family (spouse, parents, siblings, children, and in-laws) has a previous white-collar criminal conviction record
Unemployment (% of year)	Percent of the current year the individual was designated as unemployed
Unemployment (% of last year)	Percent of last year the individual was designated as unemployed

Appendix E: FBI classification of crimes

This table shows the FBI and international classification of criminal activity, we map Danish criminal codes into this international framework.

FBI NIBS Classification

1. Crimes Against Persons:
- Assault Offences
  - Aggravated Assault
  - Simple Assault
  - Intimidation
- Homicide Offenses
  - Murder and Non-negligent Manslaughter
  - Negligent Manslaughter
  - Kidnaping and Abduction
- Sex Offenses, Forcible
  - Forcible Rape (Except Statutory Rape)
  - Forcible Sodomy
  - Sexual Assault With An Object:
  - Forcible Fondling
- Sex Offenses, Non-forcible (Except Prostitution)
  - Incest
  - Statutory Rape

3. Crimes Against Society:
- Drug/Narcotic Offenses (Except D.U.I.)
  - Drug/Narcotic Violations
  - Drug Equipment Violations
- Gambling Offenses
  - Betting/Wagering
  - Operating/Promoting/Assisting Gambling
  - Gambling Equipment Violations
  - Sports Tampering
- Pornography/Obscene Material
- Prostitution Offenses
  - Prostitution
  - Assisting or Promoting Prostitution
- Assisting or Promoting Prostitution

2. Crimes Against Property:
- Arson
- Bribery (Except Sports Bribery)
- Burglary/Breaking and Entering
- Counterfeiting/Forgery
- Destruction/Vandalism of Property (Except Arson)
- Embezzlement
- Extortion/Blackmail
- Fraud Offenses (Except Counterfeiting/Forgery)
  - False Pretenses/Swindle/Confidence Game
  - Credit Card/Automated Teller Machine Fraud
  - Impersonation
  - Welfare Fraud
- Larceny/Theft Offenses
  - Pocket-picking
  - Purse-snatching
  - Shoplifting
  - Theft From Building
  - Theft From Motor Vehicle
  - Theft of Motor Vehicle Parts or Accessories
  - All Other Larceny
- Motor Vehicle Theft
- Robbery
- Stolen Property Offenses

4. All other Offenses

Appendix F: Danish mapping of crimes into FBI NIBS classification

This table shows the FBI and international classification of criminal activity, we map Danish criminal codes into this international framework.

Danish mapping into FBI NIBS classification

Code	Translated text	Original titles
1. Crimes Against Persons		
1210	Assault against public servant while in discharge of his duty	Vold o.l. mod off. myndighed
1220	Riot/ disturbance of public order	Opløb/forstyr. af off. orden
1240	Attempted homicide	Forsøg på manddrab
1252	Common assault	Simpel vold
1255	Grievous assault	Alvorligere vold
1258	Particularly grievous assault	Særlig alvorlig vold
1260	Domestic violence against innocent	Vold mod sagesløs
1270	Intentional bodily harm	Forsætlig legemskrænkelse iøv.
1280	Intentional bodily injury	Forsætlig legemsbeskadigelse
1292	Threats	Trusler
1230	Homicide	Manddrab
1283	Involuntary manslaughter/ bodily harm	Uagtsomt manddrab/legemsbesk.
1460	Involuntary manslaughter with driving accident	Uagts. manddr. mv.v/færd.uheld
1286	Crimes against life and body (e.g., contribution to suicide, not helping injured)	Forbr. mod liv og legeme
1289	Crimes against personal freedom (e.g., detention, trafficking)	Forbr. mod den pers. frihed
1110	Incest.	Blodskam mv.
1120	Rape, etc.	Voldtægt mv.
1130	Heterosexual sexual offence against child under 12 years	Heterosek. sæd.f. børn u.12 år
1131	Sexual offence against child under 12 years	Seksualforbrydelse mod barn under 12 år
1140	Heterosexual offense in general	Heteroseksuelle sædelighedsforbrydelser i øvrigt
1141	Sexual crime against child between 13 and 14 years	Seksualforbrydelse mod barn 13-14 år
1145	Sexual crime in general	Seksualforbrydelse i øvrigt
1150	Homosexual sexual offence against children under 12 years	Homosek. sæd.f. børn u. 12 år
1160	Homosexual sexual offences in general	Homosek. sæd.forbr. i øvrigt
2. Crimes Against Property		
1312	Arson	Brandstiftelse
1398	Misappropriations and offences e.g. kickbacks	Berig.forbr. og formuekrænk.
1316	Burglary from location/business	Indbr. i bank., forretn. mv.
1320	Burglary from house/apt	Indbr. i beboelser

1324	Burglary from uninhabited buildings	Indbr. i ubeboede bebyggelser
1304	Forgery	Dokumentfalsk
1308	Forgery by check	Dokumentfalsk med check
1390	Vandalism	Hærværk
1354	Embezzlement	Underslæb
1366	Blackmail and usury	Afpresning og åger
1357	Fraud	Bedrageri
1360	Check Fraud	Checkbedrageri
1363	Fraud of agent	Mandatsvig
1372	Fraud against creditors	Skyldnersvig
1328	Theft from car, boat, etc.	Tyveri fra bil, båd mv.
1332	Store Thefts etc.	Butikstyverier mv.
1336	Other thefts	Andre tyverier
1351	Larceny by finding	Ulovlig omgang med hittegods
1339	Theft of registered vehicle	Tyv./brugstyv. af indr.køretøj
1342	Theft of moped	Tyv./brugstyv. af knallert
1345	Theft of bike	Tyv./brugstyv. af cykel
1348	Theft of other vehicle	Tyv./brugstyv. af andet
1380	Robbery	Røveri
1376	Handling stolen goods	Hæleri
1394	Careless handling of stolen goods	Uagtsomt hæleri

3. Crimes Against Society

1435	Drug trafficking	Salg af narkotika mv.
1440	Drug smuggling	Smugling mv. af narkotika
3210	Euphoriants act (narcotics)	Lov om euforiserende stoffer
3855	Legislation related to gambling, licencing, trade	Love vedr. spil, bev., næring
1180	Prostitution, etc.	Utugt mv.
3410	The Firearms Act	Våbenloven

4. Other Crimes

0	Unknown	Uoplyst
1000	Unknown criminal	Uoplyst straffelov
1172	Offences against decency (by pawing)	Blufærdighedskr. v/beføling
1174	Offence against public decency (by removing cloths)	Blufærdighedskr. v/blotteri
1176	Offence against public decency (other)	Blufærdighedskr. i øvrigt
1384	Gross tax evasion	Grov skattesvig mv.
1410	Offences against official authorities	Forbr. mod off. myndighed mv.
1415	Offences by public servant	Forbr. i off. tjeneste
1420	Perjury (false statement to the court)	Falsk forklaring for retten
1425	Perjury (other)	Falsk forklaring i øvrigt

1430	Offences concerning money and evidence	Forbr. vedr. penge og bevism.
1445	General public offences	Almenskadelige forbr. mv.
1450	Illegal trade, etc.	Ulovligt erhverv mv.
1455	Family relation offence	Forbrydelser i familieforhold
1475	Privacy infringements, defamation	Tilhold
1485	Peace and defamation	Freds- og ærekrænkelser
2110	Unspecified traffic accidents	Færdselsuheld uspecificeret
2210	Traffic accident under the influence of alcohol	Færdselsuheld med spiritus
2220	Driving under the influence of alcohol	Spiritus- og promillekørsel
2410	Vehicle defect offences	Mangler ved køretøj
2610	Road traffic act	Færdselslovsovertræd. i øvrigt
3610	Income tax and fiscal act	Skatte og afgiftslove mv.
3810	Other criminal special laws	Andre strafferetlige særlove
3815	Health and social security legislation	Sundheds- og sociallove
3820	Building and housing regulation	Bygge- og boliglove
3825	Environmental laws	Miljølove
3830	Laws concerning. animals, hunting, etc.	Love vedr. dyr, jagt mv.
3835	Employment and transportation regulations	Love vedr. arb. transport mv.
3840	Companies act	Selskabs- og firmalovgiv. mv.
3845	Legislation applying to the armed forced	Love vedr. forsvaret og lign.
3850	Legislation applying to public utilities	Love vedr. off. forsyninger
3865	Special laws, other	Særlovgivning i øvrigt
3870	Unspecified legislation	Uoplyst særlovgivning

Appendix G: FBI UCR classification of white-collar offenses

Appendix G lists white-Collar offenses as outlined by the US Department of Justice and the Federal Bureau of Investigation:

Source: Barnett, Cynthia, US Department of Justice Federal Bureau of Investigation, Criminal Information Services Division, and United States of America. "Measurement of White-Collar Crime Using Uniform Crime Reporting (UCR) Data." (2000).

Crime	NIBRS Offense Category
Academic crime	Fraud (26A-26E)
Adulterated foods, drugs, or cosmetics	Fraud (26A-26E)/All Other Offenses (90Z)
Anti-trust violations	All Other Offenses (90Z)
ATM fraud	Fraud (26A-26E)
Bad checks	Bad Checks (90A)
Bribery	Bribery (510)
Check kiting	Fraud (26A-26E)/Bad Checks (90A)
Combinations in restraining in trade	Fraud (26A-26E)/All Other Offenses (90Z)
Computer crime	Substantive Offense
Confidence game	Fraud (26A-26E)
Contract fraud	Fraud (26A-26E)
Corrupt conduct by juror	Bribery (510)
Counterfeiting	Counterfeiting/Forgery(250)
Defense contract fraud	Fraud (26A-26E)
Ecology law violations	Fraud (26A-26E)/All Other Offenses (90Z)
Election law violations	Fraud (26A-26E)/All Other Offenses (90Z)
Embezzlement	Embezzlement (270)
Employment agency and education-related scams	Fraud (26A-26E)
Environmental law violations	Fraud (26A-26E)/All Other Offenses (90Z)
False advertising and misrepresentation. of products	Fraud (26A-26E)
False and fraudulent actions on loans, debts, and credits	Fraud (26A-26E)
False pretenses	Fraud (26A-26E)
False report or statement	Fraud (26A-26E)/All Other Offenses (90Z)
Forgery	Counterfeiting/Forgery(250)
Fraudulent checks	Bad Checks (90A)
Health and safety laws	Fraud (26A-26E)
Health care providers fraud	Fraud (26A-26E)
Home improvement frauds	Fraud (26A-26E)
Impersonation	Fraud (26A-26E)
Influence peddling	Bribery (510)
Insider trading	Fraud (26A-26E)
Insufficient funds checks	Bad Checks (90A)
Insurance fraud	Fraud (26A-26E)
Investment scams	Fraud (26A-26E)
Jury tampering	Bribery (510)
Kickbacks	Bribery (510)
Land sale frauds	Fraud (26A-26E)

Mail fraud	Fraud (26A-26E)
Managerial fraud	Fraud (26A-26E)
Misappropriation	Embezzlement (270)
Monopoly in restraint in trade	Fraud (26A-26E)/All Other Offenses (90Z)
Ponzi schemes	Fraud (26A-26E)
Procurement fraud	Fraud (26A-26E)
Racketeering influence and corrupt organizations	Substantive Offense
Religious fraud	Fraud (26A-26E)
Sports bribery	Sports Tampering (39D)
Strategic bankruptcy	Fraud (26A-26E)
Subordination of perjury	Bribery (510)
Swindle	Fraud (26A-26E)
Tax law violations	Fraud (26A-26E)/All Other Offenses (90Z)
Telemarketing or boiler room scams	Fraud (26A-26E)
Telephone fraud	Fraud (26A-26E)
Travel scams	Fraud (26A-26E)
Unauthorized use of a vehicle (misappropriation)	Embezzlement (270)
Uttering (forgery/counterfeiting)	Counterfeiting/Forgery(250)
Uttering bad checks	Bad Checks (90A)
Welfare fraud	Fraud (26A-26E)
Wire fraud	Fraud (26A-26E)

Appendix H: Detailed white-collar conviction counts by type of crime 2003-2012

In this table we outline the Danish criminal codes which we map into the FBI definition of white-collar crime outlined in Appendix F. The Danish description and code is provided along with the counts in our sample from 2003-2012.

English description	Danish description	Danish code	Fraud	Legal	Corporate
Forgery	Dokumentfalsk	1304	4,976		
Forgery by check	Dokumentfalsk med check	1308	1,001		
Embezzlement	Underslæb	1354	1,502		
Fraud (credit, unemployment etc.)	Bedrageri	1357	12,685		
Fraud (checks)	Checkbedrageri	1360	329		
Breach of trust (using checks, credit cards, computers)	Mandatsvig	1363	334		
Extortion and usury	Afpresning og åger	1366	709		
Debtor fraud	Skyldnersvig	1372	407		
Tax fraud	Grov skattesvig mv.	1384	798		
Serious fraud cases (Accounting fraud, etc.)	Berig.forbr. og formuekrænk.	1398	1,444		
Counterfeiting money and legal evidence	Forbr. vedr. penge og bevism.	1430	1,469		
Breaking tax laws	Skatte og afgiftslove mv.	3610	2,010		
Money laundering and related acts		3810	-		
Legal abuse, confidential breach, court Office	Forbr. i off. tjeneste	1415		147	
False statement to court	Falsk forklaring for retten	1420		728	
False statement	Falsk forklaring i øvrigt	1425		5,596	
Illegal occupation (gambling, begging, service business)	Ulovligt erhverv mv.	1450		133	
Breaches confidentiality, racial discrimination, defamation etc.	Freds- og ærekrænkelser	1485		3,451	
Health and social legislation	Sundheds- og sociallove	3815			4,417
Housing and construction laws	Bygge- og boliglove	3820			155
Environmental laws violations	Miljølove	3825			5,412
Employer violations (driving, hours, wages)	Love vedr. arb. transport mv.	3835			5,709
Corporate laws (competition, marketing, accounting, etc.)	Selskabs- og firmalovgiv. mv.	3840			887
Total convictions			27,664	10,055	16,580
Total individual-conviction observations			20,073	6,674	13,017

Appendix I: Financial misconduct experience and criminal activity – deposit customers

This table examines white-collar criminal activity and experiences made during the financial crisis. The dependent variable is an indicator variable equal to one if an individual is convicted with a crime in year *t*. The data is collapsed down to pre-crisis (years 2003-2007) and a post-crisis (years 2008-2012) periods. *Depositors in criminal banks* is an indicator for individuals who experienced the default of their own bank and the bank was investigated for financial fraud, the variable *After default* indicates the post-crisis period, and the interaction term *Depositors in criminal banks***After default* captures the difference-in-differences estimate of the probability of being charged with a crime in the post-default period. Columns 1-8 represent the different types of crimes as the dependent variable in each specification. Across the columns the sample includes individuals invested in their own retail bank stocks prior to the financial crisis. Individuals with previous white-collar crime convictions and individuals who previously worked in the financial industry are excluded. Additional control variables include the pre-crisis values of control variables shown in previous tables. Coefficients state odds ratios after a logistic regression. Standard errors are reported in parentheses and clustered at the pre-crisis bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Type of crime				
	Fraud	**Fraud**	**Fraud**	**Property crime**	**Crime against persons**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Depositors in criminal banks	0.635*	1.394**	1.187	1.285***	1.043
	(0.159)	(0.235)	(0.302)	(0.049)	(0.088)
After default	2.682***	1.787***	3.179***	0.822***	0.752***
	(0.409)	(0.169)	(0.217)	(0.021)	(0.043)
Depositors in criminal banks* After default	2.858***	0.635	0.931	0.908	1.044
	(0.667)	(0.204)	(0.240)	(0.063)	(0.120)
Additional controls	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.10	0.09	0.10	0.19	0.23
N	902,211	902,211	902,211	902,211	902,211

Appendix J: Incidence of white collar crime after criminal bank experiences

This table examines the type of white-collar criminal convictions occurring after the financial crisis for exposed individuals in our sample.

	N	**%**
A. Type of white collar crime		
Fraud	321	66.7
Forgery	82	16.9
Embezzlement	26	6.6
Counterfeiting	6	1.2
Other	10	2.1
B. Sanction		
Prison	304	62.7
Fine	126	26.0
Warning	55	11.3
Total convictions	485	
Total individual-conviction observation	403	