Dirty Money: How Banks Influence Financial Crime*

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Abstract

Banks face considerable discretion in filing suspicious activity reports (SARs), a primary tool to combat financial crimes. We investigate the incentives banks face to report money laundering activity via SARs and the implications for criminal activity. Our theoretical and empirical analyses document that banks with more profit-seeking pressure adopt lax reporting policies, attracting criminal customers and leading to more suspicious activities. Counties with higher competition, lower profitability, and deficient capital reserves are associated with higher SAR volume. A maximum likelihood estimation helps us uncover the relation between bank profitability, reporting stringency, and the demand from criminal customers. We establish causality using shale gas expansion in unrelated states and show that banks experiencing higher (lower) shale growth generate fewer (more) SARs. Reporting volume predicts future violations and is more strongly related to profitability for high-crime regions and large banks. Overall, our results suggest an assortative matching between lax banks and criminal clientele.

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> Today, the FinCEN Files — thousands of "suspicious activity reports" and other US government documents — offer an unprecedented view of global financial corruption, the banks enabling it, and the government agencies that watch as it flourishes... These documents... expose the hollowness of banking safeguards, and the ease with which criminals have exploited them. Profits from deadly drug wars, fortunes embezzled from developing countries, and hard-earned savings stolen in a Ponzi scheme were all allowed to flow into and out of these financial institutions...
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> — *BuzzFeed News*[1]

1 Introduction

Financial crimes impose tremendous economic and societal costs. Each year, the amount of money laundered globally is estimated to be between \$800 billion and \$2 trillion according to the United Nations Office on Drugs and Crime. Financial crimes create substantial costs for investors, with the largest banks purportedly spending more than \$1 billion each year in enforcing adequate anti-money-laundering compliance processes (The Wall Street Journal, 2020). While substantial, these economic costs pale in comparison to the societal costs imposed by financial crime, as it facilitates terrorism, sexual exploitation, drug smuggling, and modern slavery, among other criminal activities. The recent leak of more than 2,500 FinCEN files on September 21st, 2020 provides a stark reminder of how widespread financial crime is in the economy and underscores potential loopholes that criminals may exploit. The leak also suggests significant consequences for capital markets, as there were large negative market reactions for banks involved in money laundering in the days following the FinCEN leak.[2]

One of the most important tools for banks to help combat financial crime is the suspicious activity report (SAR), a standardized document that banks must file with FinCEN if they suspect money laundering activities. Regulators stress that SARs are "vital for law enforcement investigations and regulatory matters and are used to map key national security threats" (FinCEN, 2018). SAR activity has been steadily increasing over time, from approximately 840,000 reports in 2014 to over 1.1 million reports in 2019, according to data from FinCEN. On the surface, this increase is consistent with banks strengthening their compliance efforts over time. However, the trend is also puzzling given

[1] See "Dirty money pours into the world's most powerful banks", BuzzFeed News (2020).
[2] Please see the Internet Appendix for more details on our return analyses surrounding the FinCEN leak.

that a substantial amount of money is still laundered through the financial system, potentially highlighting a certain level of sophistication among criminals in finding loopholes. Indeed, anecdotal evidence abounds that criminals often have "favorite banks", suggesting that sophisticated criminals might navigate the system by choosing banks that have lax reporting policies.[3] This raises the possibility that banks may cater their reporting strategies to attract certain customers.

In this study, we examine the incentives that banks face to report money laundering activity by submitting SARs, and the implications of such reporting strategies for criminal activity.[4] Our analysis has several steps. First, we develop a stylized model that predicts that banks facing depressed revenues from their routine business lines and more profit-seeking pressure adopt more lax reporting policies. Such policies, in turn, attract criminals and increase SAR reporting volume. Second, we test the model using county-level data detailing SAR reporting volume. We find that counties comprised of banks with higher risk-taking incentives, including those facing heightened competition, lower profitability, and deficient capital reserves, generate *more* SAR reports. Next, to better isolate the effect of bank incentives on reporting choices, we conduct a maximum likelihood estimation that allows us to infer the level of underlying suspicious activities and banks' reporting stringency. Our estimation results reveal that bank profitability is positively associated with reporting standard stringency and that lower reporting stringency, in turn, spurs local criminal activities. Finally, we establish causality using a shale exposure experiment and conduct additional analyses that further alleviate alternative explanations. In particular, these results reveal that banks are more likely to develop lax reporting standards when they are located in regions designated as high risk for financial crimes and money laundering. Overall, our collective evidence is consistent with banks' risk-taking incentives influencing the stringency of AML standards and, in turn, local criminal activity.

We begin by first articulating the SAR process in U.S. financial institutions. SARs represent a critical part of anti-money laundering statutes and regulations, that were initially established

[3]For example, HSBC was fined in 2012 for laundering billions of pounds for Mexican drug cartels and was purportedly "the bank of choice for drug dealers" (Daily Mail, 2016). Liberty Reserve was also accused of being "the bank of choice for the criminal underworld" after allegedly laundering money through 55 million transactions (The Wall Street Journal, 2013).

[4]Throughout the study, we focus on the effects of banks' incentives on SAR reporting. We do not, however, differentiate SAR reporting from other types of AML compliance, but instead consider SAR reporting to be reflective of broader compliance at the bank-level.

under the Bank Secrecy Act of 1970. While the regulations have developed over time, current federal regulations require financial institutions and their subsidiaries to file a SAR if they detect criminal violations at a certain monetary threshold (e.g., $5,000 when a suspect can be identified). Importantly, the SAR reporting process involves multiple levels of personnel in a bank, and front-desk employees are expected to use significant discretion in filing a SAR and completing a narrative describing the events.[5] Thus, regardless of the technology system in place, there is still a significant amount of "soft information" embedded into the SAR decision. Front-desk employees at the local branch level are largely responsible for the collection and production of information relevant for the initial SAR filing, and can thus have a significant impact on the reporting process. Our study ultimately sheds light on how these employees respond to profit-seeking pressure across the bank.

Our formal analyses begin with a theoretical model, in which banks choose the stringency of their reporting policy to maximize profits. On the one hand, a more stringent policy reduces the banks' risk from executing an unreported, illegal transaction, which could be penalized by a regulator. We label this channel as the *strategic reporting effect*. On the other hand, a more stringent policy can also affect the demand from potential customers. More specifically, banks face two types of customers. First, a fixed number of safe, routine customers and second, an endogenous number of risky, new customers. Safe customers have been thoroughly screened by the bank and do not engage in illegal activities. A risky customer, however, could engage in illegal transactions and derive a benefit from such transactions if they are undetected. A more stringent policy makes it easier for the regulator to detect illegal activities and consequently the bank attracts fewer risky customers in equilibrium. We label this channel as the *strategic advertising effect*.

Our theoretical model then solves for the optimal degree of stringency that balances the increased expected fines for the bank with the reduced revenue from deterring risky customers. In particular, we formally show that less profitable banks have an incentive to choose a more lax reporting policy that caters to risky customers. When the strategic advertising effect is weak or absent, less profitable banks are expected to file fewer reports as a direct consequence of their less

[5] As noted by the BSA/AML Manual, "The decision to file a SAR is an inherently subjective judgment." A recent survey conducted by Bank Policy Institute reveals that banks only report around 4% of the alerts generated by their IT systems regarding suspicious accounts and transactions (The Bank Policy Institute, 2018).

stringent reporting standards. On the other hand, when the strategic advertising effect is dominant, the change in customer composition can offset the effect from decreased reporting stringency and as a result, *less* profitable banks file *more* reports.

Our baseline empirical analyses assess which effect from the model dominates (i.e., the strategic reporting versus the strategic advertising effect). We construct several measures of bank risk-taking incentives at the individual bank-level and project them to a county. These risk-taking measures include deposit competition, profitability, and capital adequacy (Keeley, 1990; Repullo, 2004; Martynova, 2015). Deposit competition is measured by the Herfindahl Index (HHI) based on the distribution of deposit market share or the share of branches among banks in a county. Bank profitability ratios (ROA and Net Interest Margin) and capital reserve ratios (Equity Ratio and Tier 1 Capital) are constructed at the parent bank level and then projected to a county using a shift-share measure (i.e., a Bartik instrument). For each county, we compute the weighted average of each measure based on banks that have active branches in the county, where the weights represent the percentage of local deposits occupied by a bank.

We examine the relation between proxies for bank risk-taking incentives and per capita county-level SAR volume. Our estimation controls for a stringent set of fixed effects, including state-year interactive fixed effects and county fixed effects. These fixed effects allow us to compare one county's change in SAR volume to the change in another county in the same state and year. If the strategic advertising effect dominates, we should expect that counties with more intense deposit competition, populated by less profitable banks with weaker balance sheets to generate higher SAR volume. If the strategic reporting effect dominates, we should observe the opposite relationship.

Our results suggest a positive relation between our proxies for risk-taking incentives and SAR reporting volume. We document a strong, negative relationship between deposit and branch concentration and SAR volume. The effects are economically meaningful, with a one-standard-deviation increase in the HHI measures being associated with a reduction in county-level SARs of roughly 11% to 16%, depending on the specification. Our bank profitability results yield similar inferences, indicating that more profitable banks generate fewer SAR reports. Finally, we find that banks with higher equity and Tier-1 capital ratios produce fewer SAR reports in a county. In terms of economic magnitudes, the results indicate that a one-standard-deviation increase in a bank's equity ratio is associated with about a 4% reduction in SAR reports.[6] Overall, we document strong evidence in support of the strategic advertising effect channel. Banks with higher risk-taking incentives adopt lax reporting policies. However, this lax reporting policy attracts more criminals, which offsets the effects of having a less stringent reporting policy and ultimately raises SAR volume.

The above analyses do not allow us to observe local suspicious activities because they are not, by nature, observable to econometricians unless they are reported and detected. We thus next consider a maximum likelihood estimation that allows us to infer the level of suspicious activities. Our estimation utilizes a "missing information model" (Feinstein, 1990; Wang et al., 2010; Khanna et al., 2015) that embeds separate structural equations which allow us to isolate the effects of bank profitability on reporting choices. Our estimation results reveal that bank profitability is indeed positively associated with reporting standard stringency. Less stringent reporting standards, in turn, spur local criminal activities. The results confirm the mechanism at play and illustrate how decreased bank profits translate into increases in observed SAR activities. In addition to fleshing out economic mechanisms, the structural framework allows us quantify the importance of banks' reporting strategies in attracting clients. It also highlights an assortative matching between criminal activities and banks with weakest compliance standards.

To strengthen our empirical analyses, we next conduct a wide set of tests that allow us to make stronger causal inferences. To start, we incorporate a plausibly exogenous shock to bank liquidity based on shale gas production. Recent evidence in Gilje et al. (2016) shows that shale oil and gas production generates unexpected windfalls to local banks, and that the liquidity infusion spills over to other branches of those banks. We conjecture that banks that benefit from shale extraction should have lower incentives to engage in money-laundering transactions. Consistent with expectations, our results indicate that higher (lower) levels of shale growth are associated with substantial reductions (increases) in SAR volume in counties populated by shale-exposed

[6] In the Internet Appendix (Section 1), we also show that our results are robust to using an alternative scalar based on the total deposits in a county.

banks.[7] These results further support the strategic advertising channel and demonstrate a positive causal relation between banks' risk-taking incentives and SAR volume.

We further conduct a detailed pre-trend analysis, in which we examine the relationship between SAR volume and lags and leads of profitability. This test helps address the concern that our parameter estimates might be driven by our Bartik weights, instead of by changes in bank profitability (Goldsmith-Pinkham et al., 2020).[8] For this alternative explanation to hold, we should continue to observe significant relationships between prior-period SAR volume and profitability. Our analyses indicate that this is not the case. Our profitability measures are only associated with current and future SAR volume, and bear *no* relationship with past SAR volume. This result also helps alleviate the concern that our results are driven by persistent bank or local characteristics. Overall, this analysis suggests that our baseline results reliably capture the effects of bank profitability and are not driven by the Bartik weights or other persistent bank or local characteristics.

Could our results be driven by underlying county-level characteristics correlated with both local banks' risk-taking incentives and SAR volume? For example, counties with low crime may simultaneously have fewer SARs and more profitable banks, thus suggesting that our results do not necessarily capture the effects of banks' risk taking incentives. To alleviate this concern, we augment our analyses by controlling for the level of SARs filed by non-bank institutions, which include casinos and money service businesses. The underlying assumption in these tests is that the level of SAR reports generated by non-bank institutions provides a reliable estimate of underlying criminal activity in a locality. We find that the relation between bank risk-taking and SAR reporting remains robust after controlling for the level of non-bank SARs. In addition, the inferences from our shale exposure experiment are unaffected by the inclusion of controls for the level of non-bank SAR activity. Overall, these findings suggest that our results are unlikely to be driven by underlying criminal activity in a county.

Our evidence thus far demonstrates a robust link between bank incentives and SAR volume at the county level. In the latter half of our study, we conduct several additional analyses to further

[7]These results persist after controlling for the potential for shale booms to boost loan growth and employment growth in a county.

[8]Following Goldsmith-Pinkham et al. (2020), we calculate the Rotemberg weights associated with our Bartik instruments. The weights are all small and exhibit low correlation to both bank profitability and the variation in deposit shares.

our understanding of the economic mechanisms underpinning our results and address alternative explanations.

We first consider whether our effects vary with the level of underlying crime in a region. Our theoretical model predicts that the bank profitability-SAR relationship should be more pronounced in counties with a greater supply of crime as banks face more criminals to transact with in these counties. We collect data on high intensity drug trafficking areas (HIDTA) and high intensity financial crime areas (HIFCA) and examine how our findings vary based on local crime. Consistent with expectations from the model, we find that our results are most pronounced in regions that regulators designate as HIDTA or HIFCA.

We next address two alternative explanations for our findings. The first is based on the idea that our results may be driven by financial constraints that limit a bank's ability to invest in adequate AML systems and not related to risk-taking motives. To alleviate this concern, we examine how our effects vary with bank size, as prior research indicates that size is one of the most dominant characteristics of constrained firms (Hadlock and Pierce, 2010). Under the alternative explanation, one could reason that small, constrained banks cannot afford to implement sophisticated AML systems to identify true criminals and thus file a greater volume of uninformative reports. Our results however suggest this is unlikely to be the case. The negative relation between SARs and bank profitability is concentrated among the largest banks in our sample, which are the least likely to be financially constrained.

We conclude by considering the possibility that banks are over-aggressive in filing SARs in order to "hedge" against regulatory fines. In our final analysis, we incorporate detailed data on money laundering violations from a large misconduct database maintained by the nonprofit organization *Good Jobs First*. We then assess the plausibility of the hedging explanation by examining whether SAR volume is predictive of future violations. Under the alternative "hedging" explanation, SARs should bear no relationship with future violations as they are not indicative of actual misconduct. However, we find that higher SAR volume is associated with a *greater* propensity for banks to incur a violation. This finding is at odds with the "hedging" arguments but supports our conjecture that higher SAR volume is driven by banks transacting with more risky criminals. Overall, our collective findings are most consistent with risk-taking incentives encouraging banks to transact with customers with greater criminal potential.

Our study adds to the current discussion regarding the consequences of AML regulations and the effectiveness of SAR reporting. In two concurrent studies, Ağca et al. (2020) and Williams et al. (2020) examine the effect of AML regulations on bank lending. They find that tightened regulations against money laundering could reduce bank liquidity and alter banking competition, thus influencing credit provisions to the local economy. Instead, our study focuses on a bank's reporting strategy and its consequences for financial crime. Our results suggest that a bank's SAR reporting stringency can provide a signal of its AML efforts and facilitate crime. In this respect, our paper also adds to the ongoing policy debate highlighting the limitations of SARs. For example, U.K. think tank "Royal United Services Initiative" argues that "[i]n all major financial markets, the number of reports of suspicions of money laundering continues to grow. Despite this, the estimated impact of anti-money laundering (AML) reporting, in terms of disrupting crime and terrorist financing, remains low" (Maxwell and Artingstall, 2017). Relatedly, critics claim that SAR reporting is ineffective because institutions engage in "defensive filing". Our results suggest another limitation of SAR reports in that sophisticated criminals can learn about a bank's risk culture and navigate the system by transacting with lax banks.

Our paper also contributes to the literature on bank risk-taking incentives in two ways. First, our study extends research examining the effect of competition on bank risk taking (see e.g., Keeley, 1990; Allen and Gale, 2004; Laeven and Levine, 2009; Martinez-Miera and Repullo, 2010). One key insight from this literature is that increased competition lowers bank profit and erodes charter values, which in turn leads to increases in asset risk and reductions in bank capital. Our paper complements this literature by focusing on a different kind of risk-taking behavior — banking transactions that facilitate financial crimes. Second, our study also complements research showing that banks take advantage of regulation loopholes and strategically report asset risk (see e.g., Vallascas and Hagendorff, 2013; Begley et al., 2017; Plosser and Santos, 2018). Our study reveals a novel channel through which banks take advantage of the discretion allowed by regulation and strategically alter the quality and timing of their reporting.

Finally, our paper relates to a growing academic literature examining misconduct in the financial services industry (Dimmock et al., 2018; Pacelli, 2019; Egan et al., 2019). In particular, these studies generally suggest a "catering" phenomenon whereby banks help facilitate misconduct through the counterparties they transact with. For example, recent research shows financial advisors with prior misconduct are more likely to find employment at corrupt brokerage houses (Egan et al., 2019). Our results suggest that some banks use lax reporting standards to signal their willingness to cater to criminals and facilitate financial crime.

2 Background on SAR

SARs are an important part of anti-money laundering statutes and regulations. They were initially established under the Bank Secrecy Act of 1970 for monitoring suspicious activities that would not otherwise be flagged.

The history of SAR regulation in the United States can be summarized as follows. The Bank Secrecy Act (also known as the Currency and Foreign Transactions Reporting Act) was originally enacted in 1970, following large currency deposits of illicit profits. After numerous legal battles, the constitutionality of the BSA was established by the U.S. Supreme Court in 1974. Over the next two decades, additional regulations further tightened AML regulation. Notably, FinCEN was created in 1990 to address the lack of intelligence and analysis and resources available to support financial investigations. The Bank Secrecy Act was amended several times, with some of the most significant changes occurring following the September 11$^{\text{th}}$ terrorist attacks. After the attacks, the USA Patriot Act was passed to help combat terrorism. Title III of the Patriot Act modified the BSA to make it more difficult for money launderers to operate and also make it easier for law enforcement agencies to monitor and detect money laundering operations.

Current federal regulations require banks, bank holding companies, and their subsidiaries to file a SAR if they detect:

- a criminal violation involving insider abuse
- a criminal violation aggregating $5,000 or more when a suspect can be identified
- a criminal violation aggregating $25,000 regardless of a potential suspect
- a transaction aggregating $5,000 or more in which the bank has reason to believe that money laundering or illegal activity occurred, the transaction was designed to evade BSA, or the transaction has no business or apparent lawful purpose and appears unusual

According to the BSA/AML examination manual, the process for reporting a SAR proceeds as follows. First, a bank identifies or has an alert of unusual activity. This can come through several different mechanisms, including employee identification (i.e., employee notices something suspicious), law enforcement inquiries, or transaction/surveillance monitoring system output.

After the alert comes in, the bank then focuses on investigating and evaluating the identified unusual activity. Banks are required to report suspicious activity that may involve money laundering, BSA violations, terrorist financing, and certain other crimes subject to the above thresholds. They are not obligated to investigate or confirm the underlying crime.

After thorough research and analysis, the findings of the investigation are forwarded to a final decision maker who has the authority to make the final SAR filing decision. The BSA manual specifically notes the following: "The decision to file a SAR is an inherently *subjective* judgment." In addition, examiners are encouraged to focus on whether the bank has an effective SAR decision-making process, not on whether an individual SAR decision is appropriate. This suggests that regardless of the bank's IT system, there is still a significant amount of "soft information" involved in SAR Reporting. Much of the collection and production of such soft information occurs at the local branch level, particularly among front-desk employees that interact with clients.

The bank completes and files the SAR no later than 30 calendar following the date of the initial detection of facts, or 60 days later if no suspect can be identified. According to a survey of 17 major U.S. banks conducted by the Bank Policy Institute, banks received 16 million alerts during 2017 and, after investigation, generated 640,000 suspicious activity reports. Among the reported activity, around 4% led to feedback and investigation from law enforcement. Nearly 30% of SAR reports are associated with account closures. Law enforcement may also request the bank to keep certain accounts open and actively monitor activities in these accounts.

3 The Model

In this section, we develop a simple theoretical model to guide our empirical analysis. Section 3.1 describes the model setup. Section 3.2 characterizes the bank's optimal reporting policy, the equilibrium composition of customers, and further model implications. Section 3.3 summarizes our empirical strategy for testing the model.

3.1 Model Setup

We consider a static model with the following agents. There is a financial institution ("bank"), a regulator, and two types of customers: safe and risky. The bank's business model is to execute transactions by its customers. Executing a transaction generates positive profits, normalized to \$1, for the bank. All agents are risk-neutral, there is no discounting, and the bank is protected by limited liability.

There are four dates $t \in \{0, 1, 2, 3\}$. At $t = 0$, the bank sets its reporting policy $\mathcal{R}$ and risky customers observe a signal about the chosen policy. Subsequently, at $t = 1$, customers approach the bank, which executes a single transaction for each of its customers. At $t = 2$, the bank receives private signals about each transaction and files a report to the regulator according to the chosen reporting policy. Finally, at $t = 3$, the regulator observes the bank's reports. The regulator investigates the reported and, potentially, also unreported transactions. The regulator assigns a fine to customers with an illegal transaction, if they are detected, and to the bank, if it did not report them. Figure 1 provides a timeline and summarizes the key model elements.

The bank has two types of customers, safe and risky. Safe customers can be interpreted as the bank's existing, routine customers, which have been thoroughly screened. Hence the bank is perfectly informed about this type and knows that these customers will not engage in illegal activities. We denote the fixed mass of this type by $x_0 > 0$. Risky customers, however, are more

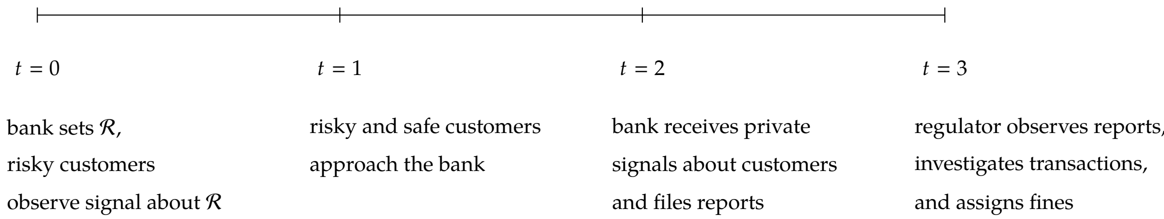


Figure 1: Timeline. This figure describes the different stages of the model and its key elements.

difficult to assess for the bank. More specifically, risky customer n is of type $\theta_n \in \{g, b\}$ with $\mathbb{P}(\theta_n = b) = \lambda \in (0,1)$. Thus, a risky customer can be either "good" ($\theta_n = g$) or "bad" ($\theta_n = b$) and λ captures the ex ante probability for the bank to face a bad customer. The only difference between customers with $\theta_n = g$ and $\theta_n = b$ is that the latter execute illegal transactions.

There is an infinite mass of potential risky customers indexed by $n \in (0, \infty)$. Each agent's private benefit from executing a transaction at the bank is given by $U_n > 0$ and we denote the decision to execute the transaction by $\mathcal{D}_n \in \{0, 1\}$. Since the agents' outside option is set to zero, they will choose $\mathcal{D}_n = 1$ as long as their private benefit exceeds the expected cost, which depends on the bank's reporting policy as shown below. The benefit for potential customer n is given by $U_n = \delta n^{\alpha}$ with $\delta > 0$ and $\alpha < 0$. This simple functional form captures the intuition that some risky clients value the bank's business higher than others. We denote the equilibrium mass of risky customers by $x_R \geq 0$. The *elasticity* parameter $\alpha = \frac{dU_n}{dn} \cdot \frac{n}{U_n}$ plays an important role in our analysis because it determines the change in the number of risky customers in response to changes in the bank's reporting policy.

The bank only receives an imperfect private signal $\sigma_n \in \{g, b, \emptyset\}$ about its risky clients' type. More specifically, this signal reveals each client's type with probability γ, i.e. $\mathbb{P}(\sigma_n = \theta_n) = \gamma \in (0, 1)$. With probability $1 - \gamma$ the signal reveals no information about the client's type and $\sigma_n = \emptyset$. The signal can be interpreted as the outcome of the bank's internal monitoring efforts. We assume the bank observes σ_n after the transactions have been executed and truthfully communicates the signal to the regulator according to the bank's reporting policy.

At $t = 0$, risky customers observe a signal about the bank's reporting policy $\mathcal{R}$. It follows that they anticipate the extent to which the bank reports their transaction to the regulator, on average.[9] Examples of such signals include criminals observing banks' investment in (screening) technology or hiring of AML-related personnel. They also include encounters with bank employees whereby employees may ask additional questions regarding the source of the funds and the purpose of the transaction. In addition, criminals can also exchange information regarding banks' AML policies and recommend lax banks to one another.[10] Finally, we note that this mechanism is consistent with the conventional wisdom that certain banks adopt a certain "risk culture" and build a reputation for a certain reporting "style" over time. In our model, we assume the signal is perfectly informative for simplicity, although all the model predictions persist to an alternative setting where the signal is imperfect and reveals the true reporting policy only with some probability.

We allow the bank to choose the reporting policy between two options: "lax" ($\mathcal{R} = l$) and "strict" ($\mathcal{R} = s$). If the bank chooses a lax reporting policy, then it only reports transactions associated with a "bad" signal to the regulator. However, if the bank chooses the strict policy, then it also reports transactions that are associated with an uninformative signal.[11] For ease of exposition, we assume that implementing either policy does not involve a direct cost for the bank. As a result, there are no "baked-in" asymmetries between the two reporting choices.

Formally, we define the bank's decision to report transaction $n \in [0, x_R]$ to the regulator by $r_n \in \{0, 1\}$, which is a function of the bank's private signal and the reporting policy:

$$r_n(\sigma_n; \mathcal{R}) = \begin{cases} 1 & \text{if } \mathcal{R} = l \text{ and } \sigma_n = b \text{ or if } \mathcal{R} = s \text{ and } \sigma_n \in \{b, \emptyset\} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The regulator observes and investigates the set of reported transactions. We assume that the regulator detects all bad types $\theta_n = b$ among the reported transactions. This assumption captures

[9]Note that customers cannot perfectly predict the bank's *realized* reporting decision because σ_n is only a noisy signal.

[10]Investigations in HSBC's money laundering practices revealed that drug traffickers used to recommend HSBC to each other because of the bank's lax reporting policy (*HSBC: Dirty Money and White Collars*, InsightCrime, 2020). Interviews of bank examiners also suggest that criminals could gauge the bank's AML stringency through their interactions with bank employees (*Confessions of a Former Money Launderer*, Bank Info Security, 2008).

[11]It should be noted that the bank would never choose to report all transactions, including those with $\sigma_n = g$, because these transactions never result in a fine for the bank. Thus the restriction to the two pure strategies $\mathcal{R} = l$ and $\mathcal{R} = s$ is without loss of generality.

the intuition that eventually the regulator will find out whether a reported transaction was truly illegal, even though these investigations might take a long time in reality. Furthermore, the regulator directly investigates the entire bank with probability $\pi \in (0, 1)$. In this case, the regulator detects all bad customers, including those that were not reported by the bank. Detected bad types incur a cost of $f > 0$, which can be interpreted as a monetary fine or the disutility from being convicted. If the bank is caught not reporting an illegal transaction, then it incurs a cost F.[12] To allow for a positive relationship between the number of unreported bad types and the fine, we impose a linear functional form for this cost and set $F = F_0 + F_1 x_R$ with $F_0, F_1 > 0$. Therefore, F_0 captures the fixed regulatory cost component and F_1 the variable component, which can also be interpreted as the bank's reputation loss upon being investigated. Yet another way to interpret F_1 is that a regulator might be more likely to investigate a bank with a greater number of risky customers that might be attracted by the bank's lax reporting standards. In this interpretation, F_1 captures the increase in the *expected fine*.[13]

3.2 Equilibrium and Implications

The equilibrium consists of a reporting choice $\mathcal{R} \in \{l, s\}$ by the bank and a depositing choice $\mathcal{D}_n \in \{0, 1\}$ by each potential risky customer. We proceed by backward induction and first solve for the equilibrium mass of risky customers, given the bank's reporting policy. For the marginal customer, the benefit U_n must be equal to the expected fine, which depends on the bank's reporting policy. We can express the ex ante probability that a risky customer is caught with an illegal transaction as

$$\mathbb{P}(d_n = 1) = \begin{cases} \lambda\left(\gamma + (1-\gamma)\pi\right) & \text{if } \mathcal{R} = l \\ \lambda & \text{if } \mathcal{R} = s \end{cases} \tag{2}$$

where $d_n \in \{0, 1\}$ represents the event that customer n is caught with an illegal transaction. Under the lax reporting policy, a bad customer is caught after being reported by the bank, which occurs with probability γ, or after being directly detected by the regulator, which occurs with probability

[12] Section 3 in the Internet Appendix validates this assumption by showing a direct, costly consequence to banks following money laundering reporting violations.

[13] An alternative mechanism is to make the investigation probability π a function of x_R. Our results are robust to this specification.

$(1-\gamma)\pi$. Under the strict policy, all bad customers are reported by the bank and thus always detected by the regulator.

Next, we solve for the equilibrium mass of risky customers for a given reporting policy by setting $U_n = \mathbb{P}(d_n = 1) f$.

Lemma 1 (Strategic advertising effect) *The bank attracts more risky customers with a lax reporting policy.*

Proof: *See Appendix A.1.*

Lemma 1 characterizes the equilibrium mass of risky customers for a fixed reporting choice. The lax policy renders it less likely that an illegal transaction is detected by the regulator and lowers the expected regulatory fine. As a result, the mass of risky customers is greater under $\mathcal{R} = l$ than under $\mathcal{R} = s$. In the following, we will refer to this channel as the *strategic advertising effect*.

At $t = 0$, the bank chooses its reporting policy $\mathcal{R} \in \{l, s\}$ to maximize its expected utility, i.e. $\max_{\mathcal{R}\in\{l,s\}} \mathbb{E}[U_b]$. The bank's utility function is given as:[14]

$$U_b(\mathcal{R}) = \max(\Pi(\mathcal{R}), 0) \tag{3}$$

where $\Pi(\mathcal{R}) \equiv x_0 + x_R(\mathcal{R}) - \mathcal{I}_{\{d_b=1\}}F$ equals the bank's profits and depends on two components. First, the profits from executing the transactions of its safe and risky customers. Second, if the bank chooses the lax reporting policy, it might be caught not reporting an illegal transaction and we denote this event by $d_b \in \{0, 1\}$. If the bank is caught, it faces a regulatory cost F. From the bank's perspective, d_b is a binary random variable. If $\mathcal{R} = s$, then it is equal to zero with probability one; if $\mathcal{R} = l$, then it is equal to zero with probability $1-\pi$ and equal to one otherwise. Hence, the bank can reduce the expected penalty by choosing the strict policy. In the following, we will refer to this channel as the *strategic reporting effect*. Finally, the bank is protected by limited liability, which implies that the loss is capped if $\Pi < 0$.

Proposition 1 (Reporting equilibrium) *In the unique reporting equilibrium, the bank's optimal choice depends on x_0 if and only if $F > x_R(l)$. In this case, the bank chooses $\mathcal{R} = s$ if $x_0 > \overline{x_0}$ and $\mathcal{R} = l$, otherwise.*

[14]Note that the bank does not have an incentive to turn down customers.

If $F \leq x_R(l)$, then the optimal choice does not depend on x_0 and the bank chooses $\mathcal{R} = s$ if $F > \overline{F}$ and $\mathcal{R} = l$, otherwise. The constants $\overline{F}$ and $\overline{x_0}$ are defined in the Appendix.

Proof: *See Appendix A.2.*

Proposition 1 shows that the bank's optimal reporting choice critically depends on the regulatory fine F and x_0, which proxies for ex ante profitability. More specifically, bank profitability only matters if the regulatory fine is sufficiently high and the limited liability constraint is binding. This constraint leads to a convexity in the bank's objective function and implies that the optimal trade-off depends on x_0. In our model, this convexity comes from potential bank failure when receiving the fine. This design helps simplify the model and highlight the mechanism transparently. However, it is important to note that our mechanism applies to more realistic scenarios without necessarily requiring bank failure. For example, our predictions persist if banks face a wide distribution of regulatory fines, whereby only the largest fines in the distribution cause bank failure (i.e., "tail risk"). Alternatively, short-term pressure to pursue profits can also lead to a convex objective function if the bank (or top management who can influence the bank's operation and reporting decisions) is rewarded for exceeding a certain earnings target.[15] We formally show in Section 4 of the Internet Appendix that this scenario leads to similar results and provide further empirical evidence for this channel.

Due to the convexity in the bank's objective function, the optimal trade-off depends on x_0. If x_0 is sufficiently small, then the bank has a high incentive to take on regulatory risk and chooses the riskier reporting policy $\mathcal{R} = l$. However, if x_0 is high, then the expected loss from the regulator's fine dominates and the bank chooses the safer reporting policy $\mathcal{R} = s$.

The bank's reporting choice affects the volume of reported transactions through the strategic advertising and reporting effects mentioned above. Since a strict reporting policy strengthens the reporting effect but weakens the advertising effect, the volume of reported transactions is not necessarily higher under this policy.[16] On the one hand, there is a positive direct effect because the bank reports transactions with $\sigma_n = b$ *and* $\sigma_n = \emptyset$ under $\mathcal{R} = s$. For a given mass of risky

[15]Such incentives might also arise from the bank management's compensation contracts.
[16]This is formally shown in Appendix A.3.

customers, this effect would clearly increase the volume of reports. On the other hand, however, there is also a negative indirect effect. Potential customers understand the increased risk of being reported by a strict bank and rationally match with lax banks. As a result, the equilibrium mass of risky customers is lower for a strict bank (see Lemma 1) and this indirect effect could offset the direct effect. More specifically, we show in Appendix A.3 that this is the case if the customers' elasticity α is sufficiently small in absolute value so that the equilibrium mass of risky customers x_R is very sensitive to changes in the expected fine.

Corollary 1 (Bank conditions and SAR volume) *Based on the reporting equilibrium in Proposition 1, we find that:*

1. *The volume of reported transactions is increasing in x_0 if $\alpha < \overline{\alpha}$ and $F > x_R(l)$;*
2. *The volume of reported transactions is decreasing in x_0 if $\alpha \geq \overline{\alpha}$ and $F > x_R(l)$;*
3. *Otherwise, the volume of reported transactions does not depend on x_0.*

The constant $\overline{\alpha} < 0$ is formally defined in the Appendix. It is decreasing in λ.

Proof: *See Appendix A.3.*

Corollary 1 formalizes the impact of x_0, a proxy for bank profitability and an inverse proxy for its willingness to take risk, on the volume of reported transactions. It illustrates that the relationship between profitability and SAR volume depends critically on the economic environment, i.e. on the customers' elasticity (α) and the regulatory fine (F). Based on these results, we expect a bank with a higher incentive to take risk to choose a lax reporting policy (see Proposition 1), which in turn attracts more suspicious customers. This bank type generates relatively *more* reports if the increase in the mass of risky customers is sufficiently large or equivalently if the customers' elasticity α is sufficiently small in absolute value.

The threshold $\overline{\alpha}$ in Corollary 1 depends on the model parameter λ. More specifically, $\overline{\alpha}$ is decreasing in λ, which captures the probability that the bank faces a criminal customer. This result suggests that SAR volume is more likely to be negatively related with profitability if underlying local criminal activity is high. Another prediction of Corollary 1 is that future violations, i.e.,

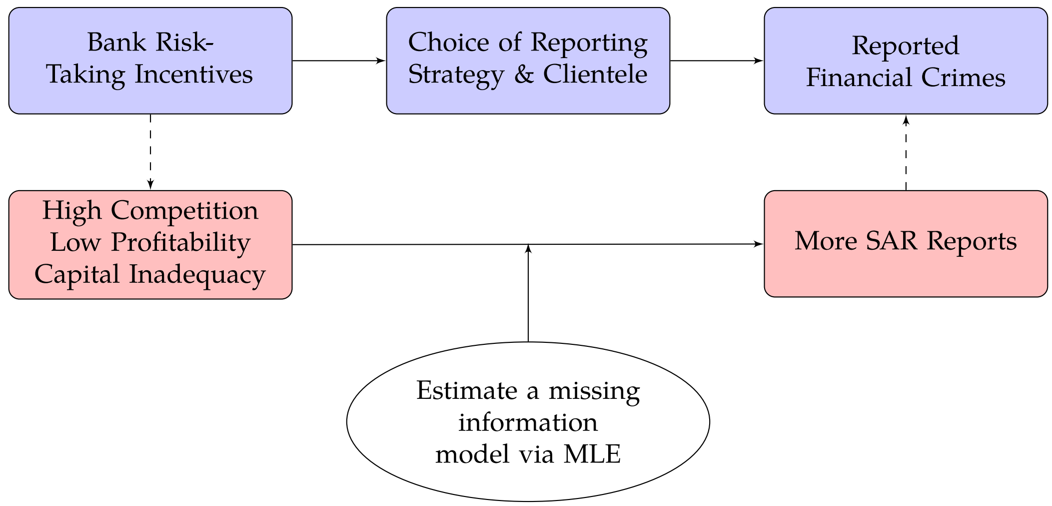


Figure 2: Empirical Framework. This figure describes the central prediction of the model and our empirical framework.

the mass of unreported criminal transactions, is positively related with SAR volume only if the strategic advertising effect dominates. In this case, lax banks will report more SARs and have a greater mass of unreported criminal transactions, leading to a higher likelihood of violation. If the strategic reporting effect dominates, this relationship is reversed.

3.3 Empirical Roadmap

In the sections to follow, we design a two-pronged approach to test the model predictions. As shown in Figure 2, the model describes how banks' risk-taking incentives shape their reporting strategy and clientele composition, which in turn affect the total volume of money-laundering activity reported by banks. We first adopt a reduced-form approach and test the relationship between bank characteristics and SAR volume. Next, we infer the "hidden" mechanism using a structural estimation approach, which helps us back out the inter-relation among bank characteristics, reporting policies, and the matching between banks and risky customers from data patterns.

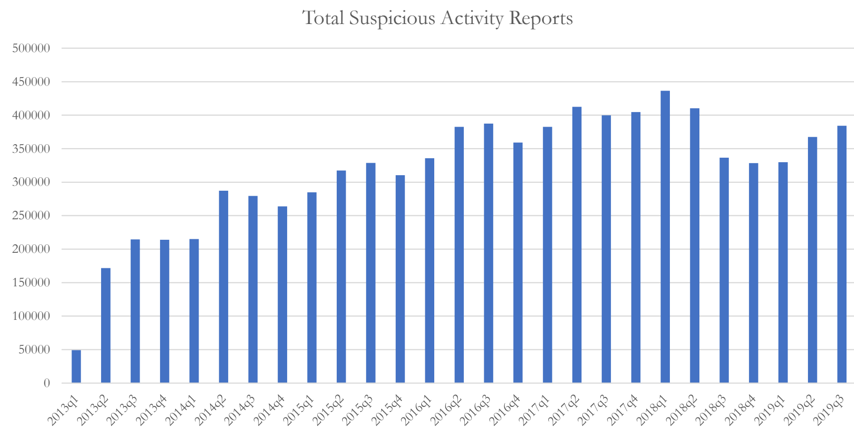


Figure 3: Suspicious Activity Reports Over Time. This figure illustrates the total number of suspicious activity reports related to money-laundering activities by U.S. depository institutions over our sample period.

4 Data and Empirical Framework

4.1 SAR Reports

We collect suspicious activity reports from the U.S. Treasury Financial Crimes Enforcement Network (FinCEN), which has maintained an online data repository tracking back to 2013.[17] The FinCEN database contains information on the location, month, and type of suspicious activity (including industry type, instrument type, product type) at the aggregate level. For our main analyses, we focus only on money laundering activities reported by deposit institutions. Using this data, we construct a measure of SAR volume that accounts for variation in population. Specifically, we sum the total SAR reports in a county-year-quarter and then divide by the county's population (SAR/Pop).[18]

Figure 3 presents the trend in SAR reporting activity over time. The X-axis displays the calendar quarter and the Y-axis displays the total number of SAR reports filed. Consistent with the discussion in Section 1, there appears to be a steady increase in SAR reporting over time. For example, in the first quarter of 2014, approximately 200,000 SAR reports were filed by depository institutions. This number doubles to approximately 400,000 by the third quarter of 2019.

In Figure 4, we further explore geographical heterogeneity in SAR reporting and crime, using data from 2016 (the middle of our sample period). For this illustration, we collect data on high

[17]FinCEN began requiring SAR reports to be efiled in 2012.
[18]In the Internet Appendix (Section 1), we also consider an alternative measure of SAR volume scaled by local deposits.

intensity financial crime (HIFCA) areas from FinCEN and high intensity drug trafficking areas (HIDTA) from the National HIDTA Assistance Center. Panel A illustrates per capita SAR reports (i.e., SAR/Pop) by county. Darker colors represent counties with higher SAR volumes. The figure generally indicates that SAR volume is greater in areas with greater population densities, which includes counties near large coastal cities on the West Coast and Northeast. This pattern is intuitive as these more populous counties likely have a larger volume of underlying criminal activity. In contrast, SAR reports are less frequent in less populous counties in the Midwest. Panel B illustrates high-financial-crime and high-drug-trafficking areas. There appears to be substantial overlap between areas with high SAR volume and those with high levels of criminal activities. Overall, these plots suggest substantial cross-county variation in SAR activity and also suggest that SAR activity reflects underlying financial crime. Our subsequent analyses will explicitly control for geographical heterogeneity through the inclusion of both county and state-year interactive fixed effects.

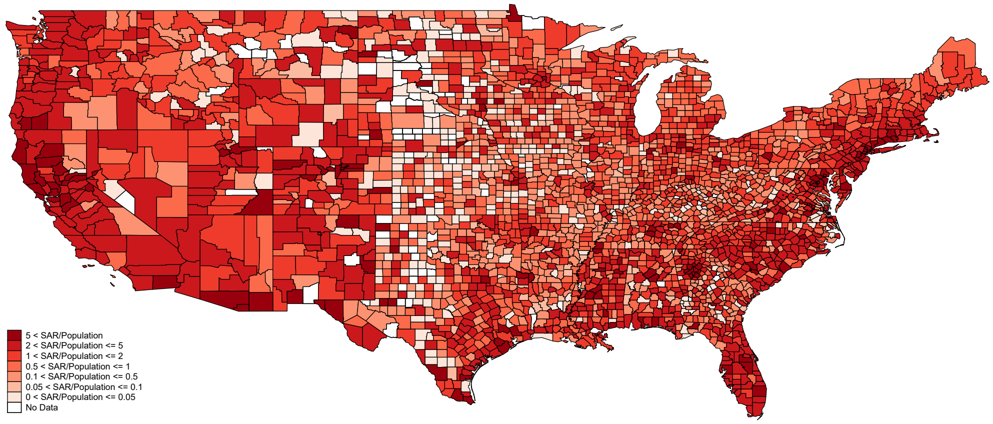
4.2 Violations Data

In our structural estimation and additional analyses, we rely on money-laundering violations data. We obtain this data from Good Jobs First, a national policy resource center promoting corporate and government accountability in economic development. Their "Violation Tracker" tool is a comprehensive database on corporate misconduct that spans from 2000 through 2019.[19] These data have been featured in numerous recent academic studies including Heese et al. (2021) and Raghunandan (2021). While regulatory enforcement is a rare event, many large banks in our sample have experienced a money-laundering violation in recent years, including JP Morgan Chase, Bank of America, Citibank, etc. As a result, 10% of branches have a violation at the headquarters level. The average fine in our sample is around \$100 million, with the highest being \$1.7 billion.

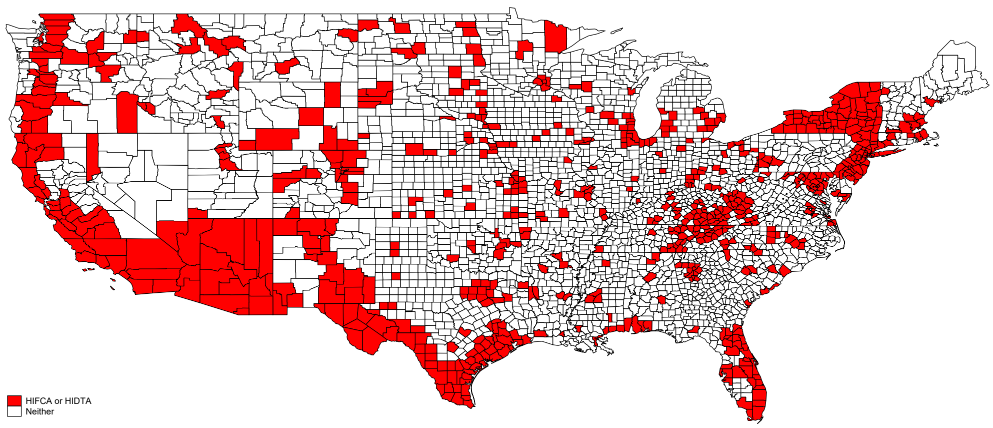
4.3 Variables of Interest

We construct several measures to reflect banks' risk-taking incentives, including local banking competition measures and bank profitability ratios. These measures are motivated by the notion

[19]https://www.goodjobsfirst.org/violation-tracker



(A) SAR per Capita by County



(B) High Financial Crime and Drug-Trafficking Counties

Figure 4: Distribution of Suspicious Activity Reports over U.S. Counties. This figure depicts the distribution of suspicious activity reports in each U.S. county. Panel A shows the per-capita SAR reports in each county. Darker colors indicate more suspicious activity reports. Panel B shows counties with high levels of financial crime activities. Red areas indicate counties classified by FinCEN as having high levels of financial crimes (HIFCA) or classified by the DEA as areas with high levels of drug trafficking activities (HIDTA).

that fierce competition and low profitability erode the franchise value of banks (Keeley, 1990) and move them closer to the convex part of their payoff distribution. Such banks are prone to take excessive risks and "gamble for resurrection" as they are protected by limited liability, and the cost of doing so (i.e., losing their franchise value in the event of failure) is relatively low. We also consider measures accounting for bank equity capital adequacy, which are the primary target of various micro prudential policies (Allen and Gale, 2004; Kim and Santomero, 1988; Demirguc-Kunt et al., 2013; Ongena et al., 2013).

Our first two measures reflect the intensity of banking competition in a county. We collect annual deposit data at the branch-level from the FDIC and compute a standard Herfindahl Index

(HHI), defined as the sum of the squared deposit-market shares of all banks that operate branches in a county in a given year.[20] As noted by Drechsler et al. (2017), this measure is frequently used by bank regulators to assess competition. Specifically, *Deposit HHI* is computed as follows:

$$Deposit\ HHI_{c,t} = \sum_b \left(\frac{Deposit_{b,c,t}}{Deposit_{c,t}} \right)^2 \tag{4}$$

where $Deposit_{b,c,t}$ represents the total deposits that bank b's branches hold in county c in year t. $Deposit_{c,t}$ represents the total deposits in county c in year t.

We also construct a supplementary concentration measure based on the share of branches a bank has in a county (*Branch HHI*):

$$Branch\ HHI_{c,t} = \sum_b \left(\frac{Branches_{b,c,t}}{Branches_{c,t}} \right)^2 \tag{5}$$

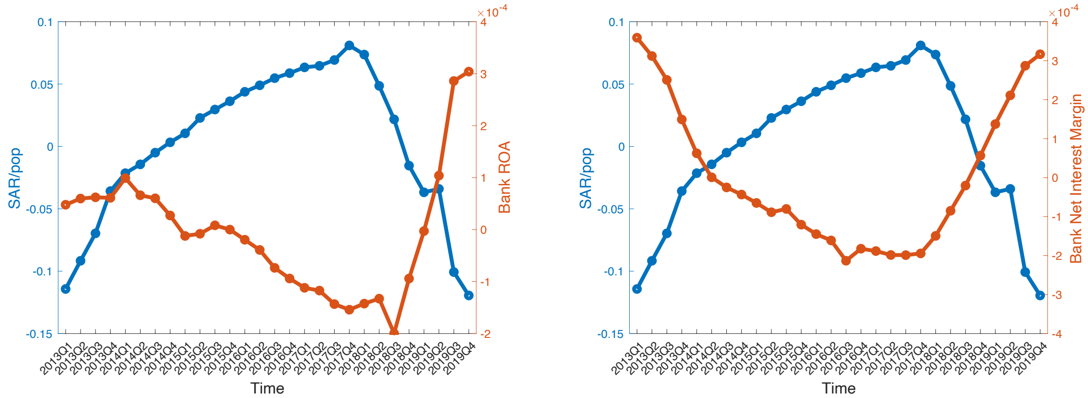
where $Branches_{b,c,t}$ represents the number of branches that bank b has in county c in year t, and $Branches_{c,t}$ stands for the total number of branches in county c. Higher levels of both *Deposit HHI* and *Branch HHI* indicate lower levels of competition.

Our remaining measures require us to gauge the *local* impact of a bank's financial health. For these measures, we collect banks' quarterly balance sheet and income statement data from Call Reports. We require banks to have no missing asset value for our sample period 2013-2018.[21] We compute profitability and capital adequacy (*ROA*, *Net Interest Margin*, *Equity Ratio* and *Tier 1 Capital Ratio*) at the bank level and project these measures to the local county where the bank's branches are located. Specifically, for each measure, we design a shift-share type instrument, defined as the weighted average of each ratio for all banks taking deposits in a given county. Our weights are based on the share of deposits that the bank takes relative to the total deposits in a county. Formally, our shift-share measures are defined as:

$$Bank\ Measure_{c,t} = \sum_b \frac{Deposit_{b,c,t}}{Deposit_{c,t}} \times X_{b,t}, \tag{6}$$

[20] Deposit data is only available on an annual basis.

[21] Our sample covers 93% of all commercial bank branches. Relaxing this requirement does not affect our results.



(A) Bank ROA and SAR (B) Bank Net Int. Margin and SAR

Figure 5: Aggregate Patterns of Bank Profitability and SAR Volume. This figure reports the time series average of bank profitability and net interest margin as well as the average SAR-to-population ratio across all counties. The horizontal axis indicates time (by quarter). Scales of SAR volume are shown on the left vertical axis and scales of bank profitability are shown on the right vertical axis. Time trends and quarterly seasonality have been removed from all series. At each point in time, we report the past four-quarter averages of each variable.

where $Bank\ Measure_{c,t} \in \{Bank\ ROA, Bank\ Net\ Interest\ Margin, Bank\ Equity\ Ratio, Bank\ Tier\ 1\ Capital\ Ratio\}$, b indexes banks, c indexes counties, and t represents year-quarters, and $X_{b,t}$ represents the above-mentioned bank characteristics.

Figure 5 depicts the correlation between bank profitability and average per-capita SAR at the aggregate level. For each quarter, we compute the average value of *Bank ROA*, *Bank Net Interest Margin*, and *SAR/Pop* across all counties, and remove time trends and seasonality from all series. We then plot the rolling average of the transformed variable over the past four quarters. There is a clear negative association between bank profitability and SAR volume, which is consistent with there being a profit-driven risk taking incentive. We focus on the micro-level variation of this relationship in our main analysis.

4.4 Controls

Our tests account for county-level demographic characteristics that could influence SAR activity. These characteristics include housing price index growth (*HPI Growth*), the natural log of the median family income in a county (*Log(Median Income)*), the percentage of African American and Asian population (*%African American* and *%Asian*), and the crime rate (*Crime Rate*). Data to construct these measures are obtained from the U.S. Census and are available on an annual basis. Detailed variable definitions are provided in Appendix B.

4.5 Empirical Framework

We assess the relationship between banks' risk-taking incentives and SAR reporting, by estimating the following regression:

$$SAR/Pop_{c,t} = \beta_1 Bank\ Incentive_{c,t-1} + \textbf{Controls} + \xi_c + \eta_{s,t} + \epsilon_{c,t}, \tag{7}$$

where c indexes county and t indexes year or calendar quarter (i.e., year-quarter).[22] *Bank Incentive* include the two competition measures (*Deposit HHI* and *Branch HHI*) and the four measures reflecting bank fundamentals projected to the county-level (*Bank ROA*, *Bank Net Interest Margin*, *Bank Equity Ratio*, *Bank Tier 1 Capital Ratio*). Control variables include HPI growth, income, population, race, and crime rate, as described above. The model features county fixed effects (ξ_c) and state-year interactive fixed effects ($\eta_{s,t}$).[23] These fixed effects control for any unobservable *time-invariant* county-level characteristics as well as unobservable *time-varying* state-level characteristics that might influence SAR activity.

4.6 Descriptive Statistics

Table 1 presents descriptive statistics for the variables in our study. The data indicate that the average county has approximately 1.4 SARs filed per 1,000 people. The average bank is profitable. The median income level is approximately $31,000 and crime rates are around 3%, on average.

Table 1 About Here

5 Main Results

We begin our analyses by examining the relationship between banks' risk-taking incentives and SAR activity using the various risk-taking proxies described above. We first examine the relationship between local banking competition and SAR activity. Panel A of Table 2 provides the results from estimating equation (7) using *Deposit HHI* and *Branch HHI* as our variables of interest.

[22] As noted above, our competition measures utilize annual data whereas our other measures utilize quarterly data. Results on bank profitability and capital adequacy are robust if we use annual data.

[23] In untabulated robustness tests, we also consider broader geographical fixed effects, defined at the census division level. Our results are robust to replacing state-year fixed effects with census division-year interactive fixed effects.

The results suggest a strong, positive relation between competition and county-level SAR volume. Both concentration measures, *Deposit HHI* and *Branch HHI* load negatively and significantly after including a robust set of fixed effects and controls (p<0.01). The economic magnitudes are also substantial. A one-standard-deviation increase in *Deposit HHI* is associated with a 16-percentage-point reduction in SAR volume. Similarly, a one-standard-deviation increase in *Branch HHI* reduces SAR activity by up to roughly 20 percentage points.

TABLE 2 ABOUT HERE

We next examine the relationship between bank profitability and SAR activity at the county-level. In Panel B, we provide the results from estimating equation (7) using *Bank ROA* and *Bank Net Interest Margin* as our variables of interest. The results indicate a negative relation between both profitability measures and SAR volume. In terms of economic magnitudes, the coefficient in Column (2) suggests that a one-standard-deviation increase in ROA reduces SAR volume by roughly 0.8 percentage points, which is 1.7% of the sample mean. In Column (4), the economic magnitudes suggest that a one-standard-deviation increase in net interest margin is associated with a 4% decrease in SAR volume.

Finally, we consider alternative risk-taking measures that reflect a bank's balance sheet strength (*Bank Equity Ratio* and *Bank Tier 1 Capital Ratio*). As discussed above, we expect highly-levered and capital-deficient banks to have stronger risk-taking incentives (Kim and Santomero 1988, Blum 1999, and Hellmann et al. 2000). Panel C of Table 2 provides the results from re-estimating equation (7) with our alternative risk-taking measures. We generally document a negative relation between both measures and SAR volume. For *Bank Equity Ratio*, the coefficients are negative and significant across both Columns (1) and (2). In terms of economic magnitudes, the results suggest that a one-standard-deviation increase in the bank equity ratio reduces SAR volume by roughly 1.8 percentage points, which is around 4% of the sample mean. We document similar effects for *Tier 1 Capital Ratio* in Column (4).

Overall, our baseline results provide strong support for the strategic advertising channel. Competition at the county-level is positively associated with county-level SARs. In addition, banks with lower profitability and banks that are capital deficient tend to generate more SARs. These analyses help establish a link between bank risk-taking incentives and reported financial crimes, as presented in Figure 2. Our results are consistent with banks relaxing their AML policies when faced with greater risk-taking incentives, and criminals responding to such lax policies by transacting with the bank. Our subsequent analyses will shed further light on the "hidden" mechanism related to banks' choice of reporting strategy and clientele.

6 Structural Estimation

In this section, we supplement our baseline analysis by adopting a maximum likelihood estimation that allows us to infer the level of local suspicious activities. One potential concern with our baseline results is that local suspicious activities, by nature, are not observable to econometricians unless they are reported and detected. Therefore, we can only test the joint implication of bank profit on their reporting strategy and the feedback effect of such choice on bank clientele. Without imposing further structure, we cannot disentangle the two effects and directly test the underlying mechanisms that we outline in Section 3. To overcome this challenge, we follow the literature of "missing information models" (Feinstein, 1990; Wang et al., 2010; Khanna et al., 2015) to infer the mechanisms by embedding structural equations that model separately the determination of local criminal activities and bank reporting strategy. We estimate the system of equations jointly using maximum likelihood, which allows us to infer the unobservable variables of interest and uncover the relationships between bank profit, their reporting stringency, and the clientele effect. This approach helps us validate whether our main results are consistent with the mechanism outlined by the model.

6.1 Underlying Suspicious Clients

Let us consider a state $s \in \{1, 2, ...S\}$ in the economy, which consists of counties $j \in \{1, 2, ...J_s\}$. We use $I_{s,t}$ $(I_{j,s,t})$ to denote the number of active bank branches in state s (county j) at time t. We denote the risky population in state s at time t, by $N_{s,t}$ ($N_{s,t}$ is state and time-specific). The risky population consists of a continuum of potential criminals, indexed by $n \in N_{s,t}$, each of which derives utility $u^n_{i,j,s,t}$ from laundering money through bank branch i in county j,

$$u^n_{i,j,s,t} = \boldsymbol{\alpha_0} \times \boldsymbol{Y}_{i,j,s,t} + \alpha_1 \times \mathbb{E}R_{i,j,s,t} + \nu_{j,s,t} + \epsilon^n_{i,j,s,t}. \tag{8}$$

$\boldsymbol{Y}_{i,j,s,t}$ is a set of controls including county-level demographic characteristics and banks' deposit shares within each county. One particularly important characteristic that potential criminals may focus on is the perceived reporting strategy, $\mathbb{E}R_{i,j,s,t}$, which measures the expected probability that the bank branch will file a SAR against a potential criminal. Intuitively, higher $\mathbb{E}R_{i,j,s,t}$ could mean that the bank's reporting strategy is more stringent, which will result in a higher probability of the transaction being reported and the criminal activity being subsequently convicted. In addition, higher $\mathbb{E}R_{i,j,s,t}$ could also be reflective of the bank having more stringent AML practices in general, indicating a greater hurdle for the criminal to launder money through the bank. If potential criminals anticipate such effects, we expect α_1 to be negative. $\nu_{j,s,t}$ is an additional local shock to the return of money laundering activities—higher $\nu_{i,j,t}$ means that it is generally more attractive to launder money within the specific county, and we will expect a higher volume of such activities. $\epsilon^n_{i,j,s,t}$ is an individual-bank branch level match-specific preference shock that captures geographical proximity or other idiosyncratic tastes not correlated with bank reporting policies or the controlled county characteristics.

The choice of individual n is given by an indicator function:

$$\mathbb{I}^n_{i,j,s,t} = \begin{cases} 1, & \text{if } u^n_{i,j,s,t} \geq \max\left\{u_0, u^n_{k,q,s,t}\right\}, \forall q \in \{1,2,...,J_s\}, k \in \{1,2,...,I_{j,s,t}\} \\ 0, & \text{otherwise}, \end{cases} \tag{9}$$

where u_0 represents the individual's outside option of not laundering money through any of the banks, the mean utility of which we normalize to 0; option $\{i,j\} : j \in \{1,2,...J_s\}, i \in \{1,2,...I_{j,s,t}\}$ corresponds to the individual's option of laundering money with a specific bank branch i in county j. We aggregate the choices across the continuum of risky individuals to compute the share of "dirty money" handled by each bank branch i in county j. Adopting the standard assumption that $\epsilon_{i,j,s,t}$ follows a generalized extreme value distribution with a cumulative distribution function given by $F(\epsilon) = \exp(-\exp(\epsilon))$, we can derive the standard logit market share, $w_{i,j,s,t}$, as follows:

$$w_{i,j,s,t} = \frac{\exp\left(\boldsymbol{\alpha_0} \times \boldsymbol{Y}_{i,j,s,t} + \alpha_1 \times \mathbb{E}R_{i,j,s,t} + \nu_{j,s,t}\right)}{1 + \sum_{q=1}^{J_s} \sum_{k=1}^{I_{j,s,t}} \exp\left(\boldsymbol{\alpha_0} \times \boldsymbol{Y}_{k,j,s,t} + \alpha_1 \times \mathbb{E}R_{k,j,s,t} + \nu_{k,s,t}\right)} \equiv \frac{\exp\left(\delta_{i,j,s,t} + \nu_{j,s,t}\right)}{1 + \sum_{q=1}^{J_s} \sum_{k=1}^{I_{j,s,t}} \exp\left(\delta_{k,j,s,t} + \nu_{k,s,t}\right)}, \tag{10}$$

where the constant 1 in the denominator corresponds to the individual's outside option. Equation (10) captures the effect that criminals may shop across banks. If a bank, or a collection of banks in a given county, chooses a more stringent policy, then we should expect risky individuals to switch away from these banks and transact with other banks in the state, or simply decide not to launder money. Last, we can multiply $w_{i,j,s,t}$ with the total volume of underlying criminals ($N_{s,t}$) to derive $M_{i,j,s,t}$, the total amount of "dirty money" laundered through bank branch i:

$$M_{i,j,s,t} = w_{i,j,s,t} \times N_{s,t} \tag{11}$$

6.2 Bank Reporting Strategy

There are a total of I banks in the economy. We use $R_{i,j,s,t}$ to denote the reporting strategy of bank branch i located in county j, state s. The strategy reflects how likely the bank is to file a report conditional on the customer being risky. We model $R_{i,j,s,t}$ to be a function of local demographic characteristics, $\mathbf{Z}_{j,s,t}$, and in particular, the bank's profit. In addition, $R_{i,j,s,t}$ includes an idiosyncratic component that captures two elements. First, it captures the discretion and knowledge that local bank officers use when forming their reporting decisions. Second, it captures the idiosyncratic variation in branch-level profitability relative to the parent. We do not model these dimensions because of data limitations. Instead, we use a random coefficient, $\mu_{i,j,s,t}$ to capture the effects. $\left\{\mu_{i,j,s,t}\right\}$ follows a normal distribution with mean 0 and variance σ_μ^2.

$$R_{i,j,s,t} = \frac{\exp\left(\boldsymbol{\gamma_0} \times \mathbf{Z}_{j,s,t} + \gamma_1 \times \text{Profit}_{i,t} + \mu_{i,j,s,t}\right)}{1 + \exp\left(\boldsymbol{\gamma_0} \times \mathbf{Z}_{j,s,t} + \gamma_1 \times \text{Profit}_{i,t} + \mu_{i,j,s,t}\right)}. \tag{12}$$

Note that we do not model the endogenous optimization of the bank's reporting stringency. Instead, we use a reduced-form equation to capture the intuition from the model described in

Section 3. Meanwhile, we keep the functional form flexible and use the data to discipline the parameters that govern the bank's reporting decisions. More specifically, if the estimated γ_1 is positive and significant, this implies that banks will exhibit risk-shifting incentives in their reporting strategies—they choose to adopt a more lax reporting strategy when their profit deteriorates. If γ_1 is estimated to be insignificant, or negatively significant, this implies that bank profit is not an important consideration in designing their reporting strategies, or other considerations, such as hedging incentives, dominate.

6.3 SAR Reports and Bank Violations

Given banks' reporting strategies and risky individuals' choices, we can express the total number of SARs filed by bank branch i as:

$$SAR_{i,j,s,t} = M_{i,j,s,t} \times R_{i,j,s,t}. \tag{13}$$

We can aggregate across all bank branches and calculate the total volume of SARs filed within county j at time t:

$$SAR_{j,s,t} = \sum_{k=1}^{I_{j,s,t}} SAR_{k,j,s,t} = N_{s,t} \times \sum_{k=1}^{I_{j,s,t}} \left(w_{k,j,s,t} \times R_{k,j,s,t} \right). \tag{14}$$

Next, we proceed to the examination of banks' AML violations. We model the probability that a bank is charged an AML violation as:

$$\mathbb{P}_{i,t} = \rho_0 + \rho_1 \times O_{i,t}, \tag{15}$$

where $O_{i,t}$ is the total volume of unreported suspicious activities handled by parent bank i.[24] To calculate $O_{i,t}$, we aggregate bank i's unreported criminal transactions across all branches in

[24] AML violations are observable only at the parent bank level.

different counties and states:

$$O_{i,t} = \sum_{h=1}^{S}\sum_{q=1}^{J_s}\left(M_{i,q,h,t} - SAR_{i,q,h,t}\right) \tag{16}$$

$$= \sum_{h=1}^{S}\sum_{q=1}^{J_s} N_{s,t} \times \left[w_{i,q,h,t} \times \left(1 - R_{i,q,h,t}\right)\right]. \tag{17}$$

Intuitively, both a lax reporting strategy and larger traffic from criminal customers contribute to higher likelihood of an AML violation subsequently.

6.4 The Likelihood Function

In this section, we construct the likelihood function, which consists of two elements: the first corresponds to the likelihood of aggregate SARs filed within different counties and the second corresponds to the likelihood of banks' AML violations.

For any two counties within the same state, 1 and $j \in J_s$, we use $r_{j,s,t}$ to denote the ratio of their SARs. Using equation (14), we can calculate $L(\hat{r}_{j,s,t};\Theta)$, which corresponds to the likelihood of having a SAR ratio of $\hat{r}_{j,s,t}$, conditional on the parameters $\Theta = \{\boldsymbol{\alpha}, \boldsymbol{\gamma}, \sigma_\nu, \sigma_\mu, \rho\}$:

$$L(\hat{r}_{j,s,t};\Theta) \equiv \mathbb{P}_{i,t}\left(\frac{SAR_{j,s,t}}{SAR_{1,s,t}} = \hat{r}_{j,s,t}\right). \tag{18}$$

Constructing the likelihood using SAR ratio allows us to control for shocks that are common in each state-quarter. Detailed expression and derivation of equation (18) can be found in Appendix C.

Next, using equation (15), we can construct the likelihood of bank AML violations:

$$L(Viol\hat{a}tion_{i,t};\Theta) = (\mathbb{P}_{i,t})^{Viol\hat{a}tion_{i,t}} \cdot (1 - \mathbb{P}_{i,t})^{1-Viol\hat{a}tion_{i,t}}, \tag{19}$$

where $Viol\hat{a}tion_{i,t}$ is an indicator that equals one if bank i faces a money laundering violation at time t, and zero otherwise.

Last, we collect the joint log likelihood for having $\{\hat{r}_{j,s,t}\}$ across all counties and all times, and $\left\{Viol\hat{a}tion_{i,t}\right\}$ across all banks and all times:

$$l(\Theta) = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{j=2}^{J_s}\log\left[L(\hat{r}_{j,s,t};\Theta)\right] + \sum_{t=1}^{T}\sum_{i=1}^{I}\log\left[L(Viol\hat{a}tion_{i,t};\Theta)\right]. \tag{20}$$

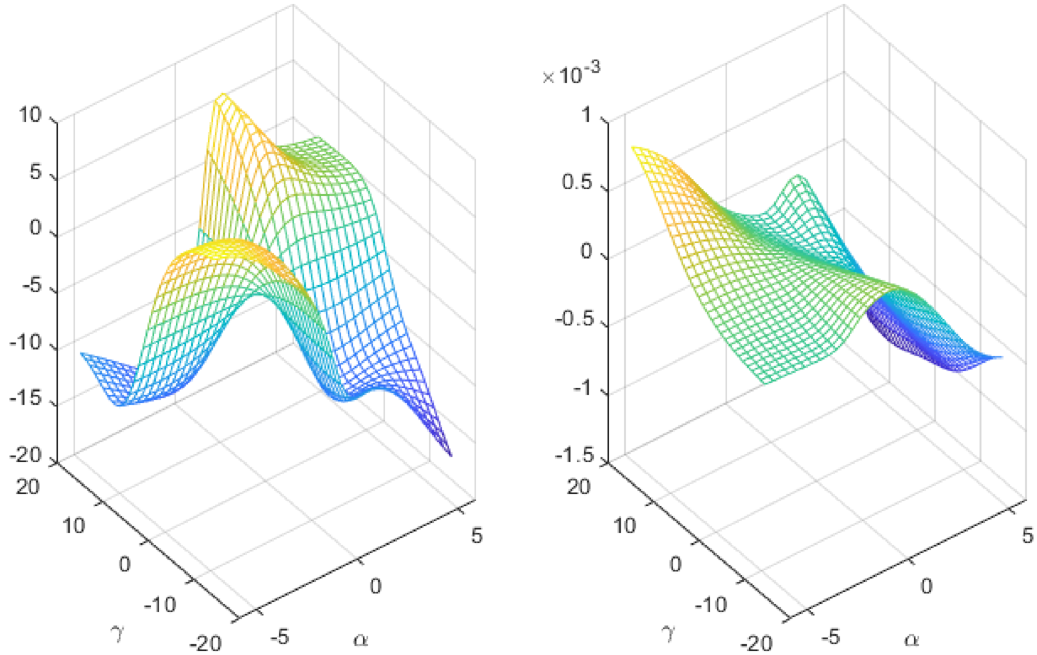
We estimate the parameter values via simulated maximum likelihood:

$$\hat{\Theta} = \arg\max_{\Theta} l(\Theta), \tag{21}$$

where our maximum likelihood estimator answers the question: what parameters best describe the joint distribution of bank profit, their AML violations, and the aggregate SARs in counties where they have active branches. The AML violations and SARs in our model are shaped by the banks' reporting stringency and the criminal clientele they handle. Higher reporting stringency and more criminal clients lead to larger volumes of SARs while lower reporting stringency and more criminal clients contribute to higher risk of subsequent AML violations. Thus, by matching the joint distribution of bank characteristics, SARs, and AML violations, our estimation allows us to separately identify the risky clientele that banks are likely to attract and their reporting strategies. Two parameters that are key in identification strategy are γ_1 and α_1—a positive γ_1 implies means banks will lower their reporting stingency when the profit declines, and a large negative α_1 suggests that these banks can attractive more risky clients with lenient reporting standards (or scare away risky clients with stringent standards), which give rise to the "strategic advertising effect".

Figure 6 illustrates how the model predicted relationship between bank profit, SARs, and AML violations vary with the underlying parameters.[25] The results in Panel A suggest that γ_1 and α_1 should have opposite signs in order to predict a strong negative relationship between SARs and profit, as reported in Table 2. This is because in our model, SARs is determined by two factors—banks' reporting stringency and the underlying criminal clients they attract as function of their reporting strategy. If the former is a decreasing function of bank profit while the latter increases with leniency (or vice versa), then the joint effect would predict a negative overall sensitivity of SARs to bank profit. In addition, the results in Panel B show that the combination of a positive γ_1 and negative α_1 can also reproduce a strong positive relation between SARs and AML violations (the empirical relationship is presented in Table 9). Note that α_1 operates through the volume of underlying criminal activities—When bank relax their reporting standards, it helps to attract larger volumes of criminal clients, which increase banks' unreported criminal transactions (which, in

[25]We measure bank profit using ROA. Using NIM as profit measure generates highly similar patterns.



Panel A. Sensitivity of SARs to Profit

Panel B. Sensitivity of Violation to SARs

Figure 6: Profit, SAR, and AML Violations This figure explores the dependence of the model-predicted relationships between profit, AML violation, and SARs on the underlying parameters. α_1 controls banks' risky clientele as defined in equation (10) and γ_1 governs banks' reporting stringency as defined in equation equation (12). In Panel A, we examine the sensitivity of SARs to bank profit, and in panel B, we examine the sensitivity of AML violations to the volumes of SARs filed within the county. Both panels are based on model predictions aggregated at the county-level.

turns, determines the likelihood of a AML violation) and SARs simultaneously. On the other hand, γ_1 controls the likelihood of filing when a bank's profit changes. A positive γ_1 implies that banks are going to file more loosely when their profit declines. The relaxed reporting standard further amplifies the increase in the likelihood of future AML violations, enhancing its relationship with changes in SARs. Our estimation results, reported in Table 3 reflect these important co-variants in the data. Our maximum likelihood estimation aims to match not only the average sensitives, but we target the joint realization of profit, SARs, and AML violations for each individual bank and county.

More formally, the success of a maximum likelihood estimation requires that the likelihood function changes shape sharply w.r.t. the underlying parameters, and the slope of the likelihood function is non-flat along any direction. In the Internet Appendix (Section 2), we report the cross derivatives of the joint likelihood to the underlying parameters $\{\alpha_1, \gamma_1, \rho\}$. The results suggest that the joint likelihood is sensitive to these parameters, and the likelihood changes shape shapely in different directions as we vary different underlying parameters (the columns of the Hessian is highly linearly independent and the matrix is non-degenerate).

6.5 Estimation Results

Results from the estimation are reported in Table 3. We find γ_1 to be positive, suggesting that holding all else equal, a decline in banks' profit is associated with less stringent reporting standards. The marginal effect of bank profit on reporting stringency, $\frac{\partial R}{\partial ROA} = 1.161$, implying that a 10 bps decline in ROA reduces the chance that a bank reports a suspicious transaction by 11.61%.

TABLE 3 ABOUT HERE

The results above provide direct support to our story. When banks' profit decline, they relax their reporting stringency ($\gamma_1 > 0$). The lax reporting standards allow banks to attract disproportionally more criminal customers—in fact, the underlying suspicious activities are very sensitive to local banks' reporting strategy with an elasticity significantly smaller than -1. As a result we see an increase in the total number of SARs filed by these banks.

With the model, we can further quantify the extent to which banks' strategic reporting role allows them to alleviate short-term profit pressure. To this end, we first calculate the sensitivity of banks' market share among risky client w.r.t. their reporting strategies, $\frac{\partial \omega_{i,j,s,t}}{\partial R_{i,j,s,t}}$ using equations (10); the sensitivity of banks' reporting stringency w.r.t. their profit measures, $\frac{\partial R_{i,j,s,t}}{\partial \, \text{Profit}_{i,j,s,t}}$ can be calculated from equation (12). In addition, we calculate the ratio of risky individuals as a percentage of total population as:

$$\frac{N_{s,t}}{Pop_{s,t}} = \frac{SAR_{s,t}}{Pop_{s,t}} \times \left[(1 - w_{0,s,t}) \sum_{k=1}^{I_{j,s,t}} \sum_{q=1}^{J_{s,t}} w_{k,q,s,t} R_{k,q,s,t} \right]^{-1}, \tag{22}$$

where $\frac{SAR_{s,t}}{Pop_{s,t}}$ is the state-level SAR to total population ratio observed in the data. $w_{0,s,t} = 1 - \sum_{k=1}^{I_{j,s,t}} \sum_{q=1}^{J_{s,t}} w_{k,q,s,t}$ represents the share of risky individuals who choose their outside option of not laundering money in state s at time t, as described in equation (9). Equation (22) estimates the percentage of risky population by dividing the number of SARs by the propensity that a risky client

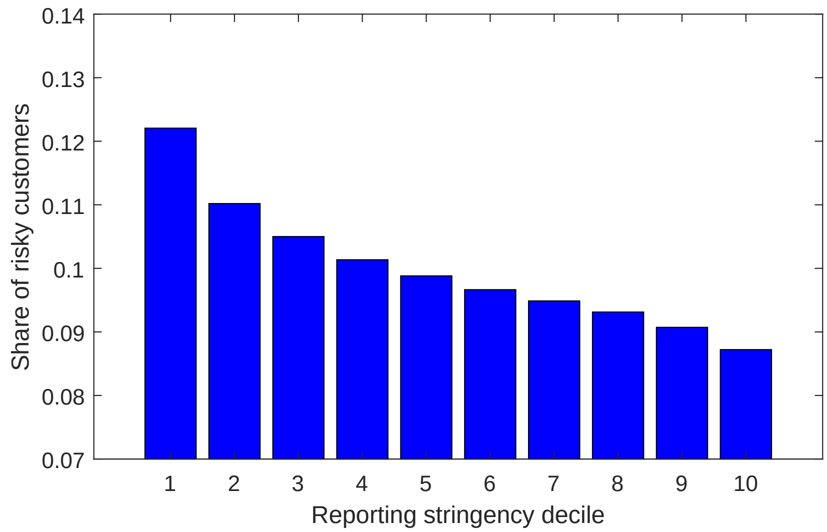


Figure 7: Bank Profit and Criminal Customers This figure presents the model-predicted relationship between banks' reporting stringency and their market share among criminal customers. We partition banks into deciles based on their reporting stringency within each state-quarter. Banks' reporting stringency is defined in equation (12) and on the *x*-axis; on the *y-axis* is the total market share among banks within a given reporting stringency decile.

triggers a SAR filing. Finally, we scale this percentage by the ratio of population who are clients to banks, which we approximate using population over 18 net of those who are either unbanked or underbanked.[26]

Using the estimates, we calculate that a 10 bps (inter-quartile) decline in bank profit (as measured by ROA, which yields a more conservative estimate) leads the bank to strategically relax their reporting strategy. This strategy in turn attracts additional risky customers that equals 24 bps of the bank's overall client base. The effect is economically sizeable.[27]

Our results also suggest a positive assortative matching between lax reporting strategy and criminal customers. As shown in Figure 7, banks' market share among criminal customers decreases monotonically with their reporting stringency, with banks adopting the most relaxed policy handling approximately 30% more criminal customers than the most stringent banks. This pattern reveals that banks specialize in servicing different groups of customers. Banks that are profitable from routine business lines focus on servicing the safe clients and building a tough reputation

[26]In 2020, 22.3% population is under the age of 18 (https://www.census.gov/quickfacts/fact/table/US/PST045219); 18% of adults are unbanked or underbanked (https://www.federalreserve.gov/publications/2021-economic-well-being-of-us-households-in-2020-banking-and-credit.htm).

[27]The magnitude seems reasonable comparable to that in (Drechsler et al., 2017), who document that an inter-quartile increase in the deposit market HHI is accompanied by a 66 bps rise in the sensitivity of deposits to the federal funds rate.

to deter criminal transactions. Unprofitable banks tend to expand the scope of their business by attracting customers that are potentially involved in money-laundering activities. The latter group of banks do so by compromising their overall compliance standards, as reflected in their SAR volume. If the regulators understand banks' reporting incentives, they could potentially target the "risky" banks. Those banks, however, also impose less stringent reporting standards, which increases the challenge of identifying and prosecuting criminal transactions.

7 Endogeneity Analyses

In this section, we consider three sets of analyses to alleviate endogeneity concerns. We first incorporate plausibly exogenous shocks from shale oil extraction to sharpen our causal inferences. We next conduct a detailed pre-trend analysis to help alleviate concerns related to our Bartik-type measures. Finally, we design an additional analysis that controls for local crime as proxied by SARs filed by non-bank institutions.[28]

7.1 Natural Experiment Using Shale Shocks

We first attempt to strengthen the causal link between banks' risk-taking incentives and SAR volume. To do so, we examine the growth of shale oil extraction in a bank's other branch locations as an exogenous source of variation in bank's liquidity.

Existing evidence (Gilje et al., 2016) suggests that shale oil and gas production generates liquidity windfalls to local banks, which in turn increases the banks' ability to lend through its other branches. We focus on nine states that account for over 95% of the shale oil and gas production in the U.S. These states include Arkansas, Louisiana, New Mexico, North Dakota, Ohio, Oklahoma, Pennsylvania, Texas, and West Virginia. We separately track the shale production in Texas for each of its 10 railroad commission (RRC) districts, given the high volume of production across the state. We consider other states as "non-shale states." We define a bank's shale production exposure to a shale region as the product of its deposit or branch share in the region and the growth rate of shale oil and gas production in that region. Deposit share is computed as the bank's total deposits in

[28] In the Internet Appendix, we also consider an additional endogeneity test based on near misses and beats of earnings targets.

that region divided by its total deposits in the U.S. Branch share is the number of branches a bank has in a region divided by the total number of its branches across the country. *Bank Shale Exposure* based on deposit exposure for a bank is defined as follows:

$$Bank\ Shale\ Exposure_{b,t} = \sum_{a \in A} \frac{Deposit_{b,a}}{Deposit_b} \times Shale\ Growth_{a,t},$$

where b represents a bank, a represents a shale region, A represents the collection of all shale production regions, and t represents a year. $Deposit_b$ stands for bank b's total deposit in 2011 and $Deposit_{b,a}$ stands for the bank's deposits in shale region a in 2011 (the year prior to the starting point of our bank profitability measure). We design an analogous measure of banks' shale growth exposure based on the number of local bank branches.

We then map banks' shale growth exposure to each county of their branch location outside of the shale regions. In each county, we again compute the shift-share measure, taking a weighted average across the shale growth exposure of the parent of all local branches. Thus, *Shale Growth Exposure* for a county is calculated as below:

$$Shale\ Growth\ Exposure_{c,t} = \sum_{b} \frac{Deposit_{b,c,t}}{Deposit_{c,t}} \times Bank\ Shale\ Exposure_{b,t}.$$

Bank Shale Exposure in a county reflects the extent to which a county is exposed to shale production growth in other parts of the country, which is a result of integration and liquidity allocation across bank branch networks.

We regress a county's SAR on its shale growth exposure. If liquidity-infused banks have a weaker incentive to attract illicit customers, we should expect the coefficient on shale growth exposure to be negative. This would be consistent with the strategic advertising effect documented in our baseline findings.

Table 4 reports the results. We consider two measures: a deposit-weighted shale growth measure (Columns (1) through (3)) and a branch-weighted shale growth measure (Columns (4) through (6)). In Columns (3) and (6), we also append additional controls to our baseline model that account for growth in bank lending and business activities in the local county. These controls include the growth rates of the bank's C&I loans, consumer loans, and total loans at the national level projected to the county level through Bartik instruments analogously defined as bank profitability. They also include county-level employment and establishment growth. These controls allows us to account for the possibility that shale booms directly influence local economic growth. This analysis is conducted using a county-year panel because we observe shale production volume at an annual frequency.

Table 4 About Here

The results indicate a strong, negative correlation between shale growth exposure and SAR volume in all specifications. The magnitudes are also on par with those produced in our baseline analyses. A one-standard-deviation increase in the deposit-weighted shale growth measure generates roughly a 4% to 9% reduction in per capita SAR relative to the sample average. The effect sizes are similar for the branch-weighted shale growth exposure measures. A one-standard-deviation increase in the branch-weighted shale growth measure generates roughly a 5% to 10% reduction in per capita SAR. Overall, this analysis provides a stronger causal link between banks' risk-taking incentives and SAR volume in a county.

7.2 Pre-Trends

We next examine whether our results are subject to pre-trends. In doing so, we seek to address the concern that our parameter estimates might be driven by our Bartik weights, which would imply significant relationships between prior-period SAR volume and profitability (Goldsmith-Pinkham et al., 2020). We re-estimate our baseline regression with profitability measured in different points in time. We fix the weights such that they are measured in the year prior to the observation point, i.e., year $t-1$. Specifically, we re-estimate the regression when profitability is measured at $t-1$, t, $t+1$, and $t+2$. The $t-1$ profitability measure corresponds to our baseline estimation.

Table 5 provides the results from this analysis. The first column present the results for *Bank ROA* and the second column presents the results for *Bank Net Interest Margin*. Each coefficient represents the results from a separate regression, with the baseline model results provided in Row

2. The analyses indicate that profitability measures are generally only correlated with SAR volume at time t when profitability is measured in periods $t-1$ and t, with the $t-1$ measure being our baseline specification. Importantly, there is no evidence of profitability measured in *t+1* and *t+2* being correlated with SAR volume. This result indicates that profitability is not correlated with prior SAR activity. As noted above, it also helps to validate that our results are not driven by endogeneity concerns related to the Bartik weights (Goldsmith-Pinkham et al., 2020).

Table 5 About Here

7.3 Controls for County-level Crime

One concern for our analyses thus far is that our results may reflect certain unobservable county-level characteristics correlated with risk-taking incentives and SAR volume. While our models include county-fixed effects and state-year fixed effects, it is still possible that some time-varying unobservable county-level characteristics explain our results. For example, counties with declining crime rates may have fewer SARs on average since there are fewer illicit activities for banks to report on. These counties may also have more profitable banks. In such a scenario, our results may not necessarily capture the effects of banks' risk taking incentives, but instead reflect the effects of being located in a county with less crime.

To alleviate this concern, we conduct an additional analysis that utilizes non-bank SARs, which are SARs filed by other institutions such as casinos or money service businesses. We examine whether results from our baseline analyses and shale exposure test persist after controlling for county-level non-bank SARs. If our results simply capture underlying criminal activity, such local dynamics should also be reflected in non-bank SARs. Controlling for non-bank SARs should help isolate the variation in our SAR measure that is less influenced by local county conditions.

Table 6 provides the results from this analysis. In Panel A, we present results for our six risk-taking proxies. In Panel B, we repeat our shale exposure experiment. In both sets of analyses, we control for the per capita number of non-bank SARs in a county. Across both sets of analyses, our inferences remain unchanged. Banks with greater risk taking incentives tend to generate more SAR reports, and unexpected shale shocks continue to reduce SAR volume. In untabulated analyses, we also conduct a placebo test where we regress non-bank SAR volume on bank risk-taking proxies. We find no statistically significant relationship between non-bank SARs and bank risk-taking, further rendering the above alternative explanation less plausible. Overall, these findings ultimately help to rule out alternative explanations related to unobservable county-level crime.

TABLE 6 ABOUT HERE

8 Additional Analyses

Having established a robust relationship between risk-taking incentives and SAR volume, we next conduct three sets of additional analyses to further our understanding of banks' SAR reporting incentives. First, we conduct cross-sectional analyses to examine how our results vary with the level of underlying crime in a region. Second, we consider two analyses that alleviate alternative explanations related to financial constraints and "hedging." We discuss these tests in more detail below.

8.1 Variation in Crime Regions

In our first set of additional analyses, we consider how our results vary with the level of underlying crime in a region. We expect that our results will be more pronounced in regions in which there is a greater supply of crime as the bank will have more potential criminals to transact with. To test this conjecture, we collect HIDTA data from the Drug Enforcement Agency and HIFTA data from FinCEN, as both HIDTA and HIFTA represent geographical risk that financial institutions consider in their AML programs. We define *High Crime* to take the value of one if a county is in a HIDTA or HIFTA county, and zero otherwise. Similarly, we define *Low Crime* as to take the value of one for regions that are not designated as HIDTA or HIFTA. We then re-estimate our baseline model after interacting *High Crime* and *Low Crime* with measures of bank profitability (*Bank ROA* and *Bank Net Interest Margin*).

Table 7 provides the results from this analysis. Columns (1) and (2) define crime regions based on HIDTA. Columns (3) and (4) define crime regions based on HIFTA. Columns (5) and (6) define crime regions as being either HIDTA or HIFTA regions. The results generally indicate that our effects are concentrated among regions that have higher levels of crime. The coefficient on *High Crime* × *Profitability* is negative and significant in all but one specification and is consistently larger than the loading on *Low Crime* × *Bank Profitability*. In untabulated analyses, we also find that these differences are statistically significant when profitability is measured using net interest margin. However, differences based on ROA are not statistically significant at traditional levels. Overall, these results provide some additional insight on the localities where banks' risk-taking incentives are more likely to prevail.

<u>TABLE 7 ABOUT HERE</u>

8.2 Alternative Explanations

8.2.1 Financial Constraints

One potential alternative explanation for our findings thus far relates to financial constraints. That is, it is possible that less profitable banks are more financially constrained and have fewer resources to invest in higher quality AML systems. This, in turn, reduces the precision in their detection technology and leads these banks to file more SAR reports, albeit with low quality.

To address this alternative explanation, we conduct a cross-sectional test based on bank size. Prior research indicates that one of the most important determinants of financial constraints is size (Kashyap and Stein, 1995; Hadlock and Pierce, 2010; Wang et al., 2020). For the alternative explanation to hold, our findings should be concentrated among smaller banks. Conversely, if our findings capture employees' discretion and response to profit-seeking pressures, the bank profit-SAR relation might be more pronounced for larger banks for which there is likely more delegation.

To test this prediction, we account for the differential effect between large and small banks by constructing separate profitability measures for each bank type as follows:

$$Large/SmallBank\ Profitability_{c,t} = \sum_{b} \frac{Deposit_{b,c,t}}{Deposit_{c,t}} \times Large/Small\ Bank_{b,t} \times Profitability_{b,t},$$

where *Large Bank* is an indicator for a bank ranking in the top 10 in terms of total asset size or total deposits, who occupy approximately a third of total branches and deposits. *Small Bank* is an indicator for the bank being in the bottom tercile based on the corresponding size metric.*Profitability* is either *Bank ROA* or *Bank Net Interest Margin*.

We regress a county's SAR reports on both measures of profitability, *Large Bank Profitability* and *Small Bank Profitability*, with the coefficients on the latter terms illustrating the incremental effect of large (or small) banks' profitability on a county's money-laundering activities relative to the effect from the average bank. We also control for the overall proportion of deposits in a county held by branches of large banks or small banks (*%Large Banks* and *%Small Banks*).

Table 8 reports the results from this analysis. In Columns (1) through (4), bank size is determined by assets and in Columns (5) and (8), bank size is determined by deposits. Across all specifications, we document negative and significant coefficients on *Large Bank Profitability* and insignificant coefficients on *Small Bank Profitability*. This suggests that risk-taking incentives are more strongly correlated with SAR activity for large banks, thus alleviating the concern that our results are driven by financially constrained banks. In the Internet Appendix, we further explore the plausibility of the financial constraints alternative explanation by considering banks' human capital investments in compliance. We find that more profitable banks hire more employees on average, but they do not hire more compliance personnel. This suggests that profitability is not strongly related to a bank's AML investment.

TABLE 8 ABOUT HERE

8.2.2 Future Violations

In our final analysis, we assess a "hedging" explanation, i.e., weak banks may purposefully over-report SARs to avoid regulatory fines. The rationale is that financially weak banks may be more concerned about regulatory fines, and thus report more transactions even if those transactions are less likely to involve money laundering. Before proceeding, we note that this hedging motive cannot explain the results from our structural estimation, where we find that less profitable banks implement *more lax* reporting policies.

We next provide further empirical evidence that appears inconsistent with this explanation. The hedging explanation implies that banks that file high levels of SARs should be less subject to regulatory penalties. We directly test this explanation using data on AML violations and estimating the following regression:

$$\%Violation_{c,t} = \beta_1 SAR_{c,t-1} + \beta_2 NonBankSAR_{c,t-1} + \textbf{Controls} + \xi_c + \eta_{s,t} + \epsilon_{c,t},$$

where *%Violation* is the share of a county's deposits held by banks with money laundering violations. We also control for non-bank SARs to account for local area crime. For the "hedging" explanation to hold, β_1 should be negative.

Table 9 provides the results from this analysis. The results indicate a consistent positive and significant relationship between SAR volume and violations. This effect is the opposite of what we should expect if the hedging story were to prevail. Overall, these findings help rule out the hedging explanation as SAR volume does not reduce violation occurrence, but is instead associated with higher violations.

Table 9 About Here

9 Conclusion

Recent events call into question the effectiveness of banks' SAR reporting and whether such reporting can curb financial crime. In this study, we examine the incentives that banks face to report money laundering activity via SAR reports, and the implications of a bank's reporting strategy for criminal activity. We provide a stylized model that predicts that banks facing depressed revenues from their routine business lines and more profit-seeking pressure adopt more lax reporting policies. These reporting policies help to attract criminals, thus increasing the underlying amount of suspicious activities that banks need to examine and report. We test the model using detailed county-level data on SAR reporting. Our results indicate that counties with banks facing higher competition and lower profitability generate higher volumes of SAR activity. Using a MLE, we provide more direct evidence on how banks react to profit pressure and its impact on criminal demand for money laundering activities. Finally, we further demonstrate a causal link between risk-taking incentives and SAR activity using shale shocks.

Our results provide important insights regarding the role of banks in influencing financial crime. Critics have raised concerns about SAR reporting facing limitations, especially in light of the staggering amount of “dirty money’ transacted through the world’s banking systems. Our results suggest another limitation of SAR reports in that sophisticated criminals can navigate the system and target banks with lax reporting systems. In other words, a bank’s reporting policy has indirect implications for local criminal activity.

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Appendix A Model Proofs

A.1 Proof of Lemma 1

To derive the equilibrium mass of risky customers, we use the expression for the costumer's net benefit $U_n = \delta n^\alpha$ and the expected cost $\mathbb{P}(d_n = 1) f$, which is derived in the text. The marginal customer has to be indifferent between joining the bank or not, so that $\delta n^\alpha = \mathbb{P}(d_n = 1) f$. It follows that the mass of risky customers is given by $x_R = \left(\frac{\lambda(\gamma+(1-\gamma)\pi)}{\delta} f\right)^{\frac{1}{\alpha}}$ under the lax policy and by $x_R = \left(\frac{\lambda}{\delta} f\right)^{\frac{1}{\alpha}}$ under the strict policy. It immediately follows that $x_R(l) > x_R(s)$ because (λ, γ, π) are strictly between 0 and 1 and $\alpha < 0$.

A.2 Proof of Proposition 1

To solve for the bank's optimal reporting policy, we differentiate two cases: (i) $F \leq x_R(l)$ and (ii) $F > x_R(l)$. Using $F = F_0 + F_1 x_R(l)$, we can also re-write these two conditions as $\frac{F_0}{1-F_1} \leq x_R(l)$ and $\frac{F_0}{1-F_1} > x_R(l)$, if $F_1 < 1$. If $F_1 \geq 1$, then $F > x_R(l)$. Throughout, we assume that the bank always chooses the lax policy when indifferent between $\mathcal{R} = s$ and $\mathcal{R} = l$.

1. $\underline{F \leq x_R(l)}$:

   In this case, the bank's limited liability constraint does not bind. It is optimal to choose $\mathcal{R} = s$ if and only if $\mathbb{E}[U_b(s)] > \mathbb{E}[U_b(l)]$. Note that the bank always chooses $\mathcal{R} = l$ if $x_R(l) - F \geq x_R(s)$. The bank chooses the strict policy if and only if:

   $$x_0 + x_R(s) > (1-\pi)(x_0 + x_R(l)) + \pi (x_0 + x_R(l) - F)$$

   which simplifies to $F > \frac{1}{\pi}(x_R(l) - x_R(s)) \equiv \overline{F}$. Hence, the reporting policy does not depend on x_0.

2. $\underline{F > x_R(l)}$:

   In this case, the bank's limited liability constraint binds if $d_b = 1$. It is optimal to choose $\mathcal{R} = s$ if and only if $U_b(s) > (1-\pi) U_b(l) \mathcal{I}_{\{d_b=0\}}$. The bank chooses the strict policy if and only if:

   $$x_0 + x_R(s) > (1-\pi)(x_0 + x_R(l))$$

   which simplifies to $x_0 > \frac{1}{\pi}((1-\pi)x_R(l) - x_R(s)) \equiv \overline{x_0}$.

A.3 Proof of Corollary 1

First, note that the volume of reported transactions χ is given by:

$$\chi(\mathcal{R}) = \begin{cases} \gamma\lambda x_R(\mathcal{R}) & \text{if } \mathcal{R} = l \\ (\gamma\lambda + 1 - \gamma) x_R(\mathcal{R}) & \text{if } \mathcal{R} = s. \end{cases} \tag{A.1}$$

Next, we plug in the expressions for x_R that are derived in Lemma 1. It follows that the volume of reported transactions is only higher under $\mathcal{R} = s$ if:

$$\alpha < \overline{\alpha} \equiv \frac{\log(\gamma + (1-\gamma)\pi)}{\log\left(1 + \frac{1-\gamma}{\gamma\lambda}\right)}. \tag{A.2}$$

The comparative statics for $\overline{\alpha} = \frac{\log(\gamma+(1-\gamma)\pi)}{\log(1+\frac{1-\gamma}{\gamma\lambda})}$ are given as follows.

1. With respect to $\pi \in (0,1)$:
$$\frac{\partial \overline{\alpha}}{\partial \pi} = \frac{1-\gamma}{(\gamma + (1-\gamma)\pi)\log\left(1+\frac{\frac{1}{\gamma}-1}{\lambda}\right)} > 0;$$

2. With respect to $\lambda \in (0,1)$:
$$\frac{\partial \overline{\alpha}}{\partial \lambda} = \frac{(1-\gamma)\log(\gamma + (1-\gamma)\pi)}{(1-\gamma(1-\lambda))\,\lambda\log\left(1+\frac{\frac{1}{\gamma}-1}{\lambda}\right)^2} < 0$$

3. With respect to $\gamma \in (0,1)$:
$$\frac{\partial \overline{\alpha}}{\partial \gamma} = \frac{\frac{\log(\gamma+(1-\gamma)\pi)}{\gamma(1-\gamma(1-\lambda))} + \frac{(1-\pi)\log\left(1+\frac{\frac{1}{\gamma}-1}{\lambda}\right)}{\gamma+(1-\pi)\gamma}}{\log\left(1+\frac{\frac{1}{\gamma}-1}{\lambda}\right)^2}$$

   This derivative could be either positive or negative. For instance, $\lim_{\gamma\to1}\frac{\partial\overline{\alpha}}{\partial\gamma} = \frac{1}{2}(1-\pi)(1-\lambda(1-\pi)) > 0$, while $\lim_{\gamma\to0}\frac{\partial\overline{\alpha}}{\partial\gamma} = -\infty$.

Appendix B Variable Definitions

- *SAR*: The ratio of total number of SAR reports related to money laundering activities submitted by depository institutions in a given county-year-quarter scaled by county population (in thousands).
- *Deposit HHI*: The sum of squared bank deposit market share in a county.
- *Branch HHI*: The sum of squared bank branch market share in a county.
- *Bank ROA*: The weighted average of a local bank's ROA, calculated as net income over total assets at the consolidated parent level. The weights are the percentage of deposits of a given county held by the bank.
- *Bank Net Interest Margin*: The weighted average of a local bank's net interest income (i.e., interest income − interest expenses) scaled by total assets at the parent level. The weights are the percentage of deposits of a given county held by the bank.
- *Bank Equity Ratio*: The weighted average of a local bank's equity ratio, measured by bank equity over total assets at the parent level. The weights are the percentage of deposits of a given county held by the bank.
- *Bank Tier 1 Capital Ratio*: The weighted average of a local bank's Tier 1 Capital Ratio, measured as Tier 1 capital scaled by total assets at the parent level. The weights are the percentage of deposits of a given county held by the bank.
- *Bank C&I Loan Growth*: The weighted average of the growth rate of commercial and industry loan amounts in the balance sheet of the parent of local banks. The weights are the percentage of deposits of a given county held by the bank.
- *Bank Consumer Loan Growth*: The weighted average of the growth rate of consumer loan amounts in the balance sheet of the parent of local banks. The weights are the percentage of deposits of a given county held by the bank.
- *Bank Total Loan Growth*: The weighted average of the growth rate of all loans in the balance sheet of the parent of local banks. The weights are the percentage of deposits of a given county held by the bank.
- *HPI Growth*: The growth rate of housing price index in a county.
- *Log(Median Income)*: The log of household median income in a county.
- *Log(Population)*: The log of county population.
- *%African American Population*: The percentage of county population that is African American.
- *%Asian Population*: The percentage of county population that is Asian.
- *Crime Rate*: The number of crimes in a county scaled by county population.
- *County Employment Growth*: The percentage growth in a county's employment in a year.
- *County Establishment Growth*: The percentage growth in a county's establishments in a year.
- *Shale Growth Exposure (Deposit-weighted)*: The weighted average of local bank's exposure to shale production growth in other states. A bank's exposure to shale production growth is computed as the weighted average of the growth in shale extraction volume in a shale-production area and a bank's reliance on that area. A bank's reliance is defined as the percentage of the bank's deposits that are held by its branches in a given area.
- *Shale Growth Exposure (Branch-weighted)*: The weighted average of local bank's exposure to shale production growth in other states. A bank's exposure to shale production growth is computed as the weighted average of the growth in shale extraction volume in a shale-production area and a bank's reliance on that area. A bank's reliance is defined as the percentage of the bank's branches that are located in a given area.

- *NonBank SAR*: The number of money-laundering related SARs reported by non-bank institutions in a county, scaled by county population.
- *Large Bank Profitability*: The weighted average of the product between a local bank's ROA or Net Interest Margin measured at the parent level and an indicator for whether the parent bank rank at the top 10 of all sample banks in terms of total assets or total deposits. The weights are the percentage of assets or deposits of a given county held by the bank.
- *%Large Banks*: The total percentage of deposits that are held by top 10 banks in a given county. Top-10 banks are defined as parent banks that rank at the top 10 of all sample banks in terms of total assets or total deposits.
- *Small Bank ROA*: The weighted average of the product between a local bank's ROA or Net Interest Margin measured at the parent level and an indicator for whether the parent bank rank at the bottom tercile among all sample banks in terms of total assets or total deposits. The weights are the percentage of assets or deposit of a given county held by the bank.
- *%Small Banks*: The total percentage of deposits that are held by small banks in a given county. Small banks are defined as parent banks that rank at the bottom tercile among all sample banks in terms of total assets or total deposits.
- *High Crime* An indicator for counties that are designated as HIDTA or HIFCA counties.
- *Low Crime* An indicator for counties that are not designated as HIDTA or HIFCA counties.

Appendix C Maximum Likelihood Estimation Details

In this appendix, we describe the details of our maximum likelihood estimation. We start by substituting equation (10) into equation (14), and we derive the expression for SAR filed by both county 1 and county j, which belong to the same state s:

$$SAR_{1,s,t} = N_{s,t} \exp\left(v_{1,s,t}\right) \times \sum_{g=1}^{I_{1,s,t}} \left(w_{g,1,s,t} \times R_{g,1,s,t}\right), \tag{A.3}$$

$$SAR_{j,s,t} = N_{s,t} \exp\left(v_{j,s,t}\right) \times \sum_{k=1}^{I_{j,s,t}} \left(w_{k,j,s,t} \times R_{k,j,s,t}\right). \tag{A.4}$$

Divide equation (A.4) by equation (A.3) and we obtain:

$$r_{j,s,t} \equiv \frac{SAR_{j,s,t}}{SAR_{1,s,t}} = \frac{\sum_{k=1}^{I_{j,s,t}} \left(w_{k,j,s,t} \times R_{k,j,s,t}\right)}{\sum_{g=1}^{I_{1,s,t}} \left(w_{g,1,s,t} \times R_{g,1,s,t}\right)} \times \frac{\exp\left(v_{j,s,t}\right)}{\exp\left(v_{1,s,t}\right)} \tag{A.5}$$

We normalize $v_{1,s,t} = 0$ for all states, in which case, $v_{j,s,t}$ will be interpreted as the attractiveness of laundering money in county $j = 2, 3, 4, ...J_s$ relative to county 1 in state s. With this normalization, the likelihood of equation (A.5) equal to $\hat{r}_{j,s,t}$ can be expressed as:

$$L(\hat{r}_{j,s,t};\Theta) = \oint_{T_k} \oint_{T_g} \mathbb{P}\left[\exp\left(v_{j,s,t}\right) = \hat{r}_{j,s,t} \times \frac{\sum_{g=1}^{I_{1,s,t}} \exp\left(\delta_{g,1,s,t}\right) \times R_{g,1,s,t}}{\sum_{k=1}^{I_{j,s,t}} \exp\left(\delta_{k,j,s,t}\right) \times R_{k,j,s,t}}\right] \prod_{k=1}^{I_{1,s,t}} d\left(R_{g,1,s,t}\right) \prod_{k=1}^{I_{j,s,t}} d\left(R_{k,j,s,t}\right) \tag{A.6}$$

$$= \oint_{T_k} \oint_{T_g} \Phi\left[\log\left(\hat{r}_{j,s,t} \times \frac{\sum_{g=1}^{I_{1,s,t}} \exp\left(\delta_{g,1,s,t}\right) \times R_{g,1,s,t}}{\sum_{k=1}^{I_{j,s,t}} \exp\left(\delta_{k,j,s,t}\right) \times R_{k,j,s,t}}\right)\right] \prod_{k=1}^{I_{1,s,t}} d\left(R_{g,1,s,t}\right) \prod_{k=1}^{I_{j,s,t}} d\left(R_{k,j,s,t}\right), \tag{A.7}$$

where $T_k = \left\{\prod_{k=1}^{I_{j,s,t}} \mu_{k,q,s,t} \in \mathbb{R}^{I_{j,s,t}} : R_{k,j,s,t} \geq 0, \forall k\right\}$, $T_g = \left\{\prod_{g=1}^{I_{1,s,t}} \mu_{g,1,s,t} \in \mathbb{R}^{I_{1,s,t}} : R_{g,1,s,t} \geq 0, \forall g\right\}$. $\Phi(\cdot)$ represents the pdf of a standard normal distribution with mean 0 and variance σ_v^2.

We next construct the likelihood for banks' AML violation. We start by reproducing equation (16) below:

$$O_{i,t} = \sum_{h=1}^{S} \sum_{q=1}^{J_s} \left(M_{i,q,h,t} - SAR_{i,q,h,t}\right) \tag{A.8}$$

$$= \sum_{h=1}^{S} \sum_{q=1}^{J_s} N_{h,t} \times w_{i,q,h,t} \times \left(1 - R_{i,q,h,t}\right) \tag{A.9}$$

$$= \sum_{h=1}^{S} \sum_{q=1}^{J_s} SAR_{q,h,t} \times \frac{w_{i,q,h,t} \times \left(1 - R_{i,q,h,t}\right)}{\sum_{k=1}^{I_{j,s,t}} \left(w_{k,q,h,t} \times R_{k,q,h,t}\right)} \tag{A.10}$$

$$= \sum_{h=1}^{S} \sum_{q=1}^{J_s} SAR_{q,h,t} \times \frac{\exp\left(\delta_{i,q,h,t}\right) \times \left(1 - R_{i,q,h,t}\right)}{\sum_{k=1}^{I_{j,s,t}} \left[\exp\left(\delta_{k,q,h,t}\right) \times R_{k,q,h,t}\right]} \tag{A.11}$$

Plug the above expression into bank i's probability of being charged an AML violation as specified in equation (15):

$$\mathbb{P}_{i,t} = \rho_0 + \rho_1 \times \sum_{h=1}^{S} \sum_{q=1}^{J_s} SAR_{q,h,t} \times \frac{\exp\left(\delta_{i,q,h,t}\right) \times \left(1 - R_{i,q,h,t}\right)}{\sum_{k=1}^{I_{j,s,t}} \left[\exp\left(\delta_{k,q,h,t}\right) \times R_{k,q,h,t}\right]}, \tag{A.12}$$

Because banks' specific reporting strategy is not observed by the econometricians, we take expectations w.r.t $\left\{R_{k,q,h,t}\right\}$ in equation (A.12), which yields:

$$\mathbb{P}_{i,t} = \rho_0 + \rho_1 \times \sum_{h=1}^{S} \sum_{q=1}^{J_s} \left\{ SAR_{q,h,t} \times \oint_{T_{q,h}} \frac{\exp\left(\delta_{i,q,h,t}\right) \times \left(1 - R_{i,q,h,t}\right)}{\sum_{k=1}^{I_{j,s,t}} \left[\exp\left(\delta_{k,q,h,t}\right) \times R_{k,q,h,t}\right]} \prod_{k=1}^{I_{j,s,t}} d\left(R_{k,q,h,t}\right) \right\}, \tag{A.13}$$

where $T_{q,h} = \left\{\prod_{k=1}^{I_{q,h,t}} \mu_{k,q,h,t} \in \mathbb{R}^{I_{q,h,t}} : R_{k,q,h,t} \geq 0, \forall k\right\}$. Note that evaluating equations (A.7) and (A.13) entails integrating over all banks' reporting decisions in a given state/county, which we rely on simulation-based techniques.

Table 1: Summary Statistics

This table provides summary statistics for the variables of interest used in our analyses. SAR Data are obtained from FinCEN, banking data are obtained from Call Reports, and demographic data are obtained from the U.S. Census. Variable definitions are provided in Appendix B.

Variable	N	Mean	Std. Dev.	P25	Median	P75
Annual Sample						
SAR/Pop	21,189	1.416	1.669	0.290	0.853	1.936
NonBank SAR/Pop	21,189	0.227	0.382	0.000	0.095	0.307
Deposit HHI	21,022	0.315	0.198	0.176	0.260	0.387
Branch HHI	21,022	0.258	0.192	0.131	0.200	0.333
Shale Exposure (Deposit-Weighted)	15,764	0.025	0.043	0.000	0.007	0.028
Shale Exposure (Branch-Weighted)	15,764	0.025	0.040	0.000	0.007	0.029
Quarterly Sample						
SAR/Pop	84,756	0.353	0.453	0.000	0.201	0.501
NonBank SAR/Pop	84,756	0.057	0.113	0.000	0.000	0.073
Bank ROA	84,028	0.003	0.001	0.002	0.003	0.003
Bank Net Interest Margin	84,028	0.008	0.001	0.007	0.008	0.009
Bank Equity Ratio	84,028	0.113	0.013	0.105	0.113	0.121
Bank Tier-1 Capital Ratio	84,028	0.098	0.013	0.090	0.096	0.104
Controls (Annual Frequency)						
HPI Growth	18,837	2.608	4.758	-0.260	2.340	5.270
Log(Median Income)	21,188	10.342	0.948	10.327	10.640	10.836
Log(Population)	21,188	10.342	0.948	10.327	10.640	10.836
%African American Population	21,189	9.694	14.022	1.200	3.032	11.573
%Asian Population	21,189	1.615	2.142	0.582	0.877	1.649
Crime Rate	21,189	0.027	0.019	0.014	0.025	0.038

Table 2: Bank Risk-Taking Incentives and SAR Activity

This table provides results from county-level regressions of SAR reporting on bank risk-taking measures. In each panel, the dependent variable is the per capita number of SARs in a county. Panel A presents the results for competition measures. *Deposit HHI* is a concentration measure based on the percentage of deposits that each branch has in a county. *Branch HHI* is a concentration measure based on the percentage of branches that a bank has in a given county. Panel B presents the results for profitability measures. *Bank ROA* is the weighted average of the ROA of banks taking deposits in a county. *Bank Net Interest Margin* is the weighted average of the net interest margin across banks that take deposits in a county. Panel C presents the results for banks' capital adequacy. *Bank Equity Ratio* is the weighted average of the equity ratio of all banks that operate branches in a county. *Bank Tier 1 Capital Ratio* is the weighted average of the Tier 1 capital ratio of all banks that have branches in a county. All bank characteristics are measured at the bank-holding-company level and the weights are the percentage of a bank's deposits in a county relative to total county deposits. County controls include HPI growth, income, population, race, and crime rate. Variable definitions are provided in Appendix B. The unit-of-observation is at the county-year-level for the competition measures (Panel A) and the county-quarter level for the remaining measures (Panels B and C). Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Competition

Dep. Var.: *SAR/Pop*	(1)	(2)	(3)	(4)
Deposit HHI	-0.9187***	-0.6545***		
	(0.233)	(0.228)		
Branch HHI			-1.1514***	-0.8916***
			(0.216)	(0.214)
State-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
Observations	18,694	18,693	18,694	18,693
Adjusted R^2	0.855	0.860	0.856	0.860

Panel B: Profitability

Dep. Var.: *SAR/Pop*	(1)	(2)	(3)	(4)
Bank ROA	-7.6765***	-8.6486***		
	(2.685)	(2.639)		
Bank Net Interest Margin			-17.7033***	-14.3789***
			(4.355)	(4.123)
State-Year-Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
Observations	74,972	74,968	74,972	74,968
Adjusted R^2	0.777	0.781	0.777	0.781

Panel C: Capital Adequacy

Dep. Var.: *SAR/Pop*	(1)	(2)	(3)	(4)
Bank Equity Ratio	-1.3010***	-0.9935***		
	(0.341)	(0.330)		
Bank Tier-1 Capital Ratio			-1.3967***	-0.9591***
			(0.371)	(0.362)
State-Year-Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
Observations	74,972	74,968	74,972	74,968
Adjusted R^2	0.777	0.781	0.777	0.781

Table 3: Inferring Suspicious Activities: A Maximum Likelihood Estimation

This table provides results from maximum likelihood estimation based on the model specified in equations (18), (19), (20), and (21). The data is at the country-year-quarter level. The first stage models the relationship between local suspicious activities and local banks' reporting stringency; the second stage pertains to how banks' reporting decisions are determined by profitability; the third stage describes the effect of unreported SAR volume on violation likelihood. County controls include HPI growth, income, population, race, and crime rate. Variable definitions are provided in Appendix B. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
Dep. Var.: **Suspicious Activities** (M)		
Bank Reporting Stringency (α_1)	-2.9532***	-7.0869***
	(0.024)	(0.041)
County Controls	Yes	Yes
State-Year FE	Yes	Yes
Dep. Var.: **Reporting Decision** (R)		
Bank ROA (γ_1)	7.3186***	
	(0.140)	
Bank Net Interest Margin (γ_1)		6.6823***
		(0.039)
County Controls	Yes	Yes
State-Year FE	Yes	Yes
Dep. Var.: **Violation**		
Unreported SAR (ρ_1)	1.2260***	2.3250***
	(0.291)	(0.229)

Table 4: Shale Growth Exposure and SAR Activity

This table provides results from county-level regressions of SAR reporting on a bank's shale growth exposure. The dependent variable is the per capita number of SARs in a county. Shale growth exposure is defined using shale production growth rates in the following states: Arizona, Louisiana, New Mexico, North Dakota, Ohio, Oklahoma, Pennsylvania, Texas, and West Virginia. Due to its high volume, the shale production in Texas is accounted separately 10 railroad commission (RRC) districts. We first calculate the share of deposits (branches) a bank has in the shale state/area relative to the bank's total deposits (branches) based on its 2011 distribution (prior to the start of our sample). We then use that as a weight to compute the bank's total exposure to shale growth in those areas. For counties outside of shale states, we account for shale growth exposure of the parent banks of local branches, and examine the relation between shale growth exposure and SARs at the county level. The unit-of-observation is at the county-year-level. Additional Business Activity Controls included in Columns (3) and (6) are defined in Appendix B and include *Bank C&I Loan Growth*, *Bank Consumer Loan Growth*, *Bank Total Loan Growth*, *County Employment Growth*, and *County Establishment Growth*. Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.: *SAR/Pop*	(1)	(2)	(3)	(4)	(5)	(6)
Shale Growth Exposure (Deposit-weighted)	-1.6876***	-1.0844***	-1.0759**			
	(0.353)	(0.335)	(0.429)			
Shale Growth Exposure (Branch-weighted)				-2.0526***	-1.3118***	-1.2064**
				(0.404)	(0.385)	(0.490)
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	No	Yes	Yes
Additional Controls	No	No	Yes	No	No	Yes
Observations	14,584	14,584	12,500	14,584	14,584	12,500
Adjusted R^2	0.859	0.864	0.887	0.859	0.864	0.887

Table 5: Pre-Trend Analysis

This table provides results from county-level regressions of SAR reporting at time t on *Bank Profitability* at times $t-2$ through $t+2$. The dependent variable is the per capita number of SARs. *Bank Profitability* is measured either by *Bank ROA* or *Bank Net Interest Margin* (defined in Table 2). The unit-of-observation is at the county-year-quarter-level. Each coefficient represents the results from a separate regression of *SAR/Pop* on the bank profitability measure plus county controls, state-year-quarter fixed effects, and county fixed effects. We vary the timing of parent banks' profitability from $t-1$ to $t+2$ while fixing the timing of the weights at $t-1$. Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.: *SAR/Pop*	(1)	(2)
Bank Profitability Measure:	*Bank ROA*	*Bank Net Interest Margin*
Bank Profitability (t-1) (Baseline)	-8.6486***	-14.3789***
	(2.639)	(4.123)
Bank Profitability (t)	-6.9019**	-9.1553**
	(3.070)	(4.004)
Bank Profitability (t+1)	2.8086	2.4505
	(3.283)	(4.798)
Bank Profitability (t+2)	-4.2642	-7.3626
	(3.111)	(5.639)
State-Year-Quarter FE	Yes	Yes
County FE	Yes	Yes
County Controls	Yes	Yes

Table 6: Controlling for Non-Bank SARs
This table provides results from analyses controlling for non-bank SARs. In Panel A, we replicate our main bank risk-taking analyses (Table 2) after controlling for non-bank SARs. In Panel B, we replicate our shale growth exposure test (Table 4) after controlling for non-bank SARs. In both analyses, non-bank SARs as measured as the per capita number of SARs related to money-laundering activities reported by non-bank institutions in a county. Variable definitions are provided in Appendix B and additional details on these tests are found in their respective tables. Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Bank Risk-Taking Incentive Analyses

Dep. Var.: *SAR/Pop*	(1)	(2)	(3)	(4)	(5)	(6)
Deposit HHI	-0.8244***					
	(0.232)					
Branch HHI		-1.0552***				
		(0.215)				
Bank ROA			-7.6877***			
			(2.618)			
Bank Net Interest Margin				-17.0167***		
				(4.195)		
Bank Equity Ratio					-1.1007***	
					(0.329)	
Bank Tier1-Capital Ratio						-1.2132***
						(0.360)
NonBank SAR Control	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,693	18,693	74,968	74,968	74,968	74,968
Adjusted R^2	0.859	0.859	0.779	0.779	0.779	0.779

Panel B: Bank Shale Exposure Analyses

Dep. Var.: *SAR/Pop*	(1)	(2)	(3)	(4)
Shale Exposure (deposit weighted)	-1.2470***	-1.2553***		
	(0.442)	(0.446)		
Shale Exposure (branch weighted)			-1.5886***	-1.6177***
			(0.504)	(0.508)
NonBank SAR Control	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
Local Business Activity Controls	No	Yes	No	Yes
Observations	9,593	9,593	9,593	9,593
Adjusted R^2	0.899	0.899	0.899	0.899

Table 7: Crime Areas, Profitability, and SAR Activity

This table provides results from county-level regressions of SAR reporting on profitability (measured by *Bank ROA* or *Bank Interest Margin*) and indicators for whether the county is a high crime or low crime area. The dependent variable is the per capita number of SARs. *High Crime* (*Low Crime*)is an indicator variable that takes the value of one if a banks is (is not) located in a HIDTA or HIFCA county, and zero otherwise. Variable definitions are provided in Appendix B. The unit-of-observation is at the county-year-quarter-level. Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.: *SAR/Pop*	(1)	(2)	(3)	(4)	(5)	(6)
Bank Profitability Measure:	*ROA*	*Interest Margin*	*ROA*	*Interest Margin*	*ROA*	*Interest Margin*
Crime Partition:	HIDTA	HIDTA	HIFCA	HIFCA	HITDA & HIFCA	HITDA & HIFCA
High Crime × *Bank Profitability*	-14.8474*	-84.2649***	-16.0803	-56.8862**	-14.4243*	-78.3209***
	(7.683)	(12.185)	(16.131)	(22.346)	(7.391)	(11.447)
Low Crime × *Bank Profitability*	-7.7293***	2.3496	-8.4144***	-12.7689***	-7.6748***	2.4945
	(2.589)	(4.418)	(2.665)	(4.200)	(2.598)	(4.464)
State-Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,968	74,968	74,968	74,968	74,968	74,968
Adjusted R^2	0.781	0.782	0.781	0.781	0.781	0.782

Table 8: Bank Size, Profitability, and SAR Activity

This table provides results examining how the relationship between SAR and profitability varies by bank size. The dependent variable is the per capita number of SARs. *Large Bank Profitability* is the Bartik instrument of the product between an indicator variable for large banks and *Bank ROA* or *Bank Net Interest Margin*. The weights in the Bartik measure are based on the percentage of a bank's deposits in a county relative to total county deposits. Large banks are defined as banks whose total assets or deposits rank among the top 10 largest banks across our sample. *%Large Banks* is the percentage of deposits in a county held by large banks. *Small Bank Profitability* is Bartik instrument measure of the product between an indicator variable for small banks and *Bank ROA* or *Bank Net Interest Margin*. Small banks are defined as banks whose total assets or deposits rank at the bottom tercile across our sample banks (so that small and large banks have similar deposit share in our sample). *%Small Banks* is the percentage of county deposits held by small banks. Variable definitions are provided in Appendix B. The unit-of-observation is at the county-year-quarter-level. Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.: *SAR/Pop*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank Profitability:	*ROA*	*ROA*	*Interest Margin*	*Interest Margin*	*ROA*	*ROA*	*Interest Margin*	*Interest Margin*
Bank Size Ranked By:	*Assets*	*Assets*	*Assets*	*Assets*	*Deposits*	*Deposits*	*Deposits*	*Deposits*
Bank Profitability	-5.7333**	-5.2034	4.9161	7.2418	-5.7333**	-5.2328	4.9161	6.7691
	(2.642)	(3.503)	(4.224)	(5.411)	(2.642)	(3.486)	(4.224)	(5.396)
Large Bank Profitability	-92.8676***	-93.1297***	-159.6324***	-161.6467***	-92.8676***	-93.1414***	-159.6324***	-161.2342***
	(15.642)	(15.785)	(17.387)	(17.647)	(15.642)	(15.763)	(17.387)	(17.644)
%Large Banks	0.3378***	0.3397***	1.1884***	1.2074***	0.3378***	0.3396***	1.1884***	1.2036***
	(0.067)	(0.067)	(0.135)	(0.138)	(0.067)	(0.067)	(0.135)	(0.138)
Small Bank Profitability		-0.9799		-7.4094		-0.9807		-5.9006
		(4.937)		(8.028)		(4.958)		(8.053)
%Small Banks		0.0444		0.0976		0.0387		0.0784
		(0.039)		(0.076)		(0.040)		(0.076)
State-Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,968	74,968	74,968	74,968	74,968	74,968	74,968	74,968
Adjusted R^2	0.779	0.779	0.782	0.782	0.779	0.779	0.782	0.782

Table 9: SAR Reports and Future Violations
This table provides results from county-level regressions of money laundering violations on SAR reporting. The dependent variable is the percentage of deposits in a county held by a bank with a money laundering violation *(%Violation)*. *SAR/Pop* and *Nonbank SAR/Pop* are the per capita number of money-laundering related SARs filed by banks and non-banks, respectively. The unit-of-observation is at the county-year-level. Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.: *%Violation*	(1)	(2)	(3)
SAR/Pop	0.0019***	0.0026***	0.0026***
	(0.001)	(0.001)	(0.001)
NonBank SAR/Pop			-0.0007
			(0.003)
State-Year-Quarter FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County Controls	No	Yes	Yes
Observations	64,128	64,124	64,124
Adjusted R^2	0.495	0.498	0.498