Dirty Money: How Banks Influence Financial Crime*

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Abstract

On September 21st, 2020, a consortium of international journalists leaked nearly 2,500 suspicious activity reports (SAR) obtained from the U.S. Financial Crimes Enforcement Network, exposing nearly $2 trillion of money laundering activity. The event raises important questions regarding what role banks play in facilitating financial crime and the effectiveness of SAR reporting. 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 first analyze banks' SAR reporting decisions using a stylized model, which 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. Empirically, we test the relation between risk-taking incentives and SAR volume at the county level. We find that counties in which banks face higher competition and lower profitability generate higher volumes of SAR activity. These effects are more pronounced for large banks, banks that are distant from regulators, and banks that face greater risk-taking incentives vis à vis earnings pressure. We establish causality using shale gas expansion in unrelated states. Consistent with risk-taking incentives influencing SARs, we find that banks experiencing shale growth increases (decreases) generate fewer (more) SAR reports. Overall, our results provide important insights regarding the role of banks in influencing financial crime, and suggest that a bank's reporting policy has indirect implications for local criminal activity.

Keywords: Banks; Risk-taking Incentives; Deposit Competition; Government Policy and Regulation; FinCEN; Money Laundering

JEL Classification: G21; G28

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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...
>
> — *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 to $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. Our analyses indicate a large negative market reaction in the days following the FinCEN leak, and also suggest that the size of the reaction is increasing in the level of revealed money laundering activity (See Figure 6).

One of the most important tools in combating 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

[1] See "Dirty money pours into the world's most powerful banks", BuzzFeed News (2020).

with banks strengthening their compliance efforts over time. However, the trend is also puzzling given the fact that financial crimes also proliferated over the same window, 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.[2] 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. 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 and find that counties with banks with higher risk-taking incentives, including heightened competition and lower profitability, 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 suspicious activities. Our estimation results reveal that bank profitability is positively associated with reporting standard stringency and that lowered reporting stringency, in turn, spurs local criminal activities. Finally, we establish causality using shale expansion and conduct cross-sectional analyses that strengthen the underlying mechanisms. In particular, these results reveal that banks are more likely to develop lax reporting standards when they are located further away from FDIC branches. Overall, our collective evidence is consistent with banks' risk-taking incentives influencing the stringency of AML standards and, in turn, local criminal activity.

We first develop 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

[2] 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).

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 renders 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 risk-shift by choosing 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 a smaller number of reports as a direct consequence of their less 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.[3]

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 measures, and measures of bank's financial strength (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 (i.e., ROA and Net Interest Margin) and financial strength 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., Bartik instrument). For each county, we compute the weighted average of each measure for banks that have branches that are active in the county, where the weights represent the percentage of local deposits occupied by a bank.

[3]That can happen when the risky customers' demand is particularly sensitive to the expected regulatory fine.

We examine the relation between 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 money-laundering activities 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 disclosure effect dominates, we should observe the opposite relationship.

Our results are consistent with the strategic advertising effect and suggest a positive relation between our proxies for risk-taking incentives and the volume of SAR reports. 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 associated with a reduction in county-level SARs of roughly 13% 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 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 2% reduction in SAR reports.[4] Overall, we document strong evidence in support of the strategic advertising effect channel. Banks with higher risk-taking incentives have less stringent reporting policies. However, this lax reporting policy attracts criminals, thus raising their SAR volume.

The above analyses 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. This estimation, which builds on the large literature related to "missing information models" embeds separate structural equations that allows us to isolate the effects of bank profitability on reporting choices. Our estimation results reveal that bank profitability is positively associated with reporting standard stringency. A lowered reporting stringency, in turn, spurs local criminal

[4]Our results are also robust to using an alternative scalar based on the total deposits in a county.

activities. The results confirm the mechanism at play and illustrate how decreased bank profit translate into increases in observed SAR activities.

To strengthen our empirical analyses, we conduct a wide set of tests that allow us to make stronger causal inferences. We first incorporate a plausibly exogenous shock to bank liquidity based on shale gas production. We build on recent evidence from Gilje et al. (2016) showing that shale oil and gas production generates unexpected windfalls to local banks, and the liquidity infusion transmits to other branches of those banks. We examine how local SAR volume changes with a bank's exposure to the growth of shale production in other states. Our results indicate that higher (lower) shale growth is associated with substantial reductions (increases) in SAR volume in counties populated by shale-exposed banks. These results further support the strategic advertising channel and demonstrate a positive causal relation between banks' risk-taking incentives and SAR volume.

Next, we examine how earnings pressure contributes to SAR volume. Prior research suggests that consensus earnings targets create pressure for firms to take short-term opportunistic actions. We examine how SAR volume varies based on whether a bank narrowly meets or beats the consensus earnings target by one cent. Our results indicate that SAR volume is positively associated with the local presence of banks that marginally meet or beat analyst consensus forecasts. This suggests that incentives to meet earnings targets motivate less stringent SAR reporting, and in turn more money laundering.

We further conduct a detailed pre-trend analysis, in which we examine the relationship between SAR volume and alternate lags and leads of profitability. Our analyses indicate that our profitability measures are associated with current and future SAR volume, but bear *no* relationship with past SAR volume. This result helps alleviate the concern that the observed profitability-SAR relation may be driven by persistent bank or local characteristics. It also addresses the concern that our parameter estimates might be driven by Bartik weights and not changes in bank profitability (Goldsmith-Pinkham et al., 2020). Under this alternative explanation, we should expect consistently significant relationships between SAR volume and profitability as we shift the timing of profitability measurement future years while keeping the Bartik weights unchanged.[5] Overall, this analysis suggests that the our baseline results capture the effects from bank profitability and not other sources of variations.

Could our results be driven be underlying county-level characteristics correlated with both local banks' risk-taking incentives and SAR volume?[6] For example, counties with low crime may have fewer SARs and may also have more profitable banks, thus suggesting that our results do not necessarily capture the effects of banks' risk taking incentives. To alleviate this concern, we conduct a placebo test in which we examine how our risk-taking incentive proxies relate to county-level non-bank SARs (e.g., SARs filed by casinos or money service businesses), which should also reflect underlying criminal activity in a locality. We find no relation between any of our risk-taking incentive proxies and non-bank SARs, which suggests that our results are unlikely to be driven by underlying criminal activity in a county.

Our evidence thus far demonstrate a strong link between bank incentives and SAR reports at the county level. In the latter half of our study, we conduct numerous analyses to further our understanding of the economic mechanisms underpinning our results.

First, what types of banks face the greatest incentives to have lax SAR reporting? We conduct cross-sectional tests to answer this question and further assess the economic mechanisms.[7] We first examine how our effect varies with bank size. This analysis helps alleviate the concern that our results may be driven by financial constraints.[8] For example, small, constrained banks cannot afford to implement anti-money laundering technologies, so they file more, but uninformative reports to hedge against regulatory risk. Our results 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 also examine how far the bank is located from the nearest FDIC field office as the FDIC frequently conducts inspections to

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

[6]Note that our analyses include county- fixed effects and state-year fixed effects. However, it is still possible that some time-varying unobservable county-level characteristics explain our results.

[7]In these tests, we reconstruct our shift-share measure to account for the cross-sectional characteristic of interest. For example, our tests of bank size (discussed below) incorporate measures of profitability based on the percentage of *large* bank's deposits in a county relative to total deposits, thus allowing us to measure the incremental effect of bank size on a county's money-laundering activities.

[8]Prior research indicates that one of the most important determinants of financial constraints is size (Hadlock and Pierce, 2010).

assess the quality of banks' AML procedures. We expect that banks located further away from FDIC branches to have more lax reporting because the threat of inspection is lessened. Consistent with our prediction, we document the largest effects for counties that are far away from local FDIC field offices. This finding helps strengthen our argument that banks' incentives, and not financial constraints, are the primary mechanism.

We next incorporate detailed data on money laundering violations from a large misconduct database provided by the nonprofit organization *Good Jobs First* to further strengthen our inferences. This data allows us to conduct two analyses. We first use this data to validate an important assumption of the model, which is that banks detected of not reporting an illegal transaction face substantial costs. To do so, we examine the consequences associated with banks' money laundering violations. We find that banks detected of anti-money-laundering deficiencies lose branches and deposits following the violation, compared to other banks in the same county over the same time frame. These results indicate that there are substantial costs associated with not reporting money laundering activities. Using the violation data, we design an analysis that helps rule out an alternative explanation, which suggests that banks are over-aggressive in filing SARs because they want to "hedge" against regulatory fines. We assess this explanation by examining the relationship between future violations and SAR volume and document a strong positive and significant effect. This effect is inconsistent with the hedging explanation, as a higher SAR volume is associated with a *greater* propensity for banks to incur a violation.

We conclude by providing a rough estimate on the economic costs associated with money laundering activity. We examine market reactions surrounding the September 21^{st} FinCEN leak and show that leaked banks suffer significant negative short-run market reactions. For example, U.S. listed banks experienced raw (abnormal) returns of -5.91% (-5.33%) in the 5-day window following the leak. We document similar effects for foreign listed banks. Importantly, the market reaction is increasing in the level of revealed money laundering activity. This evidence suggests that investors are concerned about money laundering activity, potentially because it may lead to reputation damage or regulatory fines.

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. Our study focuses on banks' reporting strategy and its consequence for financial crime. 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. Our study focuses on banks' reporting strategy and its consequence for financial crime.Our results suggest that a bank's SAR reporting quality can provide a signal of its anti-money laundering 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" claims in Maxwell and Artingstall (2017) 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." Critics claim that SAR reporting is ineffective because of institutions engaging in "defensive filing" and regulators having limited resources. Our results suggest another limitation of SAR reports in that sophisticated criminals can navigate the system and target banks with lax reporting systems.

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 relates to research showing that banks take advantage of regulation loopholes and strategically report their asset risks (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 excessive risk given that the regulatory framework surrounding money laundering activities allows banks a level of discretion in 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^{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.

The bank then completes and files the SAR. Since 2011, this has mostly been done through the E-filing system, which requires that the report is filed no later than 30 calendar days from the date of the initial detection of facts, or 60 days if no suspect can be identified. It is important to note that while banks are required to file SARs that are complete, thorough and timely, the narrative portion of the SAR report is a significant challenge. Banks do not always fill this section out appropriately, making it difficult for regulators to follow up on activity.

3 The Model

In this section, we develop a 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.

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 publicly announces the stringency of its reporting 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 announced reporting policy. Finally, at $t = 3$, the regulator observes the bank's reported signals. Based on the signals, the regulator investigates the reported transactions and, potentially, the entire bank. 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

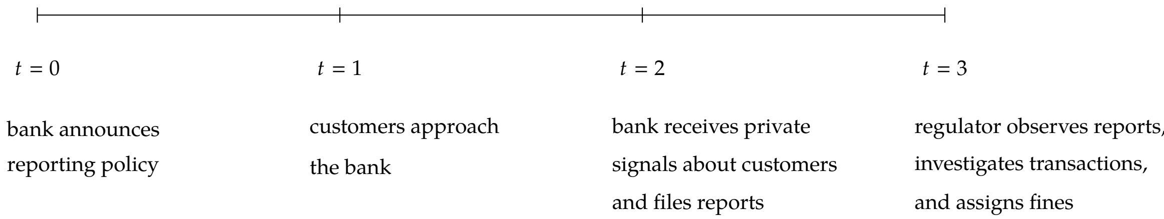


Figure 1: Model timeline.

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 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.

We assume that 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 execute the transaction $\mathcal{D}_n = 1$ as long as their private benefit exceeds the expected cost, which is specified in detail below and depends on the bank's reporting policy. We assume that the benefit for potential customer n is given by $U_n = \delta n^{-\alpha}$ with $\delta, \alpha > 0$. 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 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 $t = 0$, the bank publicly announces its reporting policy $\mathcal{R}$, which implies that the bank's customers know the extent to which the bank reports their transaction to the regulator, on average.[9] In reality, one might believe that banks cannot directly and credibly communicate their reporting policy, $\mathcal{R}$, with their customers. All of our results would hold equally well in situations when customers are endowed with signal that are informative of the banks' reporting strategy. For instance, the bank's investment in (screening) technology or its hiring of AML-related personnel are natural candidates for such signals. Our model predictions are robust to this alternative specification. We only require that risky customers are able to predict, at least to some extent, the stringency of the bank's reporting policy. This mechanism is also supported by the conventional wisdom that certain banks have built a reputation for a certain reporting "style" over time.

We restrict the bank's reporting policy to two options: "lax" ($\mathcal{R} = l$) and "strict" ($\mathcal{R} = s$). If the bank chooses a lax reporting policy, it only reports transactions associated with a "bad" signal to the regulator. However, if the bank chooses the strict policy, it also reports transactions that are associated with an uninformative signal.[10] 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:

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

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 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 an exogenous probability $\pi \in (0, 1)$. In

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

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

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, it incurs a cost F. 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 $F = F_0 + F_1 x_l$ with $F_0 > 0$ and $F_1 \in [0, 1]$. 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.

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 $(1-\gamma)\pi$. 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 (Mass of risky customers) *For a given reporting policy $\mathcal{R} \in \{l, s\}$, the mass of risky customers is given by:*

$$x_R(\mathcal{R}) = \begin{cases} \tilde{f} \times \tilde{g} & \text{if } \mathcal{R} = l \\ \tilde{f} & \text{if } \mathcal{R} = s, \end{cases} \tag{3}$$

where the constants $\tilde{g} > 1$ and $\tilde{f} > 0$ are formally defined in the Appendix.

Proof: *See Appendix A.1.*

Lemma 1 characterizes the equilibrium mass of risky customers for a fixed reporting choice. We can see that the bank can attract more risky customers with a lax reporting policy, i.e. $x_R(l) > x_R(s)$. Intuitively, the lax policy renders it less likely that an illegal transaction is detected by the regulator and leads to a lower expected cost for risky customers. 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:[11]

$$U_b(\mathcal{R}) = \max(\Pi(\mathcal{R}), 0) + \mathcal{I}_{\{\Pi > \hat{\Pi}\}} \tau \tag{4}$$

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. At $t = 0$, d_b is a binary random variable from the bank's perspective. If $\mathcal{R} = s$, it is equal to zero with probability one; if $\mathcal{R} = l$, 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, which we will label as the *strategic reporting effect*.

In addition to profits, the bank might also receive additional utility $\tau \geq 0$ from beating the earnings target $\hat{\Pi} > 0$. This component can capture the bank's incentive to take on more risks in

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

order to beat a high target. Finally, the bank is protected by limited liability, which implies that the profit component is equal to zero if $\Pi < 0$.

Proposition 1 (Reporting Equilibrium) *There is a unique reporting equilibrium:*

1. *If $F \leq x_R(l)$, the bank never fails. It chooses $\mathcal{R} = s$ if $F > \overline{F}$ and $\mathcal{R} = l$, otherwise. The optimal choice does not depend on x_0;*

2. *If $F > x_R(l)$, the bank fails if $d_b = 1$. It chooses $\mathcal{R} = s$ if $x_0 > \overline{x}$ and $\mathcal{R} = l$, otherwise.*

We provide explicit expressions for $\overline{F}$ and $\overline{x_0}$ 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, the bank's profitability only matters if the regulatory fine is sufficiently high and the limited liability constraint is binding. Due to the convexity in the bank's objective function, the optimal trade-off depends on x_0. If x_0 is sufficiently small, 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, the expected loss from the regulator's fine dominates and the bank chooses the safer reporting policy $\mathcal{R} = s$.

Next, we want to connect the firm's reporting policy to the volume of reported transactions, denoted by χ, which is given by:

$$\chi(\mathcal{R}) = \begin{cases} \gamma\lambda\tilde{f}\tilde{g} & \text{if } \mathcal{R} = l \\ (\gamma\lambda + 1 - \gamma)\tilde{f} & \text{if } \mathcal{R} = s. \end{cases} \tag{5}$$

Equation (5) shows that the volume of reported transactions is not necessarily higher under a strict reporting policy. More specifically, it is only higher under $\mathcal{R} = s$ if:

$$\gamma\lambda + 1 - \gamma > \gamma\lambda\tilde{\gamma} \Leftrightarrow \alpha > \overline{\alpha} \equiv \frac{-\log(\gamma + (1-\gamma)\pi)}{\log\left(1 + \frac{1-\gamma}{\gamma\lambda}\right)}. \tag{6}$$

This result highlights the two opposing effects, with regards to the volume of reported transactions, of a strict reporting policy. 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 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 and this indirect effect could offset the direct effect. More specifically, equation (6) shows that this is the case if α is sufficiently low, which indicates that equilibrium demand is very sensitive to changes in the expected fine.

Corollary 1 (Implications) *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 $\alpha \leq \overline{\alpha}$ and $F > x_R(l)$;*

3. *Otherwise, the volume of reported transactions does not depend on x_0.*

The constant $\overline{\alpha}$ is defined in equation (6).

Proof: *See Appendix A.3.*

Corollary 1 formalizes the ambiguous 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. Based on these results, we expect a bank with a higher incentive to take risk to choose a lax reporting policy, which in turn attracts more suspicious customers. This bank type generates relatively *more* reports if the customers' demand is sufficiently sensitive to their expected penalty. This event is more likely if the regulator is less effective at detecting illegal activities independently of reporting and if the bank is more likely to face a criminal customer.

In addition to these "gambling-for-resurrection" incentives, the bank's incentive to beat the short-term earnings target $\hat{\Pi}$ can lead to similar results. Especially banks whose predicted earnings will narrowly miss the target will have an incentive to relax their reporting strategy and take on more risky customers in order to increase their chance of beating the earnings target. It follows from our derivations in the Appendix that the effect of x_0 on χ is strengthened through the level of the earnings target. More specifically, an increase in $\hat{\Pi}$ encourages the bank to take more risk, which

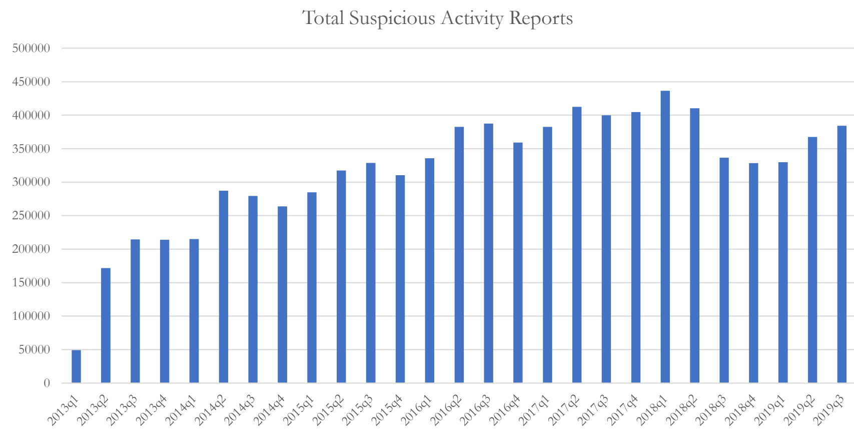


Figure 2: Suspicious Activity Reports Over Time. This figure illustrates the total number of suspicious activity reports related to money-laundering activities by U.S. depository institutions over our sample period.

in turn increases the cutoff $\overline{x_0}$ in Proposition 1. Hence, a bank that faces higher earnings pressure is more likely to choose the lax reporting policy, controlling for its profitability x_0.

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.[12] The FinCEN database contains information on the location, month, and aggregate type of suspicious activity (including industry type, instrument type, product type). For our analyses, we focus only on money laundering activity reported by deposit institutions.

We use the FinCEN data to construct a measure of SAR volume that accounts for variation in population. Our per capita SAR sums the total SAR reports in a county-year-quarter and divides by population (SAR/Pop). In robustness tests, we also consider an alternative measure of SAR volume that accounts for variation in deposit activity. Specifically, $SAR/Deposit$ is defined as the total SAR reports in a county-year-quarter divided by total deposits.

Figure 2 presents the trend in SAR report activity over time. The X-axis displays the calendar quarter and the Y-axis displays the total number of SAR reports. Consistent with the discussion in

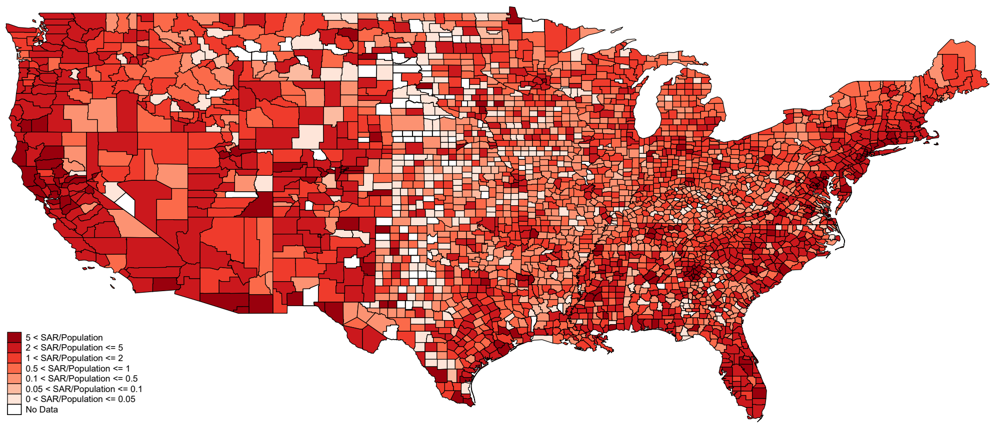
[12]FinCEN began requiring SAR reports to be efiled in 2012.

Section 1, there is 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.

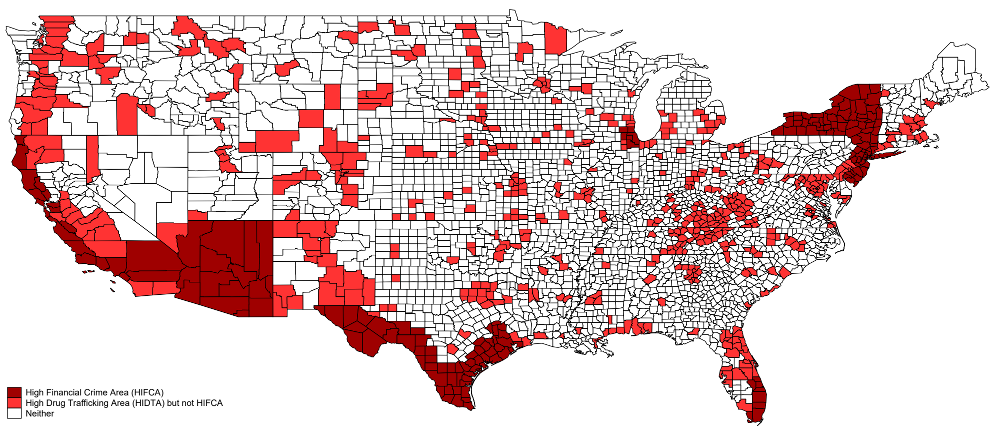
In Figure 3, we further explore geographical heterogeneity in SAR reporting and crime. We use data from 2016, the middle of our sample period, to illustrate SAR activity. We also collect data on high intensity financial crime (HIFCA) areas from FinCEN and drug trafficking areas (HIDTA) from the National HIDTA Assistance Center. Panel A illustrates per capital SAR reports (i.e., SAR/Pop) by county. Darker colors represent counties with higher SAR report volumes. The figure generally indicates that SAR reporting volume is greater in areas with greater population density, such as counties near large coastal cities on the West and Northeast. These more populous counties likely have a greater volume of underlying criminal activity. In contrast, SAR reports are less frequent in less populous counties in the midwest. Panel B illustrates counties with high levels of financial crime or drug-trafficking activities (highlighted in darker and lighter shades of red, respectively). The figure generally indicates that areas with high SAR volume, especially coastal cities, also are more likely to be high-financial crime counties. Overall, these plots suggest substantial across-county variation in SAR activity and also suggest that SAR activity reflects underlying financial crime. Our subsequent analyses will explicitly control for county and state-year interactive fixed effects.

4.2 Variables of Interest

We construct several measures to reflect banks' risk-taking incentives, including county-level competition measures and profitability ratios. Intensified competition can compress banks' profit margin (Keeley, 1990). Persistent low profit, in turn, erodes the franchise of banks 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 (losing their franchise value in a event of failure) is relatively low. We also include measures accounting for bank equity capital adequacy. These measures are also the primary target for various micro prudential policies. The risk-shifting incentives would be largely mitigated for



(A) SAR per Capita by County



(B) High Financial Crime and Drug-Trafficking Counties

Figure 3: 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. The dark red areas indicate counties classified by FinCEN as having high levels of financial crimes (HIFCA). The lighter red areas indicate counties classified by the DEA as areas with high levels of drug trafficking activities (HIDTA) that are outside of HIFCA counties.

banks with sufficient "skin in the game" who internalize the bankruptcy cost to a fuller extent. (Allen and Gale, 2004).

Our first two measures reflect the intensity of banking competition in a county. We collect deposit data at the branch-level from the FDIC, which is available on an annual basis, and compute a standard Herfindahl Index (HHI), which is the sum of the squared deposit-market shares of all banks that operate branches in a county in a given year. 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:

$$Deposit\ HHI_{c,t} = \sum_b \left(\frac{Deposit_{b,c,t}}{Deposit_{c,t}}\right)^2 \tag{7}$$

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*):

$$Branch\ HHI_{c,t} = \sum_b \left(\frac{Branches_{b,c,t}}{Branches_{c,t}}\right)^2 \tag{8}$$

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. With this data, we compute profitability (*ROA*), *Net Interest Margin*, *Equity Ratio* and *Tier 1 Capital Ratio* for each bank in our sample. 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 computed as follows:

$$Bank\ Measure_{c,t} = \sum_b \frac{Deposit_{b,c,t}}{Deposit_c} \times Parent\ Bank\ Measure_{b,t}, \tag{9}$$

where *Bank Measure*$_{c,t}$ $\in$ {*Bank ROA*, *Bank Net Interest Margin*, *Bank Equity Ratio*, *Bank Tier 1 Capital Ratio*}. t represents a year-quarter. The bank level measures are computed as follows. *Parent Bank ROA* is net income scaled by total assets. *Parent Bank Net Interest Margin* is net interest income less net interest expense scaled by total assets. *Parent Bank Equity Ratio* total equity scaled by total assets. Finally, *Parent Bank Tier 1 Capital Ratio* is Tier 1 Capital scaled by total assets. Each bank measure is first computed at the corporate level (i.e., $Parent\ Bank\ Measure_{b,t}$) and then projected to the county level.

4.3 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*). These characteristics are provided by the U.S. Census.

4.4 Empirical Framework

In our analyses, we assess the relationship between banks' risk-taking incentives and SAR reporting. We estimate the following regression:

$$SAR/Pop_{c,t} = \beta_1 Bank\ Incentive_{c,t-1} + \textbf{Controls} + \xi_c + \eta_{s,t} + \epsilon_{c,t}, \qquad (10)$$

where c indexes county and t indexes year or calendar quarter (i.e., year-quarter).[13] *Bank Incentive* include the two competition measures (*Deposit HHI* and *Branch HHI*) and the four measures reflecting bank fundamentals (*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 ($\eta_{s,t}$). These fixed effects control for any unobservable *time-invariant* county-level characteristics as well as unobservable *time-varying* state-level characteristics that might influence SARs.

4.5 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. An average county in our sample has roughly 14 banking branches, and banks are, on average profitable. The median income level is approximately $31,000 and crime rates are around 3%, on average.

TABLE 1 ABOUT HERE

[13]Our competition measures utilize annual data whereas our other measures utilize quarterly data.

5 Main Results

5.1 Competition and SAR Volume

In our first set of analyses, we examine the relationship between deposit competition and SAR activity at the county-level. We estimate equation (10) using *Deposit HHI* and *Branch HHI* as our variables of interest.

Table 2 provides the results from this analysis. We present the results for *Deposit HHI* in Columns (1) and (2) and *Branch HHI* in Columns (3) and (4). We incrementally add controls and fixed effects to the model, with our more stringent specification containing state-year, county fixed effects, and time-varying county controls.

TABLE 2 ABOUT HERE

The results suggest a strong, positive relation between competition and county-level SAR volume. Both *Deposit HHI* and *Branch HHI* load negatively and significantly in all specifications (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. Overall, these results strongly suggest that competition is positively related to SAR volume in a county. These findings support the strategic advertising channel proposed by the model.

5.2 Profitability and SAR Volume

In our next set of analyses, we examine the relationship between bank profitability and SAR activity at the county-level. We estimate equation (10) using *Bank ROA* and *Bank Net Interest Margin* as our variables of interest.

Table 3 provides the results from this analysis. We present the results for *Bank ROA* in Columns (1) and (2) and *Bank Net Interest Margin* in Columns (3) and (4). The results suggest a negative relation between both measures (*Bank ROA* and *Bank Net Interest Margin*) and SAR volume. In terms of economic magnitudes, the coefficient in Column 2 suggests that a one-standard-deviation increase in profitability reduces SAR volume by roughly 0.8 percentage point, 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 1.7% decrease in SAR volume. Overall, these analyses provide further support in favor of the strategic advertising channel.

Table 3 About Here

5.3 Other Risk-Taking Measures and 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*). Highly-levered and capital-deficient banks are likely to have stronger risk-taking incentives (Kim and Santomero 1988, Blum 1999, and Hellmann et al. 2000). Table 4 provides the results from this analysis. We present the results for *Bank Equity Ratio* in Columns (1) and (2) and *Bank Tier 1 Capital Ratio* in Columns (3) and (4). 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, around 4% of the sample mean. We document similar effects for the *Tier 1 Capital Ratio*, although we note that the findings are not significant at traditional levels in our more stringent specification, presented in Column 4. Overall, these analyses continue to provide support for the strategic advertising channel.

Table 4 About Here

5.4 Alternative Scalar

The above analyses use population as a scalar. One potential concern is that, declining profits may lead a bank to react by expanding the scale of their services, which attracts a larger fraction of the population to deposit and perform transactions through the banking sector. This scale effect alone can lead to an increase in the number of SAR reports, even holding banks' reporting strategy and clientele constant. To alleviate this concern, we re-examine our analyses after scaling SAR by total local deposits. Table 5 reports the results. We present the results for each of our risk-taking measures, after controlling for state-year fixed effects, county fixed effects, and county-level controls. Across each measure, we continue to document negative and significant relationships between each risk-taking proxy and SAR activity. Overall, these results suggest that our findings are not influenced by the choice of scalar.[14] Taken together, our evidence thus far provides strong support in favor of the strategic advertising channel.

<u>TABLE 5 ABOUT HERE</u>

6 Structural Estimation

6.1 Underlying Suspicious Clients

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 such activities by embedding two 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.

We model a state $s \in \{1, 2, 3 \ldots S\}$ in the economy as consisting of $J_{s,t}$ counties. We use $I_{s,t}$ $\left(I_{j,s,t}\right)$ to denote the number of active banks in state s (county j), time t. We denote the risky population in state s, time t by $N_{s,t}$ (we can allow $N_{s,t}$ to be state and time-specific in this setting). The risky

[14]In untabulated analyses, we also find that our inferences are similar when we test the effects of the natural log of SARs or the natural log of SAR/Pop.

population consists of a continuum of risky individuals, denoted by $n \in N_{s,t}$. For each risky individual, n, he derives a utility, $u^n_{i,j,s,t}$ from laundering money through bank i in county j,

$$u^n_{i,j,s,t} = \boldsymbol{\beta_0} \times \boldsymbol{Y}_{i,j,s,t} + \beta_1 \times \mathbb{E}R_{i,j,s,t} + \nu_{j,s,t} + \epsilon^n_{i,j,s,t}. \tag{11}$$

$\boldsymbol{Y}_{i,j,s,t}$ is a set of bank-specific characteristics including the deposit/branch share within the county. One particularly important characteristic that the risky individuals focus on is the perceived reporting strategy, $\mathbb{E}R_{i,j,s,t}$, which measures the expected probability that the bank will file a SAR against a risky individual. Intuitively, higher $\mathbb{E}R_{i,j,s,t}$ could mean that the bank's reporting strategy is more stringent, which will result in high probability that the risky individual be convicted and forfeit his money. If risky individuals anticipate this situation, then we would expect the coefficient β_1 to carry a negative sign. $\nu_{j,s,t}$ is an additional local shock to the return of money laundering activities—higher $\nu_{i,j,t}$ means that it is, on average, more attractive to launder money within the specific county, and we will expect high volume of such activities. $\epsilon^n_{i,j,s,t}$ is an individual-bank level match-specific preference shock— for instance, if individual n lives close to bank i, then $\epsilon^n_{i,j,s,t}$ is large, and the individual is more likely to choose bank i, holding other characteristics constant; on the opposite side, if the individual needs to travel across counties to launder money with a specific bank, then $\epsilon^n_{i,j,s,t}$ is likely to be small or negative.

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

$$\mathbb{I}^n_{i,j,s,t} = \begin{cases} 1, & \text{if } u^n_{i,j,s,t} \geq \max\left\{u_0, u^n_{k,q,s,t}\right\}, \forall q \in \{1,2,...,J_{s,t}\}, k \in \{1,2,...,I_{j,s,t}\} \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

where u_0 represents the individual's outside option of not laundering money through any of the banks (and stuff the money under his mattress instead), the mean utility of which we normalize to 0; option $\{i,j\} : j \in \{1,2,...J_{s,t}\}, i \in \{1,2,...I_{j,s,t}\}$ corresponds to the individual's option of laundering money with a specific bank 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 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:

$$w_{i,j,s,t} = \frac{\exp\left(\boldsymbol{\beta_0} \times \boldsymbol{Y}_{i,j,s,t} + \beta_1 \times \mathbb{E}R_{i,j,s,t} + \nu_{j,s,t}\right)}{1 + \sum_{q=1}^{J_{s,t}} \sum_{k=1}^{I_{j,s,t}} \exp\left(\boldsymbol{\beta_0} \times \boldsymbol{Y}_{k,j,s,t} + \beta_1 \times \mathbb{E}R_{k,j,s,t} + \nu_{k,s,t}\right)} = \frac{\exp\left(\delta_{i,j,s,t} + \nu_{j,s,t}\right)}{1 + \sum_{q=1}^{J_{s,t}} \sum_{k=1}^{I_{j,s,t}} \exp\left(\delta_{k,j,s,t} + \nu_{k,s,t}\right)}, . \tag{13}$$

where the constant 1 in the denominator corresponds to the individual's outside option. Equation 13 captures the effect that if a bank, or a collection of banks in a given county, chooses more stringent policy, then we should expect risky individuals to substitute away from these banks to transacting with other banks in the state, or to their outside option of not laundering money. Last, we can multiply $w_{i,j,s,t}$ to the total volume of underlying criminal activities of $N_{s,t}$ to derive $M_{i,j,s,t}$—the amount of "dirty money" laundered through bank i:

$$M_{i,j,s,t} = w_{i,j,s,t} \times N_{s,t} \tag{14}$$

6.2 Bank Reporting Strategy

There are a total of I banks in the economy. For each bank branch i located in county j, state s, we use $R_{i,j,s,t}$ represents its reporting strategy, that is, conditional on a customer being risky, what is the probability that he gets reported. We model a bank's reporting strategy as consisting of two components—the first is a parent bank-level component, which depends on the parent bank-level characteristics, $\mathbf{Z}_{i,t}$, and especially, its profit. This first component captures, on average, how these characteristics, aggregated to the parent bank level, influence the local branches' reporting decisions. In addition, there is a second component that varies across bank branches in different counties, which can capture, first, conditions of the local branch can differ from that of the parent bank and second, the local bank officers can use their discretion and personal knowledge about their clients when forming their reporting decisions. Since the data does not cover bank characteristics at the local country level, and the officers' discretionary reporting is by nature unobserveable, we use a random coefficient, $\mu_{i,j,s,t}$ to capture the effects. $\{\mu_{i,j,s,t}\}$ follows a normal distribution with mean 0 and variance σ_{μ}^2.

$$R_{i,j,s,t} = \boldsymbol{\gamma_0} \times \mathbf{Z}_{i,t} + \gamma_1 \times \text{Profit}_{i,t} + \mu_{i,j,s,t}. \tag{15}$$

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, that implies 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 insignificant, or negatively significant, that implies bank profit is not a important consideration in designing their reporting strategies, or other considerations, such as a hedging incentive, can dominate.

6.3 SAR Reports and Bank Violations

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

$$SAR_{i,j,s,t} = M_{i,j,s,t} \times R_{i,j,s,t}. \tag{16}$$

Next, we can aggregate across all banks and calculate the total volume of SAR filed within county j, time t:

$$SAR_{j,s,t} = \sum_{k=1}^{I_{j,s,t}} SAR_{k,j,s,t} = N_{s,t} \times \sum_{k=1}^{I_{j,s,t}} \left(w_{k,j,s,t} \times R_{k,j,s,t}\right). \tag{17}$$

Similarly, we can aggregate across all counties to calculate the total volume of SAR in a given state:

$$SAR_{s,t} = \sum_{q=1}^{J_{s,t}} SAR_{q,s,t} = N_{s,t} \times \sum_{q=1}^{J_{s,t}} \sum_{k=1}^{I_{j,s,t}} \left(w_{k,q,s,t} \times R_{k,q,s,t}\right). \tag{18}$$

For county $j \in J_{s,t}$, we can express its $SAR_{j,s,t}$ as a ratio of the total reports filed within the state:

$$r_{j,s,t} \equiv \frac{SAR_{j,s,t}}{SAR_{s,t}} = \frac{\sum_{k=1}^{I_{j,s,t}} \exp\left(\delta_{k,j,s,t}\right) \times R_{k,j,s,t}}{\sum_{q=1}^{J_{s,t}} \sum_{k=1}^{I_{j,s,t}} \exp\left(\delta_{k,q,s,t}\right) \times R_{k,q,s,t}} \times \exp\left(\nu_{j,s,t} - \sum_{q=1}^{J_{s,t}} \nu_{q,s,t}\right). \tag{19}$$

We use $L(\hat{r}_{j,s,t}; \Theta)$ to denote the likelihood of having a SAR ratio of $\hat{r}_{j,s,t}$, conditional on the parameters $\Theta = \{\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma_\nu, \sigma_\mu, \rho\}$, [15] [16] which can be calculated as:

$$\int \cdots \int_T L\left[\exp\left(\nu_{j,s,t} - \sum_{q=1}^{J_{s,t}} \nu_{q,s,t}\right) = \hat{r}_{j,s,t} \times \frac{\sum_{k=1}^{I_{j,s,t}} \sum_{q=1}^{J_{s,t}} \exp\left(\delta_{k,q,s,t}\right) \times R_{k,q,s,t}}{\sum_{k=1}^{I_{j,s,t}} \exp\left(\delta_{k,j,s,t}\right) \times R_{k,j,s,t}}; \Theta\right] \prod_{q=1}^{J_{s,t}} \prod_{k=1}^{I_{j,s,t}} d\left(R_{k,q,s,t}\right). \tag{20}$$

Next, we can aggregate a bank's operations across all counties and states and calculate the total volume of unreported suspicious activities at the parent bank level:

$$O_{i,t} = M_{i,t} - SAR_{i,t} = N_{s,t} \times \sum_{h=1}^{S} \sum_{q=1}^{J_{s,t}} \left[w_{i,q,h,t} \times \left(1 - R_{i,q,h,t}\right)\right]. \tag{21}$$

Combining Equations 18 and 21 allows us to express the total volume of unreported suspicious activities as:[17]

$$O_{i,t} = SAR_{s,t} \times \frac{\sum_{h=1}^{S} \sum_{q=1}^{J_{s,t}} \left[w_{i,q,h,t} \times \left(1 - R_{i,q,h,t}\right)\right]}{\sum_{q=1}^{J_{s,t}} \sum_{k=1}^{I_{j,s,t}} \left(w_{k,q,s,t} \times R_{k,q,s,t}\right)}. \tag{22}$$

We model the probability of bank i being charged an AML violation as a probit function:

$$\mathbb{P}_{i,t} = \rho\left(O_{i,t}\right) + const, \tag{23}$$

which depends on the volume of unreported suspicious activities. Based on the probability of violation, we can also construct the corresponding likelihood function as:

[15] ρ is defined below in Equation 21.

[16] $T = \left\{(\mu_{1,j,s,t}, \mu_{2,j,s,t}, ..., \mu_{I_{j,s,t},j,s,t}) \in \mathbb{R}^{I_{j,s,t}} : R_{i,j,s,t} \geq 0\right\}$.

[17] The calculation of Equations 19 and 22 can be greatly simplifies by assuming that the county-level shocks, $\{\nu_{j,s,t}\}$ and $\{\mu_{i,j,s,t}\}$are washout out at the state level.

$$L(Viol\hat{a}tion_{i,t};\Theta) = (\mathbb{P}_{i,t})^{Viol\hat{a}tion_{i,t}} \cdot (1-\mathbb{P}_{i,t})^{1-Viol\hat{a}tion_{i,t}}, \tag{24}$$

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

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

$$l(\Theta) = \sum_{j=1}^{J_{s,t}-1} \sum_{s=1}^{S} \sum_{t=1}^{T} \log\left[L(\hat{r}_{j,s,t};\Theta)\right] + \sum_{i=1}^{I} \sum_{t=1}^{T} \log\left[L(Viol\hat{a}tion_{i,t};\Theta)\right]. \tag{25}$$

Note that evaluating Equations 20 and 24 entails integrating over all banks' reporting decisions, which we rely on simulation-based techniques to calculate. We estimate the parameter values via simulated maximum likelihood, defined as:

$$\hat{\Theta} = \arg\max_{\Theta} l(\Theta). \tag{26}$$

The identifying assumption for the maximum likelihood estimator is that the shape of the likelihood function, defined in Equation 26, needs to be sensitive to the underlying parameters around the estimated values.

6.4 Estimation Results

We report the parameter estimates and a comparative static analysis of how the likelihood reacts to different parameters in Table X and Figure X, respectively. From Table X, we can see that the coefficient, γ, is 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, $\frac{\partial \ln R}{NetInterestMargin} = 0.129$ (based on the estimates in column (1))—meaning that when a banks' net interest margin decline by 1 percentage point, a bank is 13% less likely to report given that a suspicious activity has been performed through the bank.

The results above also provides direct support to our story. The estimates suggest that the underlying suspicious activities are very sensitive to local banks' reporting strategy ($\frac{\partial \ln M}{\partial \mathbb{E}R} < -1$).

When banks' profit decline, they relax their reporting strategy; the laxer reporting strategy allows these banks to attract dis-proportionally more bad customers, who are very sensitive to banks' reporting strategy. As a result we see an increase in the total number of SAR reports filed by these banks.

7 Endogeneity Analyses

In this section, we consider four sets of analyses to alleviate endogeneity concerns. We first incorporate plausibly exogenous shocks from shale oil extraction to sharpen our causal inferences. We next examine how SAR activity varies based on whether a bank narrowly meets or beats the consensus earnings target. Third, we conduct a detailed pre-trend analysis to help alleviate concerns related to the Bartik instrument. Finally, we examine a placebo test using non-bank SAR activity in a county.

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. Due to its high volume, we separately track the shale production in Texas in each of its 10 railroad commission (RRC) districts. 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 that region divided by its total deposits in the U.S. Branch share is the bank's number of branches in that region divided by the total number of its branches in the country. *Shale Growth Exposure* based on deposit exposure for a bank is defined as follows:

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

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 deposit 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 at the parent level to each county 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 banks of all local branches. Thus, *Shale Growth Exposure* for a county is calculated as below:

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

Shale Growth Exposure in a county reflects the extent to which a county is exposed to the shale production boom in other parts of the country due to the 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 6 reports the results. We consider two measures: a deposit-weighted shale growth measure (Columns 1 and 2) and a branch-weighted shale growth measure (Columns 3 and 4). This analysis is conducted using a county-year panel because we observe shale production volume at an annual frequency.

TABLE 6 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 5% to 8% increase in per capita SAR relative to 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 6% to 10% increase 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 Earnings Targets

We next examine whether short-term earnings targets influence SAR activity. A large literature in accounting and finance demonstrates that managers are willing to act opportunistically and sacrifice long-term value in order to meet short-term earnings targets (Graham et al., 2005; Bhojraj et al., 2009). We build on this literature and examine whether the pressure to meet or beat the consensus earnings target set by equity analysts also exacerbates the strategic advertising channel. Our theoretical model predicts that higher earnings pressure encourages banks to take on more risk and to choose a more lax SAR reporting policy. The earnings target setting also helps strengthen our identification as it allows us to compare banks that are just one cent above the target to other banks (including those just one cent under the target), under the assumption that these banks should not be fundamentally different across dimensions other than profit-seeking incentives, such as the distribution of their branches, technology, etc.

To test the effects of earnings targets on bank SAR activity, we begin by constructing the following county-level measure:

$$Bank\ Meet\ or\ Beat_{c,t} = \sum_{b} \frac{Deposit_{b,c,t}}{Deposit_{c,t}} \times Parent\ Bank\ Meet\ or\ Beat_{b,t},$$

where $Parent\ Bank\ Meet\ or\ Beat_{b,t}$ is an indicator variable that turns to one if parent bank b meets or beats the consensus earnings forecast by at most one penny in quarter t, and zero otherwise.

Similar to our other measures, we project the parent bank-level measure to the county-level. We then regress a county's SAR reports on *Bank Meet or Beat*.

Table 7 provides the results from this analysis. In Columns 1 and 2, we present the results for all counties. In Columns 3 and 4, we restrict the control group to be banks (and thus the associated counties) who miss earning targets by one penny. In all four columns, we document positive and significant coefficients, suggesting that counties with more banks marginally meeting or beating the consensus forecast also generate more SAR reports. In terms of economic magnitudes, a one-standard-deviation increase in the *Bank Meet or Beat* is associated with a roughly 1% increase in SAR volume, relative to the sample mean. Overall, this test provides evidence that short-term earnings incentives influence SAR activity.

<u>Table 7 About Here</u>

7.3 Pre-Trends

We next examine whether our results are subject to pre-trends. To do so, we re-estimate our baseline regression with profitability measured in different points in time. In the meanwhile, we fix the weights as those 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 $t-2$, $t-1$, t, $t+1$, and $t+2$. The $t-1$ profitability measure corresponds to our baseline estimation.

Table 8 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 when profitability is measured in periods $t-2$ through t. Importantly, there is no evidence of profitability measured in *t+1* and *t+2* being correlated with SAR volume. (Note that our county-level profitability measures are constructed using local bank's actual profitability in different years weighted by the same Bartik weight, as measured in time $t-1$). This result indicates that profitability is not correlated with prior SAR activity. It also helps to validate that our results are not driven by the endogeneity of the Bartik weights (Goldsmith-Pinkham et al., 2020). In untabulated analyses, we also calculate the Rotemberg weights associated with the Bartik instrument and verify that they all stay below 0.1. Moreover, those Rotemberg weights have low correlation to profitability shocks and the variation of bank deposit shares. Taken together, the evidence suggests that our parameter estimates have relatively low sensitivity-to-misspecification.

TABLE 8 ABOUT HERE

7.4 Placebo Tests

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 low crime 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 a placebo test utilizing non-bank SARs, which are SARs filed by other institutions such as casinos or money service businesses. We then examine how our risk-taking incentive proxies relate to county-level non-bank SARs. The logic behind this test is as follows. To the extent that our results simply reflect underlying criminal activity, we should document similar effects of non-bank SARs as this measure should also be highly correlated with criminal activity in a locality. Formally, we estimate the following regression:

$$NonBankSAR/Pop_{c,t} = \beta_1 Bank\ Incentive_{c,t-1} + \mathbf{Controls} + \xi_c + \eta_{s,t} + \epsilon_{c,t}, \tag{27}$$

where *NonBankSAR/Pop* is the per capita non-bank SARs in a county. The regression is otherwise identical to our baseline model. If our results are explained by underlying crime, we expect to see a similar, negative loading on β_1.

Table 9 provides the results from our non-bank SAR analysis. We do not find any evidence of a significant relationship between any risk-taking incentive proxy and non-bank SAR across. In some settings, the coefficients are actually positive (instead of negative), albeit not statistically significant. These findings ultimately help to rule out any confound related to unobservable county-level characteristics.

TABLE 9 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 further isolate the economic mechanisms. We further examine how SARs relate to money-laundering violations, as doing so allows us to confirm assumptions in our model and also rule out an alternative explanation related to "hedging." Finally, we conclude by more generally quantifying the costs associated with money laundering activities.

8.1 Cross-Sectional Analyses

What types of banks are most likely to succumb to strategic advertising? In this section, we address this question. We conduct cross-sectional analyses to establish some of the economic mechanisms underpinning our results and also rule out alternative explanations. In particular, we examine how our results vary based on a bank's distance to a regulator office and parent bank size.

In our first cross-sectional test, we examine the heterogeneous effects of bank incentives on money laundering activities based on how far the bank is located from the FDIC, a regulator charged with inspecting banks' AML policies. We expect that banks that are located closer to FDIC field offices should have stricter money laundering policies as they face heightened inspection risk from the local regulator. This prediction is in line with recent research showing that regulatory distance impacts firm behavior (e.g., Ayers et al., 2011; Kedia and Rajgopal, 2011).

We collect data on FDIC field locations from the FDIC and then create separate indicators for how close or far a bank is from the nearest field office. We define *Near FDIC (<=30 miles)* and *Near FDIC (<=50 miles)* to indicate counties that are within 30 or 50 miles of an FDIC field office, respectively. Similarly, we define *Far from FDIC (>30 miles)* and *Far from FDIC (>50 miles)* to indicate counties that are more than 30 or 50 miles from an FDIC field office, respectively. We then re-estimate our baseline model after interacting *Bank ROA* with these distance indicators.

Table 11 provides the results from this analysis. In Columns 1 and 2, we consider the 30 mile distance threshold and in Columns 3 and 4, we use 50 miles as a threshold. In all specifications, we document negative and significant loadings only on the interaction terms capturing counties that are located far away from FDIC field offices. These results are consistent with our theoretical model, which predicts that the negative relationship between profitability and SAR reporting is more likely if the regulator's detection technology is less effective (see Corollary 1). Therefore, the result help strengthen our inferences and suggest that banks' incentives to use lax reporting contribute to the effects we document.

Table 11 About Here

In our second cross-sectional test, we consider bank size. Our objective in this test is to alleviate concerns that our findings are driven by financial constraints. 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). If our findings are more pronounced for larger banks, we can reduce this concern as such banks are the least likely to face financial constraints.

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:

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

where *Large Bank* is an indicator for a bank being in the top 10 banks in terms of total asset size or total deposits and *Small Bank* is an indicator for the bank being in the bottom tercile based on the corresponding size metric.[18]

We regress a county's SAR reports on both *Bank ROA*, *Large Bank ROA* and *Small Bank ROA*, 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 12 reports the results from this analysis. In Columns 1 and 2, bank size is determined by assets and in Columns 3 and 4, bank size is determined by deposits. Across all four specifications, we document negative and significant loadings on *Large Bank ROA* and insignificant loadings on *Small Bank ROA*. This suggests that risk-taking incentives are more strongly correlated with SAR activity for large banks. These findings help alleviate the concern that our results are driven by financially constrained banks.

Table 12 About Here

To sum up, our cross-sectional analyses shed important insights on how banks' risk-taking incentives influence SAR activity. The strategic advertising effect appears to be stronger among large banks. The effects are also more pronounced in counties in which the FDIC faces more difficulty in monitoring banks, which is consistent with the argument that reporting incentives contribute to the effects we document.

8.2 Consequences of Money Laundering Violations

A key assumption of our model is that banks detected of not reporting bad customers incur a fine or disutility from being convicted (e.g., reduced ability to attract bad customers). We validate this assumption here. To do so, we first collect all AML deficiency violations from Good Jobs First's "Violation Tracker" tool. Good Jobs First is a national policy resource center promoting corporate and government accountability in economic development. Their "Violation Tracker"

[18] We use the bottom-tercile cutoff because the top 10 banks possess around a third of the branches in our sample.

tool is a comprehensive database on corporate misconduct containing nearly 438,000 civil and criminal cases from more than 250 U.S. agencies with penalties totaling $633 billion.[19] This dataset starts in 2000 and ends in 2019. We focus on 137 money laundering violation events. We test whether those violations are associated with adverse outcomes for banks as follows:

$$Bank\ Outcome_{b,c,t} = Post\ Violation_{b,t} + \delta_{b,c} + \eta_{c,t} + \epsilon_{b,c,t},$$

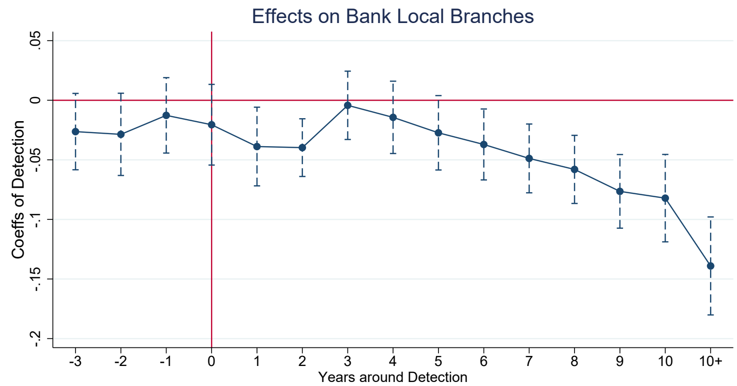
where b indexes bank, c indexes county, and t indexes month. $Bank\ Outcome_{b,c,t}$ gauges the the branches and deposits owned by a bank in each county. It includes two measures: *Log(Branches)*, the natural log of the number of branches; and *Log(Deposits)*, the natural log of deposits. The sample is a (parent) bank-county-year panel because deposit information in available annually. *Post Violation* is an indicator variable that takes the value of one following a parent bank's money laundering violation. The model controls for bank-county fixed effects ($\delta_{b,c}$) and county-year fixed effects ($\eta_{c,t}$). These stringent fixed effects allow us to compare the changes in bank deposit (or branch) levels with the changes of deposits (or branches) for other banks in the same county at the same time.

Table 13 provides the results from this analysis. Column 1 provides the results for *Log(Branches)* and Column 2 provides the results for *Log(Deposits)*. Across both columns, the coefficients attract negative and significant loadings indicating that violations reduce a bank's presence in a county. In terms of economic magnitudes, the coefficients are sizable and suggest that a violation reduces bank branches by about 3.6% and reduces deposits by 4.7%.

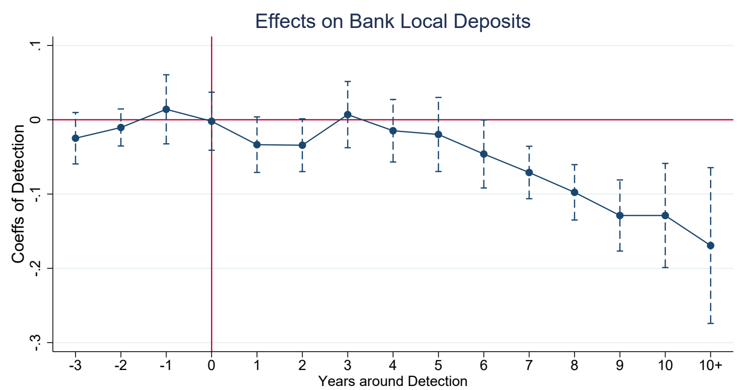
Table 13 About Here

Figure 4 plots the effects of bank violations, beginning in year $t-3$ and extending to year $t+10$. Panel A presents the results for *Log(Branches)* and Panel B presents the results for *Log(Deposits)*. Across both panels, we notice a similar pattern. Prior to the detection of a money laundering violation, there is no change in a bank's deposit share or branch share in a county. However, immediately following the violation, banks experience a steady decline in their customer base. Overall,

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



(A) Bank Local Branches After Detection



(B) Bank Local Deposits After Detection

Figure 4: The Effect of Regulatory Fines on Banks' Local Market Shares. This figure presents changes in banks' local deposits and branches following a regulatory fine regarding anti-money-laundering efforts. The sample is a bank-county-year panel that spans from 2000 till 2019. Panel A shows the effects on the log number of branches a bank has in a county. Panel B shows the effects of violation on the log of total deposits that a bank receives in a county. In each panel, the x-axis represents the years around a regulatory action. The y-axis represents regression coefficients from regressing bank local deposits or branches on indicators for years around regulatory fines. Both regressions include bank-county fixed effects and county-year fixed effects. The dashed intervals suggest 95% confidence intervals around coefficient estimates. Standard errors are double clustered by bank and county.

our evidence is consistent with the model assumption and shows a direct, costly consequence to banks following money laundering reporting violations.

8.3 Future Violations

We next assess another alternative explanation for our findings. That is, banks may purposefully be over-aggressive in filing SARs to help "hedge" against regulatory fines. The rationale is that banks have a low threshold for filing SARs because they want to insure themselves in case the customer is revealed to be involved in criminal activity. By filing a SAR, the bank can claim that it is not at fault since the appropriate steps were taken.

For the "hedging explanation" to hold, we should expect banks that file high levels of SARs to be less subject to regulatory penalties. To test this, we extend our money laundering violation setting and consider 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*$\in$ {*Have Violation*, *%Violation*}. *Have Violation* is an indicator that turns to one if at least one bank in a county faces a money laundering violation, and zero otherwise. *%Violation* is the share of a county's deposits held by banks with money laundering violations. We control for the corresponding SAR measure for non-banks. For the "hedging" explanation to hold, β_1 should be negative.

Table 14 provides the results from this analysis. In Panel A, we consider the violation dummy measure and in Panel B, we consider the violation share measure. We examine the effects of total SARs in Columns 1 through 3 and per capita SAR in Columns 4 through 6. 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 14 ABOUT HERE

8.4 Market Reactions around the BuzzFeed FinCEN leak

Our paper is based on the notion that money laundering generates economic and social harm, thus warranting an analysis of banks' SAR reporting incentives. In our final analysis, we quantify the extent to which money laundering activity harms bank value.

The primary challenge with assessing damage from money laundering activity is that such activity is generally unobservable to outsiders. In other words, investors are prohibited from observing detailed SAR reports or bank-level SAR activity. Indeed, our data only summarizes trends at the county-level. For this analysis, we conduct an event study surrounding one of the largest data leaks in recent history.

On September 21^{st}, 2020, BuzzFeed News released detailed information from their investigation of 2,500 leaked suspicious activity reports filed between 2000 and 2017. The investigation revealed an unprecedented level of "corruption and complicity" at the world's most prominent banks. Some of the more prominent revelations from the leak include evidence that Standard Chartered moved money on behalf of Al Zarooni Exchange, a business connected to the Taliban, HSBC's involvement in the WCM777 Ponzi Scheme, and several banks' connection to Viktor Khrapunov, a wanted criminal.

The data leak provides us with a unique opportunity to assess how capital markets react to money laundering activity. To the extent that money laundering activity hurts firm value, either through reputation damage or potential fines, we expect the market to react negatively to the FinCEN data leak.

For our analysis, we first download the data provided to the public from the FinCEN leak. This data, maintained by the International Consortium of Investigative Journalists, provides us with the names of all financial institutions related to a suspicious transaction as well as the number and dollar value of suspicious transactions. We manually match the names of the involved banks to tickers and then retrieve returns data around the leak date from Yahoo! Finance. We calculate cumulative returns up to a 5-day window after the event. We employ two benchmarks: the stock's own past-one-year average return and the S&P index.

We first provide graphical evidence on the effect of the FinCEN data leak. In Figure 5, we plot cumulative returns for banks in our sample from day $t-5$ to day $t+9$. The trends are striking, with cumulative returns plummeting on the leak date and remaining highly negative through the nine day post-event window.

Our evidence also suggests that the market reaction is more severe when a bank is revealed to have facilitated a higher dollar amount of suspicious transactions. In Figure 6, we plot the relationship between cumulative abnormal market return reactions during the 5-day post-event

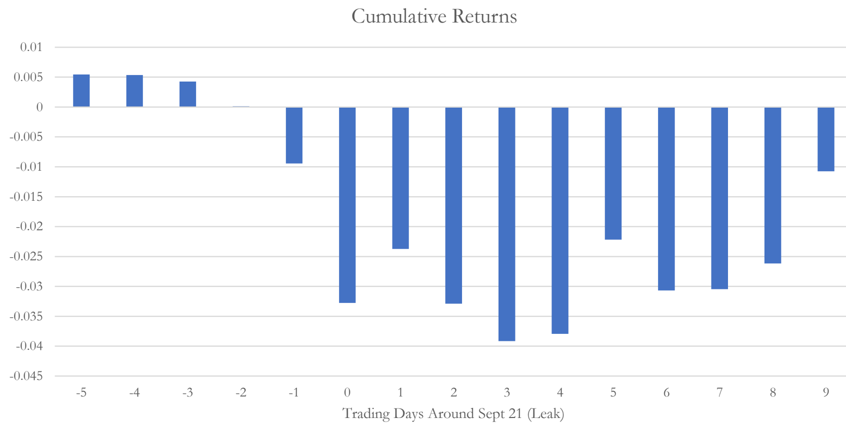


Figure 5: Cumulative Return Reaction Around FinCEN Leak. This figure presents the cumulative return reaction around the leak of FinCEN files on September 21^{st}, 2020 for banks involved in the leak. The base date is September 14^{th}. The y-axis represents cumulative returns relative to one week prior to the leak, and the x-axis represents the trading days relative to the leak.

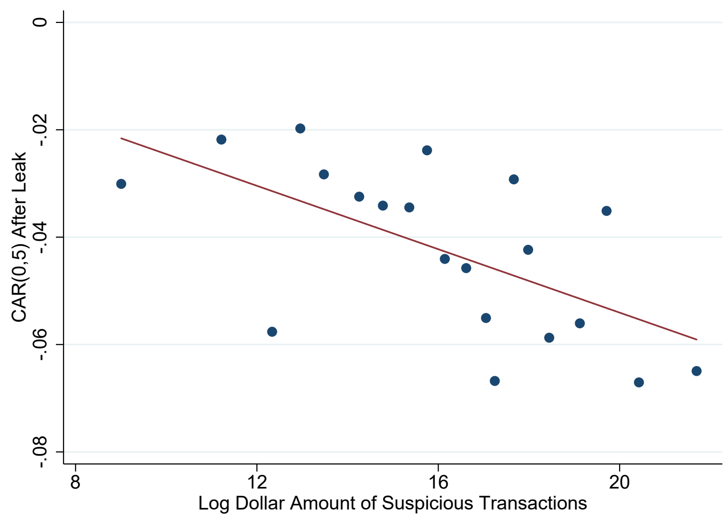


Figure 6: CAR(0,5) Following FinCEN Leak. This figure shows the relationship between the cumulative abnormal market returns for banks involved in the FinCEN leak and the log dollar amount of suspected money laundering activities. The dots represent the average CAR for each of the 20 bins of suspicious transaction amount. The solid line represents a fitted regression line between CAR and the transaction amount.

windows (Y-axis) and the dollar amount of suspicious transactions (X-axis). The solid line represents a fitted regression line between the stock return reactions and the leaked volume. There is a strong negative relationship, suggesting that market reactions are tied to the severity of the leak.

We next tabulate mean returns for all of the return windows and benchmarks. Table 15 provides the results from this analysis. Panel A presents cumulative returns for all banks (including international banks) and Panel B focuses on only banks listed in the United States (including

NYQ and PNK). We present cumulative returns for three windows: the announcement date, three days after the announcement date, and five days after the announcement date. The columns indicate whether the returns represent raw returns or are benchmarked against a bank's own past-one-year average returns or S&P returns.

TABLE 15 ABOUT HERE

The results reveal a large and statistically significant negative reaction to the FinCEN leak. In Panel A, we find that announcement date returns are approximately -1% to -2.5%, depending on the benchmark. These returns further decline as we extend the window to three and five days, reaching -5% by the fifth day. The results in Panel B, which focus on only U.S. banks reveal a similar pattern. These effects are highly significant at the 1% level.

Overall, the returns analyses depict a clear picture of how equity market investors respond to money laundering. Banks experienced significant negative market reactions following the most prominent SAR leak in history. Markets react most negatively for banks revealed to be most involved in illegal activities. These results motivate our investigation of the incentives banks face to file SAR reports, and its implications for crime.[20]

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

[20]We note that these results could be rationalized in a slight variation of our theoretical model. Suppose that claims to the bank's terminal value are traded in a financial market and that traders face some uncertainty about bank profitability (x_0 in the model). Because profitability and SAR volume are correlated in equilibrium, traders should rationally update their beliefs about bank profitability after a leak of SAR reports. This revision in beliefs should then be reflected in the bank's stock price. The negative response in the data is consistent with a *negative* profitability-SAR relationship and therefore further supports the strategic advertising effect.

county-level data on monthly SAR reporting. Our results indicate that counties with banks facing higher competition and lower profitability generate higher volumes of SAR activity. Using shale gas activity in unrelated states, we demonstrate a causal link between risk-taking incentives and SAR activity. In addition, we show that pressure to meet public earnings targets exacerbates the strategic advertising effect.

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 exponential growth in financial crime. 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.

References

Allen, F. and D. Gale (2004). Competition and financial stability. *Journal of Money, Credit and Banking 36*(3), 453–480.

Ağca, S., P. Slutzky, and S. Zeume (2020). Anti-money laundering enforcement, banks, and the real economy. *Available at SSRN*.

Ayers, B. C., S. Ramalingegowda, and P. E. Yeung (2011). Hometown advantage: The effects of monitoring institution location on financial reporting discretion. *Journal of Accounting and Economics 52*(1), 41–61.

Begley, T. A., A. Purnanandam, and K. Zheng (2017). The strategic underreporting of bank risk. *The Review of Financial Studies 30*(10), 3376–3415.

Bhojraj, S., P. Hribar, M. Picconi, and J. McInnis (2009). Making sense of cents: An examination of firms that marginally miss or beat analyst forecasts. *The Journal of Finance 64*(5), 2361–2388.

Blum, J. (1999). Do capital adequacy requirements reduce risks in banking? *Journal of Banking & Finance 23*(5), 755–771.

BuzzFeed News (2020, September). Dirty money pours into the world's most powerful banks. BuzzFeed News, September 20. https://www.buzzfeednews.com/article/jasonleopold/fincen-files-financial-scandal-criminal-networks.

Daily Mail (2016, February). Why cherie's bank is still a haven for crooks. Daily Mail, February 22. https://www.dailymail.co.uk/news/article-3459374/Why-Cherie-s-bank-haven-crooks-HSBC-reveals-monitor-installed-fined-1-1bn-money-laundering-flagged-concerns-pace-progress.html.

Dimmock, S. G., W. C. Gerken, and N. P. Graham (2018). Is fraud contagious? coworker influence on misconduct by financial advisors. *The Journal of Finance 73*(3), 1417–1450.

Drechsler, I., A. Savov, and P. Schnabl (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics 132*(4), 1819–1876.

Egan, M., G. Matvos, and A. Seru (2019). The market for financial adviser misconduct. *Journal of Political Economy 127*(1), 233–295.

Feinstein, J. S. (1990). Detection controlled estimation. *The Journal of Law and Economics 33*(1), 233–276.

FinCEN (2018, August). Prepared remarks of fincen director kenneth a. blanco, delivered at the 11th annual las vegas anti-money laundering conference and expo. FinCEN, August 13. https://www.fincen.gov/news/speeches/prepared-remarks-fincen-director-kenneth-blanco-delivered-11th-annual-las-vegas-1.

Gilje, E., R. Ready, and N. Roussanov (2016). Fracking, drilling, and asset pricing: Estimating the economic benefits of the shale revolution. Technical report, National Bureau of Economic Research.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020). Bartik instruments: What, when, why, and how. *American Economic Review 110*(8), 2586–2624.

Graham, J. R., C. R. Harvey, and S. Rajgopal (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics 40*(1-3), 3–73.

Hadlock, C. J. and J. R. Pierce (2010). New evidence on measuring financial constraints: Moving beyond the kz index. *The Review of Financial Studies 23*(5), 1909–1940.

Hellmann, T. F., K. C. Murdock, and J. E. Stiglitz (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? *American economic review 90*(1), 147–165.

Kashyap, A. K. and J. C. Stein (1995). The impact of monetary policy on bank balance sheets. In *Carnegie-rochester conference series on public policy*, Volume 42, pp. 151–195. Elsevier.

Kedia, S. and S. Rajgopal (2011). Do the sec's enforcement preferences affect corporate misconduct? *Journal of Accounting and Economics 51*(3), 259–278.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *The American Economic Review 80*(5), 1183–1200.

Khanna, V., E. H. Kim, and Y. Lu (2015). Ceo connectedness and corporate fraud. *The Journal of Finance 70*(3), 1203–1252.

Kim, D. and A. M. Santomero (1988). Risk in banking and capital regulation. *The journal of finance 43*(5), 1219–1233.

Laeven, L. and R. Levine (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics 93*(2), 259–275.

Martinez-Miera, D. and R. Repullo (2010). Does competition reduce the risk of bank failure? *The Review of Financial Studies 23*(10), 3638–3664.

Martynova, N. (2015). *Bank profitability and risk-taking*. International Monetary Fund.

Maxwell, N. J. and D. Artingstall (2017). The role of financial information-sharing partnerships in the disruption of crime. *Royal United Services Institute for Defence and Security Studies*.

Pacelli, J. (2019). Corporate culture and analyst catering. *Journal of Accounting and Economics 67*(1), 120–143.

Plosser, M. C. and J. A. Santos (2018). Banks' incentives and inconsistent risk models. *The Review of Financial Studies 31*(6), 2080–2112.

Repullo, R. (2004). Capital requirements, market power, and risk-taking in banking. *Journal of Financial Intermediation 13*(2), 156–182.

The Wall Street Journal (2013, May). U.s. says firm laundered billions. The Wall Street Journal, May 28. https://www.wsj.com/articles/SB10001424127887323855804578511121238052256.

The Wall Street Journal (2020, October). Banks can only tighten their belts so much. The Wall Street Journal, Oct 2. https://www.wsj.com/articles/banks-can-only-tighten-their-belts-so-much-11601636550.

Vallascas, F. and J. Hagendorff (2013). The risk sensitivity of capital requirements: Evidence from an international sample of large banks. *Review of Finance 17*(6), 1947–1988.

Wang, T. Y., A. Winton, and X. Yu (2010). Corporate fraud and business conditions: Evidence from ipos. *The Journal of Finance 65*(6), 2255–2292.

Wang, Y., T. M. Whited, Y. Wu, and K. Xiao (2020). Bank market power and monetary policy transmission: Evidence from a structural estimation. Technical report, National Bureau of Economic Research.

Williams, T., P. Slutzky, M. Villamizar-Villegas, et al. (2020). Drug money and bank lending: The unintended consequences of anti-money laundering policies. Technical report.

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, such 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. The constants used in the Lemma are given by $\tilde{f} \equiv \left(\frac{\lambda}{\delta} f\right)^{-\frac{1}{\alpha}} > 0$ and $\tilde{g} \equiv (\gamma + (1-\gamma)\pi)^{-\frac{1}{\alpha}} > 1$.

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) $F > x_R(l)$. We assume that the bank always chooses the lax policy when indifferent between $\mathcal{R} = s$ and $\mathcal{R} = l$.

1. <u>$F \leq x_R(l)$</u>:

   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 $x_R(l) - F \geq x_s$. If $x_s > x_R(l) - F$, we have to take into account the earnings target $\hat{\Pi}$.

   (a) If $\hat{\Pi} < x_0 + x_R(l) - F$, the bank chooses the strict policy if and only if:

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

   which simplifies to $\pi F > x_R(l) - x_R(s)$.

   (b) If $x_0 + x_R(s) > \hat{\Pi} \geq x_0 + x_R(l) - F$, the bank chooses the strict policy if and only if:

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

   which simplifies to $\pi F > x_R(l) - x_R(s) - \pi\tau$.

   (c) If $x_0 + x_R(l) > \hat{\Pi} \geq x_0 + x_R(s)$, the bank chooses the strict policy if and only if:

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

   which simplifies to $\pi F > x_R(l) - x_R(s) + (1-\pi)\tau$.

   (d) If $\hat{\Pi} > x_0 + x_R(l)$, 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 $\pi F > x_R(l) - x_R(s)$.

2. <u>$F > x_R(l)$</u>:

   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 $U_b(s) > (1-\pi)U_b(l)\mathcal{I}_{\{d_b=0\}}$. As above, we solve for the optimal reporting choice depending on the earnings target $\hat{\Pi}$.

(a) If $\hat{\Pi} < x_0 + x_R(s)$, the bank chooses the strict policy if and only if:

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

which simplifies to $x_0 > \frac{1}{\pi}\left((1-\pi)x_R(l) - x_R(s)\right) + \frac{1-\pi}{\pi}\tau$.

(b) If $x_0 + x_R(l) > \hat{\Pi} \geq x_0 + x_R(s)$, the bank chooses the strict policy if and only if:

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

which simplifies to $x_0 > \frac{1}{\pi}\left((1-\pi)x_R(l) - x_R(s)\right) - \tau$.

(c) If $\hat{\Pi} \geq x_0 + x_R(l)$, the bank chooses the strict policy if and only if:

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

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

A.3 Proof of Corollary 1

The first part of the Corollary is proven in the main text. The comparative statics for $\overline{\alpha} = -\frac{\log(\gamma+(1-\gamma)\pi)}{\log(1+\frac{1-\gamma}{\gamma\lambda})}$ are given by:

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

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

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 local bank's ROA, calculated as net income over total assets at the consolidated parent level. The weights are the percentage of deposit of a given county held by the bank.
- *Bank Net Interest Margin*: The weighted average of 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 deposit of a given county held by the bank.
- *Bank Equity Ratio*: The weighted average of local bank's equity ratio, measured by bank equity over total assets at the parent level. The weights are the percentage of deposit of a given county held by the bank.
- *Bank Tier 1 Capital Ratio*: The weighted average of 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 deposit 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.
- *SAR/Deposits*: The number of money-laundering related SARs reported by depository institutions in a county scaled by total county deposits.
- *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.
- *Bank Meet or Beat*: The weighted average across all banks operating in a county of an indicator for whether a parent bank narrowly meet or beat analysts' consensus earnings forecast. The indicator turns to one if a bank's earnings equals the analyst forecasted earnings or exceeds the forecast by 1 cent, and zero otherwise. The weight is a bank's deposit share in a given county.
- *NonBank SAR/Pop*: The number of money-laundering related SARs reported by non-bank institutions in a county, scaled by county population.
- *Large Bank ROA*: The weighted average of the product between a local bank's ROA 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 deposit 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 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 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.
- Near FDIC: An indicator for whether a county is located within a 30-mile or 50-mile radius surrounding the zipcode of a FDIC office.
- Far from FDIC: An indicator for whether a county is located outside a 30-mile or 50-mile radius surrounding the zipcode of a FDIC office.
- *Post Violation*: A dummy variable that equals one if a bank has received a regulatory fine regarding anti-money-laundering deficiencies in the past.
- *Log(Branches)*: The log number of branches a bank has in a county
- *Log(Deposits)*: The log dollar amount of deposits a bank has in a county
- *CAR(0, T)*: The cumulative abnormal return of a publicly traded bank around September 21st.

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	21,189	1.416	1.669	0.290	0.853	1.936
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
Quarterly Sample						
SAR	84,756	0.353	0.453	0.000	0.201	0.501
Bank ROA	83,572	0.003	0.001	0.002	0.003	0.003
Bank ROE	83,572	0.025	0.009	0.021	0.025	0.029
Bank Net Interest Margin	83,532	0.008	0.001	0.007	0.008	0.009
Bank Equity Ratio	83,572	0.112	0.014	0.104	0.111	0.119
Bank Tier 1 Capital Ratio	54,372	0.097	0.013	0.088	0.094	0.103
Controls (Annual Sample)						
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)	18,162	10.373	1.400	9.413	10.230	11.195
%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 Competition and SAR Activity

This table provides results from county-level regressions of SAR reporting on bank competition. The dependent variable is the per capita number of SARs in a county. *Deposit HHI* is a concentration measure based on the percentage of deposits that each branch has in a county. *Branch HHI* is a concentration meaure based on the percentage of deposits that all branches of a given bank have a in a given county. Variable definitions are provided in Appendix B. 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.: *SAR/Pop*	(1)	(2)	(3)	(4)
Deposit HHI	-0.9187***	-0.7929***		
	(0.233)	(0.296)		
Branch HHI			-1.1514***	-1.0321***
			(0.216)	(0.260)
State-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
Observations	21,014	18,013	21,014	18,013
Adjusted R^2	0.843	0.855	0.843	0.855

Table 3: Bank Profitability and SAR Activity
This table provides results from county-level regressions of SAR reporting on bank profitability. The dependent variable is per capita number of SARs. *Bank ROA* is the percentage of a bank's deposits in a county relative to total deposits multiplied by ROA. *Bank Net Interest Margin* is the percentage of a bank's deposits in a county relative to total deposits multiplied by net interest margin. 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)
Bank ROA	-7.3999***	-8.6296***		
	(2.367)	(2.492)		
Bank Net Interest Margin			-17.7622***	-17.3293***
			(4.008)	(4.201)
State-Year-Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
Observations	74,576	63,888	74,536	63,852
Adjusted R^2	0.777	0.793	0.777	0.793

Table 4: Other Risk-Taking Measures and SAR Activity

This table provides results from county-level regressions of SAR reporting on measures indicating bank balance sheet strength, including net worth and capital adequacy. The dependent variable is per capita number of SARs. *Bank Equity Ratio* is the weighted average of equity ratio of all banks that operate branches in a county, with the weights being the percentage of a bank's deposits in a county relative to total county deposits. Equity ratio is defined as total equity scaled by total assets, measured at the parent bank level. *Bank Tier 1 Capital Ratio* is the weighted average of Tier 1 capital ratios of all banks that have branches in a county, with the weights being the percentage of a bank's deposits in a county relative to total county deposits. 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)
Bank Equity Ratio	-1.1595***	-1.3127***		
	(0.331)	(0.376)		
Bank Tier 1 Capital Ratio			-0.7761**	-0.4961
			(0.353)	(0.362)
State-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
Observations	74,576	63,888	49,064	38,376
Adjusted R^2	0.777	0.793	0.807	0.835

Table 5: Risk-Taking Incentives and SAR Activity: Alternative Scalar
This table provides results from county-level regressions of SAR reporting on bank risk-taking measures, when the dependent variable is defined as the number of SARs scaled by deposits (*SAR/Deposit*). *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 deposits that all branches of a given bank have a in a given county. *Bank ROA*, *Bank Net Interest Margin*, *Bank Equity Ratio*, and *Bank Tier 1 Capital Ratio* are the weighted average of bank characteristics across all banks that operate branches in a county. The weight is the percentage of a bank's deposits in a county relative to total county deposits. 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/Deposits*	(1)	(2)	(3)	(4)	(6)	(7)
Deposit HHI	-0.0747***					
	(0.026)					
Branch HHI		-0.0445*				
		(0.026)				
Bank ROA			-0.5317***			
			(0.166)			
Bank Interest Margin				-2.6506***		
				(0.520)		
Bank Equity Ratio					-0.0918***	
					(0.027)	
Bank Tier1-Capital Ratio						-0.0512**
						(0.023)
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,022	16,022	63,880	63,844	63,880	38,372
Adjusted R^2	0.867	0.867	0.786	0.786	0.786	0.826

Table 6: 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 SAR 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 in 10 railroad commission (RRC) districts. We first calculate the share of deposits or branches a bank has in the shale state/area relative to the bank's total share and deposit based on its 2011 distribution. We then use that as a weight to compute the bank's total exposure to shale growth in those areas. In a county outside of the shale states, we account for the shale growth exposure of the parent banks of local branches, and examine the relation between shale growth exposure and the suspicious activity report at the county level. 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.: *SAR/Pop*	(1)	(2)	(3)	(4)
Shale Growth Exposure (Deposit-weighted)	-2.8748***	-1.7178***		
	(0.411)	(0.427)		
Shale Growth Exposure (Branch-weighted)			-3.4220***	-2.1990***
			(0.451)	(0.481)
State-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
Observations	14,486	12,416	14,486	12,416
Adjusted R^2	0.860	0.872	0.860	0.872

Table 7: Earnings Targets and SAR Activity

This table provides results from county-level regressions of SAR reporting on earnings pressure arising from analysts' consensus forecast. The dependent variable is the per capita number of SARs in a county. *Bank Meet or Beat* is the weighted average of an indicator variable that takes the value of one if a (parent) bank meets or beats the analyst consensus forecast by at most one cent, and zero otherwise. The weight is a bank's deposit share in a county. Columns (1) and (2) include all sample bank and counties. Columns (3) and (4) restrict the sample to only banks (and their branch locations) that meet or beat the analyst consensus forecast by one cent or miss the forecast by one cent. 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)
Sample:	All	All	Near Zero	Near Zero
Bank Meet or Beat	0.0171***	0.0150***	0.0111**	0.0112**
	(0.004)	(0.004)	(0.004)	(0.004)
State-Year-Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
Observations	60,104	53,350	43,440	39,220
Adjusted R^2	0.782	0.795	0.809	0.819

Table 8: Pre-Trend Analysis
This table provides results from county-level regressions of SAR reporting at time t on bank profitability or net interest margin at time $t-2$ 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 3). 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 $t-2$ 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-2)	-0.8655	-23.5207***
	(2.181)	(4.009)
Bank Profitability (t-1) (Baseline)	-8.6296***	-17.3293***
	(2.492)	(4.201)
Bank Profitability (t)	-9.9778***	-15.1754***
	(2.611)	(4.359)
Bank Profitability (t+1)	-1.4437	0.2588
	(2.442)	(4.801)
Bank Profitability (t+2)	-3.6777	1.3148
	(2.370)	(5.982)
State-Year-Quarter FE	Yes	Yes
County FE	Yes	Yes
County Controls	Yes	Yes

Table 9: Placebo Test based on Non-Bank SARs
This table provides results from county-level regressions of non-bank SAR volume on competition, bank profitability and other risk-taking measures. The dependent variable is the per capita number of SARs related to money-laundering activities reported by non-bank institutions in a county. *Deposit HHI* is the Herfindahl Index based on banks' deposit shares in a county. *Branch HHI* is the Herfindahl Index based on banks' branch shares (i.e., percentage of number of branches) in a county. *Bank ROA*, *Bank Net Interest Margin*, *Bank Equity Ratio*, and *Bank Tier 1 Capital Ratio* are the weighted average of bank characteristics across all banks that operate branches in a county. The weight is the percentage of a bank's deposits in a county relative to total county deposits. 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.: *NonbankSAR/Pop*	(1)	(2)	(3)	(4)	(5)	(6)
Deposit HHI	-0.0011					
	(0.001)					
Branch HHI		-0.0008				
		(0.001)				
Bank ROA			-0.0117			
			(0.017)			
Bank Net Interest Margin				0.0046		
				(0.028)		
Bank Equity Ratio					0.0015	
					(0.003)	
Bank Tier1-Capital Ratio						-0.0021
						(0.002)
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	15,041	15,041	52,850	52,835	52,850	33,741
Adjusted R^2	0.572	0.572	0.431	0.431	0.431	0.545

Table 10: Inferring Suspicious Activities: A Maximum Likelihood Estimation

This table provides results from maximum likelihood estimation based on the model specified in equations (**??**) and (**??**). Profit in equation (**??**) is measured using either bank ROA or the net interest margin, both expressed in percentage points. The data is at country-year-quarter level. The first stage models the determination of local suspicious activities; and the second stage models pertains to banks' reporting decisions. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
First Stage: Suspicious Activities				
Bank Reporting Stringency	-1.6031***	-1.8952***	-1.6258***	-1.9207***
	(0.025)	(0.025)	(0.028)	(0.028)
Second Stage: Reporting Decision				
Bank ROA	1.1612***	1.1462***		
	(0.018)	(0.018)		
Bank Net Interest Margin			1.5759***	1.7632***
			(0.016)	(0.016)
Controls	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Pseudo Log-likelihood	-41,856	-41,631	-41,856	-41,631

Table 11: Regulatory Distance, Profitability, and SAR Activity
This table provides results from county-level regressions of SAR activity on banks' profitability based on the distance from the FDIC. The dependent variable is the per capita number of SARs. *Near FDIC (<=30 miles)* and *Near FDIC (<=50 miles)* indicates counties that are within 30 or 50 miles of an FDIC field office, respectively. *Far from FDIC (>30 miles)* and *Far from FDIC (>50 miles)* indicates counties that are more than 30 or 50 miles from an FDIC field office, respectively. *Bank ROA* is the weighted average ROA acorss banks that operate branches in a county, with the weight being the percentage of a bank's deposits in a county relative to total county deposits. 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)
*Near FDIC (<=30 miles)*Bank ROA*	6.1734	7.9727		
	(7.506)	(10.005)		
*Far from FDIC (>30 miles)*Bank ROA*	-9.1424***	-10.7583***		
	(2.362)	(2.481)		
*Near FDIC (<=50 miles)*Bank ROA*			-0.3166	-4.8753
			(4.030)	(4.732)
*Far from FDIC (>50 miles)*Bank ROA*			-10.2657***	-10.1173***
			(2.644)	(2.816)
Controls	No	Yes	No	Yes
State-Year-Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	74,576	63,888	74,576	63,888
Adjusted R^2	0.777	0.793	0.777	0.793

Table 12: Bank Size, Profitability, and SAR Activity
This table provides results from county-level regressions of SAR reporting on large banks' profitability. The dependent variable is the per capita number of SARs. *Large Bank ROA* is the Bartik instrument measure of the product between an indicator variable for large banks and bank ROA. The weights in the Bartik measure is 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 at the top 10 across our sample banks. *%Large Banks* is the percentage of deposits in a county held by large banks. *Small Bank ROA* is Bartik instrument measure of the product between an indicator variable for small banks and bank ROA. The weights in the Bartik measure is the percentage of a bank's deposits in a county relative to total county deposits. Small banks are defined as banks whose total assets or deposits rank at the bottom tercile across our sample banks. *%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)
Bank Size Ranked By:	*Assets*	*Assets*	*Deposits*	*Deposits*
Bank ROA	-4.3539*	-4.8286*	-4.6298*	-4.6421*
	(2.523)	(2.896)	(2.538)	(2.807)
Large Bank ROA	-147.7660***	-146.7478***	-107.6129***	-107.2718***
	(18.620)	(18.658)	(15.189)	(15.229)
%Large Banks	0.4543***	0.4516***	0.3346***	0.3332***
	(0.072)	(0.072)	(0.061)	(0.061)
Small Bank ROA		3.7806		1.3744
		(5.163)		(5.993)
%Small Banks		0.0662		0.1038*
		(0.069)		(0.062)
State-Year-Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
Observations	63,888	63,852	63,888	38,376
Adjusted R^2	0.794	0.795	0.796	0.835

Table 13: Response to Bank Violations
This table provides results from bank-county-level regressions of deposit and branch changes following a money laundering violation. The dependent variable is the natural log of a bank's local branches (*Log(Branches)*) in Column 1 and the natural log of a bank's local deposits (*Log(Deposits)*) in Column 2. *Post Violation* is an indicator variable that takes the value of one following a money laundering violation, and zero otherwise. Variable definitions are provided in Appendix B. The unit-of-observation is at the bank-county-year-level. Standard errors are double clustered at the parent bank and county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
Dep. Var.:	*Log(Branches)*	*Log(Deposits)*
Post Violation	-0.0357***	-0.0470**
	(0.011)	(0.019)
Bank-County FE	Yes	Yes
County-Year FE	Yes	Yes
Observations	513,846	569,544
Adjusted R^2	0.943	0.932

Table 14: 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 *NonbankSAR/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	0.0020***	0.0028***	0.0028***
	(0.001)	(0.001)	(0.001)
NonbankSAR/Pop			-0.0318
			(0.066)
Controls	No	Yes	Yes
State-Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	55,667	45,756	45,756
Adjusted R^2	0.516	0.517	0.517

Table 15: Market Reactions Surrounding September 21st FinCEN Data Leak

This table provides the market reactions surrounding the September 21st FinCEN data leak. The analysis includes banks listed in the FinCEN data leaked by the International Consortium of Investigative Journalists. Cumulative returns are provided for three windows: announcement date (*CAR(0,0)*), announcement date through day *t+3* (*CAR(0,3)*), and announcement date through day *t+3* (*CAR(0,5)*). Panel A presents the results for all banks (including international banks) and Panel B focuses on only banks listed in the United States (including NYQ and PNK). The columns indicate whether the return is computed as raw return or benchmarked based on a bank's past-one-year average returns or S&P returns. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: All Bank Stocks

Benchmark:	Raw	Past Average	S&P Returns
CAR(0, 0)	-2.46%***	-2.42%***	-1.31%***
	(0.0011)	(0.0011)	(0.0011)
CAR(0, 3)	-5.12%***	-4.93%***	-2.95%***
	(0.0019)	(0.0018)	(0.0019)
CAR(0, 5)	-4.83%***	-4.60%***	-4.23%***
	(0.0020)	(0.0020)	(0.0020)

Panel B: U.S. Listed Stocks Only

Benchmark:	Raw	Past Average	S&P Returns
CAR(0, 0)	-2.91%***	-2.87%***	-1.75%***
	(0.0019)	(0.0019)	(0.0019)
CAR(0, 3)	-5.55%***	-5.38%***	-3.37%***
	(0.0028)	(0.0028)	(0.0028)
CAR(0, 5)	-5.91%***	-5.70%***	-5.33%***
	(0.0033)	(0.0033)	(0.0033)