Internet Appendix for: Dirty Money: How Banks Influence Financial Crime*

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Abstract

This Appendix provides additional background information and results, not reported in the paper. In Section 1, we present tests based on alternative scalars; Section 2 presents the Hessian Matrix from our structural estimation; Section 3 reports results regarding banks' response to violations; Next, in Section 4, we provide a theoretical framework and analysis incorporating earnings shocks; In Section 5, we assess the market reactions to the September 21^{st} FinCEN data leak; Finally, in Section 6, we analyze banks' investment in AML personnel, based on job postings data.

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

JEL Classification: G21; G28

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1 Alternative Scalars

Our main 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 IA.1 reports the results. We present the results for each of our risk-taking measures, after controlling for state-year (state-quarter) fixed effects, county fixed effects, and county-level controls. Across all measures, 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.[1]

TABLE IA.1 ABOUT HERE

2 Estimation Results: Hessian Matrix

We present in Table IA.2 the Hessian Matrix from our estimation results. As shown in the table, the joint likelihood function is sensitive to these parameters. The derivatives suggest that the likelihood value changes shapely in different directions as we vary underlying parameters (the rows of the Hessian is highly linearly independent).

TABLE IA.2 ABOUT HERE

3 Response to Bank 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.

[1]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.

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" 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.[2] 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:

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

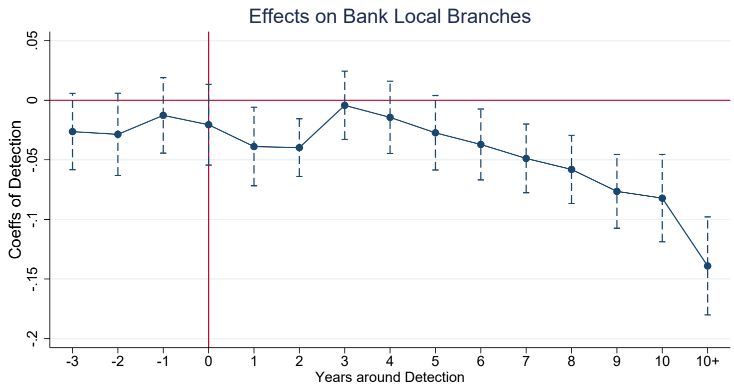
where b indexes bank, c indexes county, and t indexes month. $Bank\ Outcome_{b,c,t}$ gauges the the branches and deposits owned by a bank in each county. It includes two measures: *Log(Branches)*, the natural log of the number of branches; and *Log(Deposits)*, the natural log of deposits. The sample 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 changes in deposits (or branches) for other banks in the same county at the same time.

Table IA.3 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%.

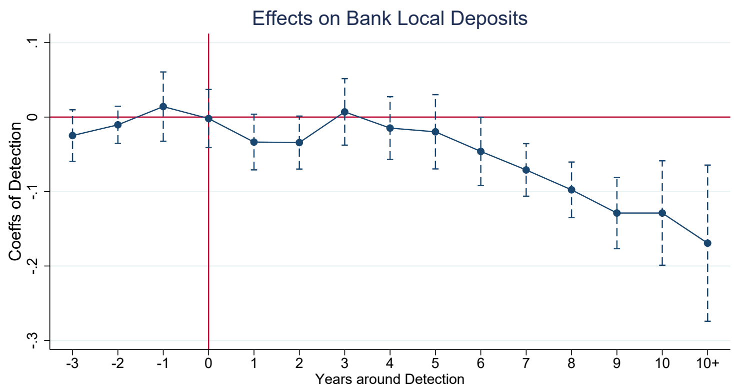
<u>TABLE IA.3 ABOUT HERE</u>

Figure IA.1 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)*.

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



(A) Bank Local Branches After Detection



(B) Bank Local Deposits After Detection

Figure IA.1: The Effect of Regulatory Fines on Banks' Local Market Shares. This figure presents changes in banks' local deposits and branches following a regulatory fine related to 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 violations 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.

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

4 Earnings Shocks: Theory and Analysis

We consider an extension of the main model and specify the bank's objective function as:

$$U_b(\mathcal{R}) = \max(\Pi(\mathcal{R}), 0) + \mathcal{I}_{\{\Pi > \hat{\Pi}\}}\tau \tag{1}$$

where $\hat{\Pi} > 0$ represents the earnings target. The bank receives an additional utility $\tau \geq 0$ from beating this target. This reward can give them an additional incentive to take on more risks. All other model elements are the same as in the main model. Hence, this extension collapses to the main model if $\tau = 0$.

In addition to the "gambling-for-resurrection" incentives that are highlighted in the main model, 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 the following derivations that the effect of x_0 on SAR volume is strengthened by the presence of earnings pressure.

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

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

   In this case, the bank's limited liability constraint does not bind. It is optimal to choose $\mathcal{R} = s$ if and only if $\mathbb{E}[U_b(s)] > \mathbb{E}[U_b(l)]$. Note that the bank always chooses $\mathcal{R} = l$ if $x_R(l) - F \geq x_R(s)$. If $x_R(l) - F < x_R(s)$, then we have to take into account the earnings target $\hat{\Pi}$.

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

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

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

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

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

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

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

In cases (a)–(d), the bank's reporting policy does not depend on x_0.

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

In this case, the bank's limited liability constraint binds if $d_b = 1$. It is optimal to choose $\mathcal{R} = s$ if and only if $U_b(s) > (1-\pi)U_b(l)\mathcal{I}_{\{d_b=0\}}$. As above, we solve for the optimal reporting choice depending on the earnings target $\hat{\Pi}$.

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

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

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

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

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

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

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

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

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

Therefore, earnings pressure matters only in cases (a) and (b). In these two cases, a higher earnings target $\widehat{\Pi}$ increases the threshold $\overline{x_0}$ for the strict reporting policy.

Empirically, we 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. As discussed above, 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 the 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 IA.4 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.[3]

TABLE IA.4 ABOUT HERE

5 Market Reactions to FinCEN Data 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 this section, 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.

[3] We generate similar results after controlling for non-bank SARs (untabulated).

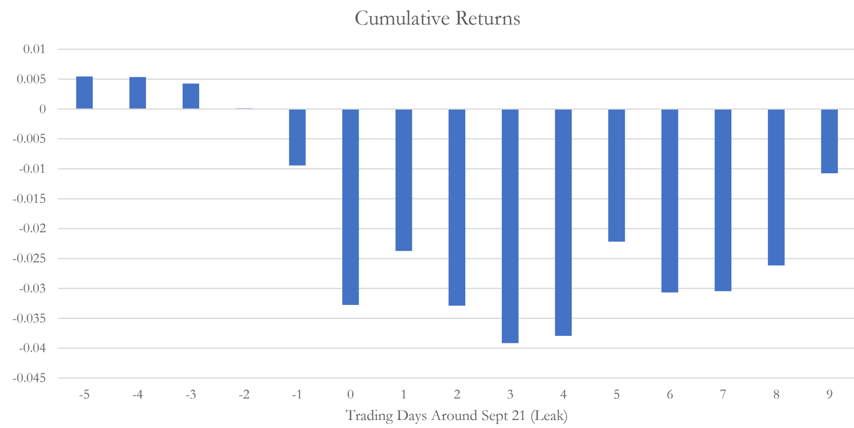


Figure IA.2: Cumulative Return Reaction Around FinCEN Leak. This figure presents the cumulative return reaction around the leak of FinCEN files on September 21^{st}, 2020 for banks involved in the leak. The base date is September 14^{th}. The y-axis represents cumulative returns relative to one week prior to the leak, and the x-axis represents the trading days relative to the leak.

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 IA.2, 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 IA.3, we plot the relationship between cumulative abnormal market return reactions during the 5-day post-event 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

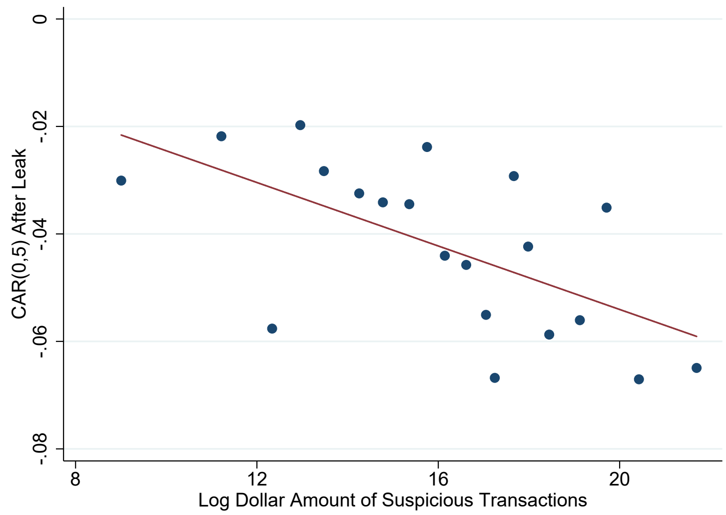


Figure IA.3: CAR(0,5) Following FinCEN Leak. This figure shows the relationship between the cumulative abnormal market returns for banks involved in the FinCEN leak and the log dollar amount of suspected money laundering activities. The dots represent the average CAR for each of the 20 bins of suspicious transaction amount. The solid line represents a fitted regression line between CAR and the transaction amount.

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 IA.5 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 returns benchmarked against a bank's own past-one-year average returns or S&P returns.

Table IA.5 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 their implications for crime.[4]

6 Job Posting Analyses

One alternative explanation for our results is that more profitable banks face fewer financial constraints. This allows such banks to invest in better screening technologies, resulting in fewer SARs since the system is more likely to identify and report bad customers.

In this section, we further test the validity of this alternative explanation. To do so, we collect job postings data from Burning Glass Technologies (BGT) and then examine how bank profitability relates to the demand for bank examiners using the following regression:

$$Bank\ Outcome_{b,t} = Bank\ ROA_{b,t} + Bank\ Size_{b,t} + Bank\ Outcome_{b,t-1} + \eta_t + \epsilon_{b,t},$$

where *Bank Outcome* is either the natural log of total job ads (*Log(Job Ads)*), the natural log of total job ads indicating an examiner vacancy (*Log(Examiners)*), or the natural log of total job ads indicating a vacancy for sales personnel (*Log(Sales Personnel)*). The model controls for bank size, the lagged dependent variable, and year fixed effects. For the financial constraint explanation to hold, we expect that more profitable banks will will hire more examiners.

Table IA.6 provides the results from this analysis. In Columns (1) and (2), we first examine the relationship between profitability and total job postings. The coefficient on *Bank ROA* is positive and significant, indicating that more profitable banks hire more personnel. This result persists after controlling for bank size in Column (2), as well as the lagged value of *Log(Jobs Ads)*. In Columns (3) and (4), we consider *Log(Examiners)* as our dependent variable, and find no relation between bank

[4]We note that these results could also 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.

profitability and hiring. This suggests that more profitable banks hire more personnel, but these human capital investments do not appear to be concentrated among bank examiners. In Columns (5) and (6), we shed some more light on how banks focus their hiring efforts, by examining how profitability relates to sales personnel postings. We document a positive and significant loading on *Bank ROA*, which suggests that profitable banks hire more sales personnel. Taken together, the results suggest that profitable banks do indeed hire more personnel, but there is no evidence that this investment is focused on improving SAR reporting or AML compliance. This renders the alternative explanation based on financial constraints less plausible.

TABLE IA.6 ABOUT HERE

References

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Table IA.1: 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 of the manuscript. 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			-0.5565***			
			(0.191)			
Bank Interest Margin				-0.9810***		
				(0.311)		
Bank Equity Ratio					-0.0503**	
					(0.024)	
Bank Tier1-Capital Ratio						-0.0616**
						(0.026)
State-Year FE	Yes	Yes				
State-Quarter FE			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	74,652	74,652	74,652	74,652
Adjusted R^2	0.867	0.867	0.769	0.769	0.769	0.769

Table IA.2: Hessian Matrix

This table reports the Hessian matrix for the maximum likelihood estimation based on the model specified in equations (**??**), (**??**), (**??**), and (**??**). The data is at the country-year-quarter level. Entries in the Hessian matrix correspond to the second derivatives of the joint likelihood, defined in equation (**??**), w.r.t to the underlying parameters. The subscripts, *crm*, *emp*, *inc*, and *hpi* correspond to county-level crime rate, employment rate, income per capita, and hpi growth, respectively, which we use as control variables in our estimation. Panel A presents the results where we measure bank profit using ROA; Pane B corresponds to a separate estimation where bank profit is measured using NIM.

Panel A: Profit Measured by Bank ROA

	γ_1	γ_0^{crm}	γ_0^{emp}	γ_0^{inc}	γ_0^{hpi}	α_1	α_0^{crm}	α_0^{emp}	α_0^{inc}	α_0^{hpi}	α_0^{crm}	ρ_1	ρ_0
γ_1	-136.84	-49.77	4.45	8.50	832.25	-37.65	3.96	3.10	0.29	-61.01	-12.38	0.01	-0.05
γ_0^{crm}	-49.77	-880.75	21.71	-13.14	-14.45	43.54	40.13	-15.29	-0.35	-3.40	24.63	0.00	0.00
γ_0^{emp}	4.45	21.71	-113.54	-15.99	-288.17	51.16	-8.82	-0.82	1.66	31.64	68.49	0.00	0.00
γ_0^{inc}	8.50	-13.14	-15.99	-16.05	-134.85	13.63	-1.25	1.27	1.45	12.64	13.92	0.00	0.00
γ_0^{hpi}	832.25	-14.45	-288.17	-134.85	-49464.94	448.44	-48.53	-1.29	-10.41	708.49	425.52	0.00	0.00
α_1	-37.65	43.54	51.16	13.63	448.44	9.66	27.76	-7.03	-22.66	-168.04	-14.18	-0.08	0.53
α_0^{crm}	3.96	40.13	-8.82	-1.25	-48.53	27.76	-3846.59	13.87	50.15	-139.72	82.84	0.02	-0.47
α_0^{emp}	3.10	-15.29	-0.82	1.27	-1.29	-7.03	13.87	1.03	7.52	20.11	-10.35	0.00	0.09
α_0^{inc}	0.29	-0.35	1.66	1.45	-10.41	-22.66	50.15	7.52	20.17	37.53	-22.61	0.00	-0.08
α_0^{hpi}	-61.01	-3.40	31.64	12.64	708.49	-168.04	-139.72	20.11	37.53	-163.98	-129.56	-0.01	-0.41
α_0^{crm}	-12.38	24.63	68.49	13.92	425.52	-14.18	82.84	-10.35	-22.61	-129.56	-5.89	-0.08	0.37
ρ_1	0.01	0.00	0.00	0.00	0.00	-0.08	0.02	0.00	0.00	-0.01	-0.08	-1.62	-0.22
ρ_0	-0.05	0.00	0.00	0.00	0.00	0.53	-0.47	0.09	-0.08	-0.41	0.37	-0.22	-1.19

Panel B: Profit Measured by Bank NIM

	γ_1	γ_0^{crm}	γ_0^{emp}	γ_0^{inc}	γ_0^{hpi}	α_1	α_0^{crm}	α_0^{emp}	α_0^{inc}	α_0^{hpi}	α_0^{crm}	ρ_1	ρ_0
γ_1	-270.38	256.45	103.83	37.02	696.37	-281.11	-160.83	-36.12	-13.47	-262.55	-373.30	0.16	0.18
γ_0^{crm}	256.45	-3913.32	184.35	-443.72	-625.37	340.34	1177.67	52.95	-4.37	1764.21	425.06	0.00	0.00
γ_0^{emp}	103.83	184.35	-24.85	-99.49	-252.07	141.05	95.88	87.05	10.43	897.89	216.46	0.00	0.00
γ_0^{inc}	37.02	-443.72	-99.49	29.14	-121.29	53.92	-12.95	-8.19	1.28	-130.21	40.09	0.00	0.00
γ_0^{hpi}	696.37	-625.37	-252.07	-121.29	-48706.67	1011.75	63.78	51.63	19.30	6811.78	1127.41	0.00	0.00
α_1	-281.11	340.34	141.05	53.92	1011.75	-576.31	-237.97	-51.06	-8.95	-611.28	-748.86	-2.38	-3.13
α_0^{crm}	-160.83	1177.67	95.88	-12.95	63.78	-237.97	-722.20	51.49	18.84	855.10	-245.48	-0.42	-0.48
α_0^{emp}	-36.12	52.95	87.05	-8.19	51.63	-51.06	51.49	-34.99	-2.93	138.81	-40.91	-0.14	-0.14
α_0^{inc}	-13.47	-4.37	10.43	1.28	19.30	-8.95	18.84	-2.93	-1.77	3.14	-7.51	0.08	0.04
α_0^{hpi}	-262.55	1764.21	897.89	-130.21	6811.78	-611.28	855.10	138.81	3.14	-3158.21	-409.94	-0.02	-0.35
α_0^{crm}	-373.30	425.06	216.46	40.09	1127.41	-748.86	-245.48	-40.91	-7.51	-409.94	-1016.86	-2.03	-2.65
ρ_1	0.16	0.00	0.00	0.00	0.00	-2.38	-0.42	-0.14	0.08	-0.02	-2.03	-4.59	-2.20
ρ_0	0.18	0.00	0.00	0.00	0.00	-3.13	-0.48	-0.14	0.04	-0.35	-2.65	-2.20	-2.66

Table IA.3: 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 of the manuscript. 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 IA.4: Earnings Targets and SAR Activity

This table provides results from county-level regressions of SAR reporting on earnings pressure arising from analysts' consensus forecasts. 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 IA.5: 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 against 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)

Table IA.6: Bank Job Postings
This table provides results from bank-level regressions of job postings on bank profitability. The dependent variable is the natural log of the total number of postings (*Log(Job Ads)*), the total number of postings for bank examiners (*Log(Examiners)*), or the total number of postings for sales personnel (*Log(Sales Personnel)*). Controls include bank size and the lagged dependent variable. Postings for bank examiners are ones that contain "AML", "BSA", or "money" and "launder" in the job titles. Postings for sales personnel are those that contain requirements for sale-related skills, as classified by Burning Glass Technologies (BGT). The unit-of-observation is at the bank-year-level. Standard errors are clustered at the parent bank. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.:	*Log(Jobs Ads)*		*Log(Examiners)*		*Log(Sales Personnel)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Bank ROA	45.4157***	10.6647**	7.9024	2.8627	32.5540***	10.7105**
	(13.405)	(4.355)	(5.445)	(2.957)	(12.589)	(4.439)
Bank Size		0.0886***		0.0489***		0.0916***
		(0.010)		(0.006)		(0.010)
Lagged DV		0.8355***		0.8200***		0.8162***
		(0.011)		(0.015)		(0.012)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,218	8,071	11,218	8,071	11,218	8,071
Adjusted R^2	0.014	0.768	0.134	0.618	0.019	0.734