Money laundering and bank risk: evidence from US banks

ABSTRACT

We test for a link between bank risk and enforcements issued by US regulators against banks for money laundering (ML) in a sample of 960 publicly listed US banks over 2004-2015. ML-related enforcements are associated with increased bank risk on several measures of risk with the result robust to a variety of estimation methodologies. Moreover, the impact of money laundering on bank risk is accentuated by the presence of powerful CEOs and only partly mitigated by large and independent executive boards.

Keywords: Bank risk, money laundering, bank boards, CEO power, US banks

JEL classifications: G20, G21, G34

1. Introduction

The literature on the determinants of bank risk has largely ignored the impact of engaging in money laundering (ML). This is surprising for several reasons. First, combatting ML is a major focus of US (and other) bank regulators concerned with the stability of the financial system. For example, the US Office of the Comptroller of the Currency views it as posing risks to the safety and soundness of the financial industry and the safety of the nation more generally as terrorists employ ML to fund their operations.[1] The intergovernmental body, the Financial Action Task Force cites changes in money demand, prudential risks to bank soundness, contamination effects on legal financial transactions, and increased volatility of international capital flows and exchange rates

[1] See the statement of the OCC on money laundering on its web site at: https://www.occ.gov/topics/compliance-bsa/bsa/index-bsa.html

due to unanticipated cross-border asset transfers as potential adverse economic consequences of ML.[2] One result of the focus on ML has been an extraordinary growth of anti-money laundering (AML) legislation since the mid-1980s that has imposed a heavy burden on financial institutions, especially as the legislation has shifted to the financial system the responsibility for keeping criminal money out of, and reporting instances when they suspect that it has entered into, legitimate institutions (Levi and Reuter, 2011).[3] Second, ML exposes banks to serious reputational, operational, compliance and concentration risks that could result in significant financial costs (e.g. through fines and sanctions by regulators, termination of wholesale funding facilities, claims against the bank, investigation costs, asset seizures and freezes, and loan losses) and the diversion of valuable management time and operational resources to resolve ML-related problems. Third, the risks to banks from ML have been increased by the growth in volume of cross-border transactions that have made banks inherently more vulnerable, by the fact that regulators are continually revising rules as their focus expands from organized crime to terrorism, and because governments have expanded their use of economic sanctions to target individual countries, entities, and even specific individuals as part of their foreign policies (Kittrie, 2009). The risks to banks have been highlighted by several enforcement actions taken by regulators and the corresponding direct and indirect costs incurred by banks due to their lack of diligence in applying appropriate risk management policies.[4] In this

[2] On the Financial Action Task Force, see for example, http://www.fatf-gafi.org/faq/moneylaundering/.

[3] The key US anti-money laundering legislation in recent years includes: the Bank Secrecy Act 1970; the Money Laundering Control Act (1986); the Anti-Drug Abuse Act of 1988; the Annunzio-Wylie Anti-Money Laundering Act (1992); the Money Laundering Suppression Act (1994); the Money Laundering and Financial Crimes Strategy Act (1998); the Uniting and Strengthening America by Providing Appropriate Tools Required to Intercept and Obstruct Terrorism Act of 2001 (USA PATRIOT Act); and the Intelligence Reform & Terrorism Prevention Act of 2004.

[4] Notable recent examples include: (i) HSBC having to pay a $1.9bn (£1.4bn) fine in 2012 for helping drug cartels launder money in Mexico and for contravening sanctions to do business with Iran; potential penalties included further multi-billion dollar fines or having its US banking licenses revoked, which could have crippled the bank (Withers, 2017); and (ii) in 2018 the Dutch bank ING agreeing to pay €775m in penalties for compliance failures that allowed companies to allegedly launder hundreds of millions of euros and pay bribes over six years (Arnold, 2018).

context, the European Systemic Risk Board (2015) has stated that the weight of the fines and litigation expenses of financial misconduct more generally have cut severely into banks' earnings and complicated their keeping up with regulatory capital requirements.

Assessing the impact of ML on bank risk is complicated by the dearth of quantitative data about the extent of ML and the efforts to control it. The existing academic literature comprises mainly law review articles directed towards: (i) identifying the necessary components of an effective AML regime and explaining the laws in force to control money laundering; (ii) criminology and historical analysis, much of which is highly judgmental; (iii) macroeconomic estimates of money laundering based on the size of the underground economy; and (iv) microeconomic studies that focus on different types of crimes and on estimating the income from each (for surveys of this literature see Reuter and Truman, 2004, and Levi and Reuter, 2011). While there are no reliable estimates of the amount of money laundered by banks,[5] an assessment of the impact of ML on bank risk can made by making use of data on ML-related enforcements issued by the main bank regulatory agencies. That is what we do in this paper. Specifically, we assess the impact on bank risk of ML enforcements by the main US bank regulatory agencies in a panel of 960 publicly listed US banks over 2004-2015. We find that ML-related enforcements are associated with increased bank risk on several measures of risk and that the result is robust to a variety of estimation methodologies. Our findings regarding other drivers of bank risk are in line with previous research.

We make four contributions to the banking literature. First, we contribute directly to the literature on the determinants of bank risk, which have been shown to include, for example, banks' business

[5] Levi and Reuter (2011) note that the Financial Action Task Force abandoned an effort to quantify the amount of money laundered through the financial system.

models (Altunbaş et al., 2017), the regulatory and supervisory framework (Laeven and Levine, 2009), market competition (Beck et al., 2013), monetary and macro-prudential policy (Altunbaş et al., 2018a; Dell'Ariccia et al., 2017), and bank ownership structures (Laeven and Levine 2009). Our paper is the first that we are aware of to show that ML is also a significant driver of bank risk. Second, our paper is related to the growing literature on the determinants and consequences of corporate misconduct (see Cumming et al., 2015, 2018 for recent surveys) to which we contribute by focusing on the bank risk dimension of ML. Third, we contribute to the literature on governance in banking (for recent surveys see Srivastav and Hagendorff, 2016; Hagendorff, 2014) by showing that board size and board independence can mitigate but not fully offset the impact of ML on bank risk. Finally, we contribute to the literature on the effects of CEO power on firm performance (e.g., Adams et al., 2005; Abernathy et al., 2015) by showing that powerful CEOs impact adversely on bank risk taking and accentuate the adverse impact of ML on risk.

2. Related literature

Although we know of no studies of the impact of ML on bank risk, there is a burgeoning literature on the impact of financial misconduct more generally on firm behavior that is of direct relevance to our study. For example, Köster and Pelster (2018) examine the impact of financial penalties imposed for misconduct on banks' systemic risk in a sample of 68 international banks between 2007-2014 and find that penalties increase banks' systemic risk exposure but do not significantly affect banks' contribution to systemic risk. Additionally, the link between financial penalties and systemic risk exposure is weaker in regulatory and supervisory systems that have more prompt corrective power. Karpoff et al. (2008) show that the reputational losses for firms as the result of engaging in misconduct are much larger than the financial penalties imposed on firms. They examine the impact of penalties imposed on 585 firms targeted by SEC enforcement actions for financial misrepresentation during 1978–2002. Their point estimate of the reputational penalty (defined as the expected loss in the present value of future cash flows due to lower sales and higher contracting and financing costs) is over 7.5 times the sum of all penalties imposed through the legal and regulatory system. For each dollar that a firm misleadingly inflates its market value, on average, it loses this dollar when its misconduct is revealed, plus an additional $3.08, of which $2.71 is due to lost reputation. Murphy et al. (2009) examine the relationship between allegations of corporate misconduct appearing in *The Wall Street Journal Index* between January 1, 1982, and December 31, 1996 and changes in profitability and risk of the alleged offender and find that misconduct allegations are associated with decreases in earnings and increases in risk. Köster and Pelster (2017) examine the impact of financial penalties on the profitability and stock performance of banks employing a dataset of 671 financial penalties imposed on 68 international listed banks over the period 2007 to 2014. They find a negative relation between financial penalties and pre-tax profitability (banks are allowed to deduct specific financial penalties from their taxable income). However, they report a positive relation between financial penalties and buy-and-hold stock returns, suggesting that investors are pleased that cases are closed and that the banks successfully manage the consequences of misconduct and that the financial penalties imposed are smaller than the accrued economic gains from the banks' misconduct.

Most of the remaining financial misconduct literature can be grouped around three broad themes (see Cumming et al., 2015): the circumstances that provide opportunities to commit and benefit from misconduct; external factors that impact on the incentives to engage in misconduct; and governance factors that can exacerbate or mitigate the ability to commit misconduct. One thread of the latter theme has stressed the importance of governance channels as affecting risk-taking, including executive board attributes. The board of directors is widely regarded as the cornerstone of an effective internal corporate governance framework (Fama and Jensen, 1983), having the ultimate responsibility for risk management and setting the tone for a bank's risk-taking culture. The board ensures bank stability by monitoring executives over the impact of firm policies on bank risk, evaluating whether current and future risk-exposure is consistent with risk appetite, and designing executive incentives to promote prudent risk-taking. Most of the research in this area has been with respect to nonfinancial firms (e.g., Adams and Ferreira, 2008; Almazan and Suarez, 2003; Harris and Raviv, 2008; Hermalin and Weisbach, 1998; Raheja, 2005). However, the evidence of the impact of executive boards on bank risk-taking is ambiguous. For example, Akhigbe and Martin (2006) study the impact of the Sarbanes-Oxley Act on financial institutions and show that firms with independent boards see a decline in their stock volatility over the long term. Erkens et al. (2012) fail to find any impact of board independence on bank risk during the 2007-2009 financial crisis for a sample of large international banks. In contrast, Pathan (2009) reports that boards which are smaller and exhibit stronger shareholder rights are positively related to bank risk-taking. However, the author reports that boards characterized by a higher fraction of independent directors pursue less risky policies. Beltratti and Stulz (2012) present evidence to show that banks with a shareholder-friendly board were riskier, although the results do not hold when the authors use different measures of risk. An important element that moderates the effectiveness of boards of directors is CEO power with powerful CEOs viewed as able to influence board decisions and prevent boards from effective monitoring and implying that powerful CEOs pursue policies that result in riskier outcomes (Adams et al., 2005; Combs et al., 2007; Hermalin and Weisbach, 1998). The misconduct literature has stressed the incentives for CEOs to be instigators of misconduct. For example, Alexander and Cohen (1999) find that misconduct occurs less frequently among firms in which management has a larger ownership stake; Hass et al. (2015) report that the relative performance evaluation feature of CEO promotion tournaments results in a higher likelihood of CEO misconduct; Khanna et al. (2015) find that the connections CEOs develop with top executives and directors through their appointment decisions increase the risk of corporate misconduct; and Altunbaş et al. (2018b) report that the likelihood that a bank will engage in misconduct increases if the CEO has had a relatively long tenure. In addressing the issue of the impact of ML enforcements on bank risk, we control for some of the governance channels raised in the misconduct literature as well as the more traditional explanators of bank risk.

3. Model and data

Our baseline specification is the following panel regression:

$$(1) \quad r_{it} = \beta_0 + \beta_1 ML_{it} + \beta_2 BSIZE_{it} + \beta_3 BINDEP_{it} + \beta_4 CEOP_{it} + \delta X_{it-1} + D_t + \varepsilon_i$$

The dependent variable, r_{it}, measures the risk of bank *i* in period *t*. We employ three measures of bank risk. The first measure is *default risk* as indicated by the z-score of each bank. The assumption here is that ML enforcements could lead to the failure of an individual bank because of reputational damage and/or the impact of severe financial penalties on bank capital. The z-score equals the return on assets plus the capital asset ratio divided by the standard deviation of asset returns.[6]

[6] The z-score measures the distance from insolvency where insolvency is defined as a state in which losses surmount equity ($E< -\pi$) (where E is equity and π is profits). The probability of insolvency, therefore, can be expressed as prob (-ROA<CAR), where ROA ($=\pi/A$) is the return on assets and CAR (= E/A) is the capital assets ratio. If profits are

Following the literature, we define the inverse of the probability of insolvency as the z-score such that a higher z-score indicates that the bank is more stable.

The second measure is *systematic* risk, where, for example, ML in the banking sector could be so widespread so as not to be diversifiable against within the sector. For example, in its Fall 2017 semi-annual risk assessment report, the Office of the Comptroller of the Currency (OCC) stated that bank offerings based on new technological platforms create vulnerabilities that criminals can exploit as vehicles for ML. This measure of risk describes the average stock market reaction of each bank to movements on the overall stock market index and is constructed using a simple capital asset pricing model, based on the following equation:

$$(2)\ R_{it} = \beta_0 + \beta_1 R_t + \beta_2 int_t + \varepsilon_{it}$$

where, R_{it} is the equity return of bank *i* at time (trading day) *t*; R_t is the return of the S&P 500 index at time (trading day) *t*; and int_t is the yield on the three-month Treasury bill rate at time (trading day) *t*. β_0 is the intercept; β_1 is the systematic risk of bank *i* at time *t*; and β_2 is the interest rate risk.

The final measure of risk is a measure of *systemic risk*, which captures the reaction of individual banks to *systemic* events. It measures tail dependence in the stock market returns of individual banks and equates the magnitude of tail dependence estimates as a measure of systemic risk. ML

normally distributed, then the inverse of the probability of insolvency equals (ROA+CAR)/σ(ROA), where σ (ROA) is the standard deviation of ROA.

may make a bank more vulnerable to systemic events, for example, because financial penalties and other costs associated with enforcements have debilitated the bank. A case in point is Deutsche Bank with widespread press reports in September 2016 that the US Department of Justice was seeking a $14 billion civil settlement for misconduct. The proposed fine was equivalent to about four-fifths of the bank's market capitalization and raised doubts about its future viability and the systemic consequences should it fail (Stewart 2016). Systemic risk is estimated via the marginal expected shortfall (MES) following the model by Acharya et al. (2017) at a standard risk level of 5% as follows:

$$(3)\ MES_i^{5\%} = {}^{1}\!/_{days}\ \Sigma_t R_i$$

where $MES_i^{5\%}$ is the marginal expected shortfall of bank i in 5% worst days; $days$ is the number of 5% worst days in the market; R_i is the average return of bank i in 5% worst days.

Our key independent variable, ML_{it}, comprises regulatory enforcements and class action litigation for ML activities issued against publicly listed US banks. We compile data from the Board of Governors of the Federal Reserve System Enforcement Action database; the Office of the Comptroller of the Currency Enforcement Actions database; the Federal Deposit Insurance Corporation Enforcement Decisions and Orders database; the Stanford Law School Securities Class Action Clearinghouse Filings database; and the Office of Thrift Supervision Enforcement Order Archive. Our examination of data for 960 publicly listed banks revealed 85 enforcements involving 50 banks over 2004–2015. Table 1 shows that enforcements for money laundering were on a rising trend throughout the period and that about 34% of the banks in the sample were repeat offenders. In Table 2 we provide information on the US States in which the banks subject to regulatory enforcements were located, the number of banks in each state, and the financial penalties imposed by regulators. The table makes clear that the number of enforcements relative to the number of banks operating in each state was modest, though we include only enforcements issued by regulators and not ongoing investigations by law enforcement agencies.

The variables $BSIZE_{it}$ and $BINDEP_{it}$ represent executive board size (the number of directors) and independence (the percent of outside directors), respectively, and $CEOP_{it}$ is an index of CEO power calculated by applying principal components analysis to proxies of CEO power (see, for example, Adams et al., 2005; Abernethy et al., 2015). Our four proxies are CEO tenure, where a CEOs' power is expected to increase with length of tenure because it helps build decision-making autonomy and the CEO can influence the selection of other board members (Combs et al., 2007); CEO/Chair duality, where the same person holding the CEO and Chair positions simultaneously increases CEO power because it diminishes the role of the board of directors in controlling CEO decisions (Hermalin and Weisbach, 1998) and is a 1-0 dummy with 1 indicating CEO/Chair duality; whether a CEO is also an investor in the firm because the 'convergence of interests' hypothesis predicts that share ownership binds the CEO's economic interests with those of shareholders and provides the CEO with an incentive to maximise firm performance (Fama and Jensen, 1983), and which is a 1-0 dummy with 1 indicating that the equity-based compensation of the CEO is greater than his/her the direct compensation in a given year; and the size of a CEO's network because networks have been viewed as a means for executives to protect each other on their respective boards (El-Khatib et al., 2015), and which is measured by the total number of people with whom the CEO is acquainted through current and past employment, education, and social contacts.[7] $X_{i,t}$ is a vector of other bank-specific characteristics that includes measures of leverage, profitability, liquidity, asset quality, capital, efficiency, bank size, and institutional ownership. Finally, D_t is a dummy variable equal to 1 during 2007-2008 (0 otherwise) to capture the effects on bank risk of the financial crisis.

Descriptive statistics of the variables are given in Table 3 and variable definitions are presented in Appendix Table 2. We begin our analysis in Table 4, which compares the means and medians of the three measures of bank risk for ML and non-ML banks. Columns 1 to 3 of the table show that the means and medians of each measure of risk are higher for ML banks than for non-ML banks and that the differences are statistically significant. In columns 4 to 6 we compare the mean and median measures of risk for ML banks only before and after the regulatory enforcement was issued. Default risk falls after the enforcement, systematic risk increases, and there is no statistically significant difference in mean or median of systemic risk. We interpret these results as consistent with enforcements reducing the likelihood of default by an individual bank (perhaps because they deter further money laundering), but that they do not impact on the ability of diversify against ML in the banking sector more generally.

We initially estimate equation (1) with time and bank fixed effects (FE) but we suspect the results to be biased because of endogeneity.[8] At least two sources of endogeneity can be pointed out here. The first is possible inverse causality between some covariates and the dependent variable. For example, banks with a reputation for excessive risk-taking might attract staff more likely to engage

[7] The coefficients for each component (proxy), their eigenvalues, and the proportion of the variance explained are reported in Appendix Table I.
[8] To avoid outlier observations impacting on our results, all bank-specific variables are winsorized at the 1% and 99% levels.

in money laundering. Another potential source of endogeneity is the omitted variable bias, since we are certainly not controlling for all the determinants of bank risk. We address potential endogeneity in several ways. First, in the fixed effects estimates we lag the bank-specific variables one period. Second, we present instrumental variables (IV) estimates in which we instrument for money laundering by taking advantage of the likely close ties between money laundering and the trade in illegal drugs.[9] We construct two instruments: the number of deaths by drug overdoses in US counties and the number of drug-related arrests in US counties, with both series expressed as ratios of county population. We then match these series with the geographic location of banks in our sample. Our logic is that the two instruments are closely related to money laundering but are unlikely to be linked to the measures of bank risk.[10] Third, we present estimates based on an alternative instrumental variables approach, system GMM (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). The dynamic panel GMM estimator potentially improves on OLS and traditional fixed-effects estimates because it allows us to include bank-fixed effects to account for (fixed) unobservable heterogeneity; it allows current ML to be influenced by previous realizations of, or shocks to, bank risk and, if the underlying economic process itself is dynamic (in our case, if current ML is related to past bank risk) then it may be possible to use some combination of variables from the bank's history as valid instruments for current ML to account for simultaneity.

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[9] See, for example, The United Nations Office on Drugs and Crime, Introduction to Money Laundering, available at: https://www.unodc.org/unodc/en/money-laundering/introduction.html?ref=menuside.

[10] We compile data from 3,318 counties over 1998-2016. Data on drug-related deaths are from the National Center for Health Statistics, Center for Disease Control and Prevention available at: https://wonder.cdc.gov/controller/datarequest/D76;jsessionid=DDAD9C85DB93EA4F59EB59F54330AA66. Data on arrests for drug-related offences are from The Federal Bureau of Investigation, Uniform Crime Reporting Program Data: County-Level Detailed Arrest and Offense Data, available at: https://www.openicpsr.org/openicpsr/project/108164/version/V3/view;jsessionid=D1BBA0E8347A1A3800C47D019D71988C.

4. Empirical results

Results for the baseline estimates of equation (1) for each measure of bank risk are reported in Table 5. The coefficients on the ML variable are positive and statistically significant whether we employ FE, IV or system GMM estimation and indicate that ML is associated with an increase in bank risk on each measure of risk.[11] The economic size of the ML coefficient is modest in the case of default risk but more substantial for systematic and systemic risk. For example, in the system GMM estimates a one standard deviation change in the money laundering variable (0.244) is associated with increases in the default, systemic and systemic risk of 0.10, 0.13, and 0.11, respectively, where the respective sample means of the risk measures are -7.90, 0.02, and 0.48. The coefficient on the CEO power index is also positive and statistically significant in most of the estimates indicating that greater CEO power is associated with more risk-taking behavior by banks. In the GMM estimates, a one standard deviation in change in CEO power (1.227) increases by risk by 1.00, 0.43, and 0.11 on the default, systematic and systemic measures of risk, respectively. This suggests that CEOs face similar incentives as shareholders towards risk-taking as suggested by Jensen and Meckling (1976). The statistical significance of the coefficients on board size and independence are less consistent across the estimates, but when they significant they suggest that large and independent boards are associated with less risk-taking behavior, though the economic size of the coefficients is generally smaller than those for money laundering. For example, in the system GMM estimates a one standard deviation change in board size (3.869) reduces bank risk

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[11] At the suggestion of a referee, we also estimated equation (1) employing a sample in which the non-ML banks were chosen on the basis of propensity score matching with the propensity scores derived from a probit estimation of the likelihood that ML will be detected (see, for example, Wang, 2013). These results are reported in Appendix Table 3. The coefficients on the ML variable are positive and statistically significant confirming the baseline results reported in Table 5 that ML enforcements are associated with an increase in measures of risk.

by 0.05 and 0.07 on the default and systemic measures of risk, respectively, and a one standard deviation change in board independence (0.129) reduces risk by 0.02, 0.07, and 0.01 on the default, systematic and systemic measures of risk, respectively. Large and more independent boards appear to act in the interests of regulators and other stakeholders who are concerned with the safety of the bank, but they do not fully offset the impact on risk of ML.

The coefficients on the other bank-specific variables are mostly statistically significant. Higher levels of capital and liquidity provide buffers that reduce the probability of a bank distress and reduce bank risk (Bernanke and Lown, 1991; Gambacorta and Mistrulli, 2004), and more profitable banks are less risky because it is easier to accumulate capital via higher retained earnings (Flannery and Rangan 2008). In contrast, loan provisioning increases bank risk suggesting that it is designed to smooth earnings and inhibit outside monitoring (Bushman and Williams, 2012); leverage increases risk-taking because banks do not internalize the losses imposed on depositors and bondholders (Dell'Ariccia et al., 2017); large banks are riskier because they are considered as "too big to fail" (Afonso et al., 2014); inefficient banks are riskier because they reduce the scope for strengthening capital levels (Berger and De Young, 1997); and a larger proportion of institutional ownership increases bank risk consistent with the short-termism theory of institutional investors (Callen and Fang, 2013). Finally, the financial crisis was associated with an increase in bank risk taking. In the IV estimates the Stock and Yogo (2005) test statistics reject the null hypothesis of weak instruments, and in the system GMM estimates the Arellano-Bond and Hansen test statistics indicate, respectively, that there is no second order serial correlation in the disturbances and that the instruments used are not correlated with the residuals.

In Tables 6-8, we look more closely at the accentuation of bank risk by CEO power and the mitigation of risk by executive boards. We report results from adding interaction variables—i.e., by multiplying the CEO power and executive board variables by ML. In these results, the coefficients on ML and the governance variables reflect their conditional effects on bank risk. In Table 6 the coefficient on ML remains positive and statistically significant in each set of estimates and for each measure of bank risk. The coefficient on the $Money\ laundering * CEO\ power$ interaction is positive though not always statistically significant. In the GMM estimates, the results indicate that a one standard deviation increase in CEO power raises the effect of a 1 percentage point increase in ML on bank risk by 0.41, 0.04 and 0.74 for the default, systematic and systemic measures of risk.[12] Thus, there is some evidence to suggest that CEO power accentuates the adverse impact of ML on bank default risk.

In Table 7, we report results in which the interaction variable is $Money\ laundering * Board\ size$. The coefficient on ML remains positive and statistically significant for each set of estimates and for measure of bank risk. The coefficients on the interaction term are negative in all estimates but statistically significant only for default (IV and GMM estimate) and systemic risk (FE and GMM). A one standard deviation increase in board size reduces the effect of a 1 percentage point increase in ML on default risk by 0.35 to 0.59 percentage point and on systemic risk by between 0.31 to 0.37 percentage point. In Table 6, we report results in which the interaction variable is $Money\ laundering * Board\ independence$. The coefficients on the interaction term are negative in all estimates and are statistically significant for all measures of risk in the case of the GMM estimates and significant for systemic risk in the FE estimate. A one standard deviation

[12] 0.41=0.331(coefficient on the interaction term from GMM estimate)*1.227(the standard deviation on the CEO power index reported in Table 2).

increase in board independence reduces the effect of a 1 percentage point increase in ML on bank risk by about 0.01 percentage point for each measure of risk.

Overall, the impact of ML on bank risk is statistically significant, positive though generally modest. The results indicate that the magnitude of the effect of ML on risk is lower for banks with large and independent boards than it is for other banks. In contrast, the magnitude of the effect of ML is greater for banks with more powerful CEOs. As the coefficients on ML are larger than those on the executive board variables and the board interaction terms, board size and independence mitigate but do not offset the adverse impact of ML enforcements on bank default risk.

5. Conclusions

The banking literature on the determinants of risk-taking has largely ignored the potential role of ML. In this paper, we tested for a link between bank risk and enforcements issued by US regulators against banks for ML in a sample of 960 publicly listed US banks over 2004-2015. Our results suggest that ML enforcements are associated with an increase in bank risk on several measures of risk. In addition, the impact of ML is accentuated by the presence of powerful CEOs and only partly mitigated by large and independent executive boards. The result is robust to several estimation methodologies. We conclude that banks with powerful CEOs warrant the particular attention of regulators engaged in AML efforts, especially when boards of directors are small and not independent.

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TABLE 1 Money laundering enforcement issued against publicly listed US banks, 2004–2015.

Panel A: Time distribution of money laundering cases

	Database				
Year	**FED**	**OCC**	**FDIC**	**OTS**	**Total**
2004	5				5
2005	1	2		2	5
2006		2			2
2007	1			1	2
2008				1	1
2009	2		1	1	4
2010	2	3	1		6
2011		1		8	9
2012	4	4	2		10
2013	4	8	1		13
2014	2	5	3		10
2015	9	5	4		18
Total	30	30	12	13	85

Panel B: Banks engaged repeatedly in money laundering

	Once	**More than once**	**More than twice**	**Total**
Number of banks	33	12	5	50

Sources: Board of Governors of the Federal Reserve System (FED) Enforcement Action database (https://www.federalreserve.gov/apps/enforcementactions/search.aspx); the Office of the Comptroller of the Currency (OCC) Enforcement Actions database (http://apps.occ.gov/EASearch/); the Federal Deposit Insurance Corporation (FDIC) Enforcement Decisions and Orders database (https://www5.fdic.gov/edo/DataPresentation.html); the Office of Thrift Supervision (OTS) Enforcement Order Archive (https://www.occ.treas.gov/static/ots/enforcement/ots-enforcement-order-listing.xlsx).

TABLE 2. Money laundering enforcements against US banks

US State	Number of banks	Number of banks with enforcements	Number of enforcements	Total civil money penalty (US$)
Alabama	153	1	1	10,000,000
California	203	3	6	251,943,057
Florida	203	1	1	26,950
Georgia	219	1	8	95,000
Illinois	482	4	5	5,000
Indiana	153	1	2	576,000
Maryland	89	1	1	0
Massachusetts	143	2	2	0
Michigan	120	1	2	115,000
Minnesota	338	2	2	14,125,000
Mississippi	100	1	1	64,000
New York	220	21	39	6,677,404,654
North Carolina	89	2	2	720,000,000
Oklahoma	230	1	1	0
Pennsylvania	183	3	5	2,225,075
South Carolina	78	1	1	0
Utah	54	1	1	8,000,000
Virginia	125	1	2	43,198,105
Washington	83	1	1	0
Wisconsin	231	1	2	625,000
Total	3496	50	85	7,728,402,841

Sources: Board of Governors of the Federal Reserve System (FED) Enforcement Action database (https://www.federalreserve.gov/apps/enforcementactions/search.aspx); the Office of the Comptroller of the Currency (OCC) Enforcement Actions database (http://apps.occ.gov/EASearch/); the Federal Deposit Insurance Corporation (FDIC) Enforcement Decisions and Orders database (https://www5.fdic.gov/edo/DataPresentation.html); the Office of Thrift Supervision (OTS) Enforcement Order Archive (https://www.occ.treas.gov/static/ots/enforcement/ots-enforcement-order-listing.xlsx). Data on number banks per state is from the FDIC: https://www7.fdic.gov/idasp/advSearchLanding.asp

TABLE 3 Descriptive statistics

Variables	**N**	**Mean**	**Median**	**Standard deviation**	**Minimum**	**Maximum**
Bank risk:						
Default risk (z score)	4620	-7.900	-7.661	4.682	-65.150	5.530
Systemic risk	4620	0.019	0.015	0.788	-9.216	15.490
Systematic risk	4620	0.485	0.324	0.752	-9.918	7.578
Money laundering	4620	0.023	0.000	0.244	0.000	8.000
CEO power index	4620	0.000	-0.160	1.227	-3.064	3.945
Board size	4620	11.038	10.000	3.869	3.000	33.000
Board independence	4620	0.765	0.790	0.129	0.261	1.000
Liquidity	4620	22.970	21.730	11.120	0.820	58.820
Leverage	4620	79.400	82.760	13.240	8.044	94.990
Loan provisions	4620	0.206	0.086	0.380	0.020	5.0150
Capital	4620	10.330	9.370	5.363	0.070	65.420
Efficiency	4620	69.890	66.750	19.590	6.360	197.400
Profitability	4620	0.548	0.840	1.784	-9.990	9.510
Size	4620	0.317	-0.133	1.917	-4.416	8.027
Institutional investors	4620	32.590	25.680	26.640	0.050	100.00

Notes. Descriptive statistics are derived from the average values of annual data unless otherwise stated. Bank risk, board size and independence, and bank specific variables are calculated from the average values for each bank from 2004 to 2015. The z-score is defined the inverse of the probability of insolvency where a higher z-score indicates that the bank is more stable.

TABLE 4 Mean and median differences in bank risk of money laundering and non-money laundering banks

	Money laundering banks	Non-money laundering banks	t-score	Before regulatory enforcement	After regulatory enforcement	t-score
			Panel A. Mean differences			
Default risk	-18.70	-24.75	3.951***	17.72	21.40	-2.968**
Systematic risk	0.79	0.46	-10.960***	0.76	0.87	-2.084*
Systemic risk	-2.01	-1.19	6.918***	-1.99	-2.04	0.150
			Panel B. Median differences			
Default risk	-13.82	-17.36	2.862	13.810	18.170	-3.138**
Systematic risk	0.86	0.29	-14.220***	0.808	0.983	-2.795***
Systemic risk	-1.35	-0.66	9.089***	-1.345	-1.542	1.230

Notes. Default risk (the z-score) is defined the inverse of the probability of insolvency where a higher z-score indicates that the bank is more stable. Statistical significance of mean differences is tested using the t-test and for the median differences using the Wilcoxon rank sum test.*** and ** indicate statistical significance at the 1 and 5% levels, respectively.

TABLE 5 Money laundering, governance and bank risk: baseline estimates

	Default risk			Systematic risk			Systemic risk		
	FE	**IV**	**GMM**	**FE**	**IV**	**GMM**	**FE**	**IV**	**GMM**
Lag of risk indicator			0.714***			0.263***			0.499***
			(0.012)			(0.019)			(0.013)
Money laundering	0.149*	0.410**	0.414**	0.085**	0.127***	0.536***	0.908*	0.606*	0.466***
	(0.086)	(0.201)	(0.200)	(0.034)	(0.063)	(0.198)	(0.490)	(0.317)	(0.254)
CEO power	0.286***	0.153**	0.818***	0.030*	0.023	0.354***	0.304***	0.083	0.094***
	(0.084)	(0.062)	(0.164)	(0.017)	(0.016)	(0.037)	(0.102)	(0.073)	(0.028)
Board size	-0.197***	-0.039	-0.013*	-0.013*	-0.006	-0.019**	-0.145***	-0.030	-0.002
	(0.045)	(0.026)	(0.007)	(0.007)	(0.007)	(0.009)	(0.054)	(0.037)	(0.004)
Board independence	-0.028	-0.105***	-0.142***	-0.005	-0.007	-1.773***	-0.099***	-0.026	-1.201***
	(0.036)	(0.032)	(0.025)	(0.025)	(0.008)	(0.245)	(0.038)	(0.035)	(0.220)
Capital	-0.150***	-0.420***	-0.099***	-0.001	-0.004	-0.011**	-0.019	-0.036	-0.003***
	(0.051)	(0.016)	(0.011)	(0.005)	(0.003)	(0.005)	(0.044)	(0.025)	(0.001)
Liquidity	-0.028**	-0.048***	-0.017**	-0.06***	-0.007***	-0.010***	-0.070***	-0.013*	-0.010*
	(0.013)	(0.006)	(0.007)	(0.002)	(0.001)	(0.003)	(0.012)	(0.007)	(0.004)
Loan provision	0.008	1.091***	0.668***	0.062*	0.065***	0.116*	0.054	0.030	0.091**
	(0.127)	(0.086)	(0.151)	(0.036)	(0.025)	(0.069)	(0.095)	(0.106)	(0.053)
Funding	0.039***	0.016*	0.005***	0.003	0.001	0.013***	0.002	0.005	0.006*
	(0.012)	(0.007)	(0.003)	(0.002)	(0.002)	(0.002)	(0.013)	(0.009)	(0.003)
Efficiency	0.004	0.005*	0.036***	0.001**	0.001**	0.001	0.007**	-0.006**	0.001
	(0.004)	(0.002)	(0.004)	(0.000)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
Profitability	-0.341	-0.758***	-0.143***	-0.001	-0.013*	-0.003	-0.008	0.137***	-0.004
	(0.066)	(0.023)	(0.022)	(0.011)	(0.006)	(0.010)	(0.025)	(0.030)	(0.014)
Size	0.145	0.453**	0.378	0.404***	0.400***	0.220**	1.627***	0.244	0.248***
	(0.135)	(0.217)	(0.262)	(0.041)	(0.035)	(0.101)	(0.544)	(0.361)	(0.063)
Institutional ownership	0.031**	0.011***	0.008**	0.007***	0.006***	0.017***	0.002	-0.009**	0.005***
	(0.005)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.001)
Crisis dummy	2.824***	2.246***	2.465***	0.139***	0.029	0.048**	0.214**	2.005***	0.026
	(0.095)	(0.078)	(0.060)	(0.023)	(0.021)	(0.022)	(0.098)	(0.107)	(0.019)
R^2	0.252	0.525		0.245	0.099		0.163	0.114	
Observations	6187	4821	3736	6112	4733	4963	6109	5025	5605
Arellano-Bond test for AR(2) (p-value)			0.558			0.463			0.513
Hansen test for overidentification			0.894			0.899			0.860
Stock and Yogo (2005) test for weak instruments:									
First stage F-statistic		21.844			21.322			21.290	
Critical value		11.59			11.59			11.59	

Notes: FE equals estimates are regressions with bank and time fixed effects and independent variables are lagged one period to mitigate endogeneity problems. IV estimates are instrumental variables instrumenting for money laundering. GMM estimates are system GMM. The Stock and Yogo (2005) test is of the null. hypothesis of weak instruments and is rejected when the test statistic exceeds a given threshold. The Arellano-Bond test reports *p* -values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. The Hansen test reports *p* -values for the null hypothesis that the instruments used are not correlated with the error term***, **, and * indicate statistical significance at the 1, 5 and 10% levels, respectively.

TABLE 6 Money laundering, governance and bank risk with misconduct-CEO power interaction

	Default risk			Systematic risk			Systemic risk		
	FE	IV	GMM	FE	IV	GMM	FE	IV	GMM
Lag of risk indicator			0.713**			0.233***			0.441***
			(0.011)			(0.022)			(0.013)
Money laundering	0.574*	0.404**	0.919***	0.150**	0.128**	0.608***	1.001*	0.603*	1.066***
	(0.300)	(0.203)	(0.130)	(0.061)	(0.063)	(0.211)	(0.533)	(0.317)	(0.351)
Money laundering*CEO power	0.033	0.166**	0.331***	0.003	0.022	0.032*	0.746*	0.085	0.606***
	(0.064)	(0.063)	(0.104)	(0.015)	(0.016)	(0.018)	(0.388)	(0.073)	(0.149)
CEO power	-0.121***	0.040	0.633***	0.054**	0.004	0.251***	0.303***	-0.027	0.115***
	(0.041)	(0.145)	(0.131)	(0.023)	(0.031)	(0.038)	(0.105)	(0.162)	(0.033)
Board size	-0.121***	-0.040	-0.011	-0.001	-0.005	-0.028***	-0.143**	-0.030	-0.029***
	(0.041))	(0.026)	(0.007)	(0.010)	(0.007)	(0.010)	(0.055)	(0.037)	(0.007)
Board independence	-0.042	-0.104***	-0.138***	-0.005	-0.008	-1.471***	-0.087**	-0.026	-1.149***
	(0.046)	(0.033)	(0.025)	(0.003)	(0.008)	(0.550)	(0.038)	(0.035)	(0.220)
Capital	-0.407***	-0.421***	-0.101***	-0.010**	-0.005	-0.009**	-0.025	-0.036	-0.002
	(0.144)	(0.016)	(0.011)	(0.005)	(0.003)	(0.004)	(0.052)	(0.025)	(0.001)
Liquidity	0.330***	-0.048***	-0.030***	-0.001	-0.008***	-0.007**	-0.067***	-0.013*	-0.009*
	(0.082)	(0.006)	(0.005)	(0.002)	(0.002)	(0.003)	(0.012)	(0.007)	(0.005)
Loan provisions	-0.805***	1.114***	0.636***	0.109***	0.060**	0.058	0.047	0.029	0.102*
	(0.305)	(0.087)	(0.145)	(0.038)	(0.025)	(0.077)	(0.098)	(0.106)	(0.059)
Funding	-0.030*	0.016**	0.004	0.007**	0.001	0.010***	0.051***	0.005	0.004
	(0.012)	(0.007)	(0.003)	(0.003)	(0.002)	(0.002)	(0.016)	(0.009)	(0.003)
Efficiency	0.004	0.005**	0.035***	0.002***	0.001*	0.007***	0.007**	-0.006*	0.001
	(0.004)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
Profitability	-0.179**	-0.752***	-0.152***	-0.018*	-0.012**	-0.023**	-0.002	-0.137***	-0.009
	(0.073)	(0.023)	(0.022)	(0.011)	(0.006)	(0.009)	(0.026)	(0.030)	(0.007)
Size	0.103	0.434**	0.299	0.288***	0.403***	0.347***	1.568***	0.246	0.249***
	(0.127)	(0.218)	(0.267)	(0.067)	(0.035)	(0.102)	(0.553)	(0.361)	(0.060)
Institutional ownership	-0.050***	0.011***	0.009***	0.007***	0.006***	0.014***	0.002	-0.009*	0.177***
	(0.009)	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)	(0.004)	(0.004)	(0.064)
Crisis dummy	2.785***	2.254***	2.389***	0.209***	0.030	0.022	0.295***	2.005***	0.005***
	(0.091)	(0.079)	(0.060)	(0.032)	(0.021)	(0.024)	(0.099)	(0.107)	(0.001)
R^2	0.251	0.521		0.244	0.100		0.161	0.114	
Observations	6187	4741	3815	6112	4675	5282	6109	5025	5008
Arellano-Bond test for AR(2) (p-value)			0.198			0.257			0.121
Hansen test for overidentification			0.888			0.749			0.799
Stock and Yogo (2005) test for weak instruments:									
First stage F-statistic		22.137			21.604			21.572	
Critical value		11.59			11.59			11.59	

Notes: FE equals estimates are regressions with bank and time fixed effects and independent variables are lagged one period to mitigate endogeneity problems. IV estimates are instrumental variables instrumenting for money laundering. GMM estimates are system GMM. The Stock and Yogo (2005) test is of the null. hypothesis of weak instruments and is rejected when the test statistic exceeds a given threshold. The Arellano-Bond test reports *p* -values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. The Hansen test reports *p* -values for the null hypothesis that the instruments used are not correlated with the error term***, **, and * indicate statistical significance at the 1, 5 and 10% levels, respectively.

TABLE 7 Money laundering, governance and bank risk with misconduct-board size interaction

	Default risk			Systematic risk			Systemic risk		
	FE	**IV**	**GMM**	**FE**	**IV**	**GMM**	**FE**	**IV**	**GMM**
Lag of risk indicator			0.687***			0.233***			0.423***
			(0.011)			(0.062)			(0.013)
Money laundering	0.220*	0.438**	1.053***	0.111**	0.164**	1.262**	0.927*	0.615*	0.475*
	(0.124)	(0.221)	(0.104)	(0.043)	(0.077)	(0.496)	(0.500)	(0.317)	(0.269)
Money laundering*board size	-0.018	0.153**	-0.090**	-0.006	0.023	-0.096	-0.097***	0.083	-0.081***
	(0.023)	(0.062)	(0.042)	(0.006)	(0.017)	(0.070)	(0.037)	(0.073)	(0.023)
CEO power	-0.206***	-0.010	0.509***	0.031*	-0.007	0.091***	0.293***	0.025	0.074**
	(0.070)	(0.032)	(0.170)	(0.017)	(0.009)	(0.026)	(0.102)	(0.033)	(0.035)
Board size	-0.140***	-0.039	-0.014**	-0.013*	-0.003	-0.012	-0.140**	-0.029	-0.032***
	(0.036)	(0.026)	(0.007)	(0.007)	(0.007)	(0.015)	(0.054)	(0.037)	(0.012)
Board independence	-0.046	-0.105***	-0.120***	-0.005	-0.009	-0.708	-0.096**	-0.026	-0.152
	(0.035)	(0.032)	(0.022)	(0.007)	(0.008)	(0.816)	(0.038)	(0.035)	(0.246)
Capital	-0.400***	-0.420***	-0.103***	-0.001	-0.004	-0.046*	-0.018	-0.035	-0.001
	(0.088)	(0.016)	(0.011)	(0.005)	(0.004)	(0.026)	(0.044)	(0.025)	(0.001)
Liquidity	-0.035***	-0.048***	-0.017**	-0.006***	-0.007***	-0.016**	-0.070***	-0.013*	-0.003
	(0.010)	(0.006)	(0.007)	(0.002)	(0.002)	(0.008)	(0.012)	(0.007)	(0.004)
Loan provisions	0.798***	1.091***	0.946***	0.062*	0.062**	0.041	0.055	0.030	0.080
	(0.218)	(0.086)	(0.125)	(0.036)	(0.026)	(0.062)	(0.098)	(0.106)	(0.055)
Funding	0.028**	0.016**	0.007**	0.003	0.001	0.009***	0.004	0.005	0.009***
	(0.014)	(0.007)	(0.003)	(0.002)	(0.002)	(0.002)	(0.013)	(0.009)	(0.003)
Efficiency	0.010***	0.005*	0.015***	0.001*	0.001	0.007***	0.007**	-0.006**	0.001
	(0.004)	(0.002)	(0.002)	(0.000)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)
Profitability	-0.090	-0.757***	-0.333***	-0.001	-0.011*	-0.086***	-0.009	0.137***	-0.011*
	(0.071)	(0.023)	(0.014)	(0.011)	(0.006)	(0.022)	(0.025)	(0.030)	(0.007)
Size	3.357***	0.452**	0.137	0.404***	0.410***	0.492*	1.619***	0.242	0.327***
	(0.262)	(0.217)	(0.247)	(0.041)	(0.039)	(0.298)	(0.543)	(0.361)	(0.058)
Institutional ownership	0.018***	0.011***	0.010***	0.007***	0.005***	0.019***	0.002	-0.009**	0.004***
	(0.005)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.001)
Crisis dummy	3.057***	2.245***	2.508***	0.139***	0.028	0.041	0.220***	2.004***	0.038***
	(0.095)	(0.078)	(0.056)	(0.023)	(0.088)	(0.031)	(0.099)	(0.107)	(0.018)
R^2	0.252	0.525		0.245	0.088		0.161	0.115	
Observations	6187	4821	4582	6112	4298	5689	6109	5025	5008
Arellano-Bond test for AR(2) (p-value)			0.533			0.129			0.130
Hansen test for overidentification			0.797			0.806			0.824
Stock and Yogo (2005) test for weak instruments:									
First stage F-statistic		18.958			18.463			18.433	
Critical value		11.59			11.59			11.59	

Notes: FE equals estimates are regressions with bank and time fixed effects and independent variables are lagged one period to mitigate endogeneity problems. IV estimates are instrumental variables instrumenting for money laundering. GMM estimates are system GMM. The Stock and Yogo (2005) test is of the null. hypothesis of weak instruments and is rejected when the test statistic exceeds a given threshold. The Arellano-Bond test reports *p* -values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. The Hansen test reports *p* -values for the null hypothesis that the instruments used are not correlated with the error term***, **, and * indicate statistical significance at the 1, 5 and 10% levels, respectively.

TABLE 8 Money laundering, governance and bank risk with misconduct-board size interaction

	Default risk			Systematic risk			Systemic risk		
	FE	**IV**	**GMM**	**FE**	**IV**	**GMM**	**FE**	**IV**	**GMM**
Lag of risk indicator			0.633***			0.347***			0.438***
			(0.011)			(0.043)			(0.014)
Money laundering	0.205*	2.239**	1.934***	0.126**	0.127**	1.268*	0.928*	0.722**	1.061*
	(0.118)	(0.938)	(0.331)	(0.043)	(0.063)	(0.564)	(0.500)	(0.364)	(0.543)
Money laundering*board independence	-0.036	0.170***	-0.112***	-0.009	0.023	-0.120**	-0.123**	0.090	-0.090**
	(0.023)	(0.063)	(0.039)	(0.007)	(0.016)	(0.054)	(0.050)	(0.080)	(0.037)
CEO power	-0.199***	-0.177**	0.199***	0.029*	0.001	0.119***	0.291****	0.010	0.093**
	(0.073)	(0.082)	(0.109)	(0.017)	(0.008)	(0.019)	(0.102)	(0.033)	(0.041)
Board size	-0.130***	-0.043	-0.008	-0.013*	-0.006	-0.020*	-0.141**	-0.010	-0.068**
	(0.036)	(0.026)	(0.008)	(0.007)	(0.007)	(0.011)	(0.054)	(0.041)	(0.029)
Board independence	-0.147***	-0.102***	-0.118***	-0.005	-0.007	-2.474***	-0.097**	-0.011	-0.752***
	(0.037)	(0.033)	(0.023)	(0.007)	(0.008)	(0.341)	(0.038)	(0.040)	(0.256)
Capital	-0.188***	-0.423***	-0.151***	-0.003	-0.004	-0.024	-0.017	-0.050*	-0.003**
	(0.056)	(0.016)	(0.013)	(0.004)	(0.003)	(0.021)	(0.044)	(0.028)	(0.001)
Liquidity	-0.031**	-0.048***	-0.038***	-0.006***	-0.007***	-0.002	-0.070***	-0.014*	-0.009**
	(0.013)	(0.006)	(0.007)	(0.002)	(0.001)	(0.002)	(0.012)	(0.008)	(0.004)
Loan provisions	0.816***	1.144***	1.090***	0.063*	0.065***	0.105***	0.055	0.004	0.033
	(0.253)	(0.091)	(0.125)	(0.035)	(0.025)	(0.038)	(0.095)	(0.111)	(0.054)
Funding	0.033**	0.016**	0.015***	0.001	0.001	0.004***	0.004	0.007	0.008***
	(0.014)	(0.007)	(0.003)	(0.002)	(0.002)	(0.001)	(0.013)	(0.011)	(0.003)
Efficiency	0.010***	0.006***	0.016***	0.001*	0.001**	0.002**	0.007**	-0.005**	0.001
	(0.004)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)
Profitability	-0.140*	-0.755***	-0.307***	-0.001	-0.013**	-0.001	-0.009	0.134***	-0.018
	(0.085)	(0.023)	(0.013)	(0.011)	(0.006)	(0.011)	(0.025)	(0.032)	(0.015)
Size	3.205***	0.474**	0.110	0.404***	0.400***	0.407***	1.621***	0.533	0.303***
	(0.312)	(0.221)	(0.261)	(0.041)	(0.035)	(0.041)	(0.543)	(0.410)	(0.064)
Institutional ownership	0.003	0.011***	0.011***	0.007***	0.006***	0.011***	0.002	-0.006	0.004***
	(0.005)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.001)
Crisis dummy	2.998***	2.247***	2.423***	0.131***	0.029	0.056**	0.219**	2.084***	0.034*
	(0.086)	(0.079)	(0.065)	(0.022)	(0.021)	(0.027)	(0.098)	(0.114)	(0.019)
R^2	0.253	0.519		0.245	0.099		0.162	0.119	
Observations	6187	4679	4544	6112	4733	5689	6109	4441	5008
Arellano-Bond test for AR(2) (p-value)			0.199			0.146			0.177
Hansen test for overidentification			0.857			0.839			0.792
Stock and Yogo (2005) test for weak instruments:									
First stage F-statistic		17.832			17.135			17.135	
Critical value		11.59			11.59			11.59	

Notes: FE equals estimates are regressions with bank and time fixed effects and independent variables are lagged one period to mitigate endogeneity problems. IV estimates are instrumental variables instrumenting for money laundering. GMM estimates are system GMM. The Stock and Yogo (2005) test is of the null. hypothesis of weak instruments and is rejected when the test statistic exceeds a given threshold. The Arellano-Bond test reports *p* -values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation. The Hansen test reports *p* -values for the null hypothesis that the instruments used are not correlated with the error term***, **, and * indicate statistical significance at the 1, 5 and 10% levels, respectively.

APPENDIX 1 CEO power measure: principal components analysis

	First component	**Second component**	**Third component**	**Fourth component**
CEO tenure	0.308	0.917	0.198	0.161
CEO ownership	0.573	-0.282	-0.193	0.745
CEO duality	0.514	-0.281	0.749	-0.308
CEO network size	0.559	0.042	-0.601	-0.601
Eigenvalue	1.500	0.961	0.817	0.722
Proportion of variance explained	0.375	0.240	0.204	0.180

Notes: This table presents the results of applying principle components analysis to four proxies of power based on CEO ability to exercise decision-making power. CEO tenure is the number of years the CEO has served in position at given year. CEO ownership is a binary variable equal to 1 if the equity-based compensation of the CEO is greater than the direct compensation of the CEO at given year. CEO duality is a dummy variable equal to 1 if the CEO is also the Chairman in a given year. CEO network size is the number of CEO's with whom the selected CEO overlaps while in employment, other activities, or education roles at the same company, organization, or institution in a given year. The eigenvectors are reported in orthonormal form.

A**PPENDIX TABLE 2** Variable definitions

Variables	**Description**
Default risk (z-score)	Return on assets plus capital asset ratio divided by total by the standard deviation of return on assets at given year.
Systematic risk	Coefficient of the return of S&P 500 index in the estimation of the two-index market model at given year.
Systemic bank risk	Marginal expected shortfall in 5 percent worst days at given year.
Money laundering	The number of enforcements for money laundering offences
CEO power	Derived from the application of Principal Components analysis to four proxies for CEO power: CEO tenure; CEO ownership; CEO duality; CEO network size (see below)
CEO tenure	The number of years the CEO has served in position at given year.
CEO ownership	Binary variable that is 1 if the equity-based compensation of the CEO is greater than the direct compensation of the CEO at given year.
CEO duality	Binary variable that is 1 if the CEO is also chairman in given year, otherwise 0.
CEO network size	The number of CEO's with whom the selected CEO overlaps while in employment, other activities, or education roles at the same company, organization, or institution at given year.
Board size	The number of directors sitting on the board at given year.
Board independence	The percentage of independent non-executive directors on the board at given year.
Leverage	The ratio of total book value of liabilities to total assets at given year.
Profitability	The ratio of earnings before interest and taxes (to book value of total assets at given year.
Liquidity	The ratio of liquid assets to total assets at given year.
Loan provisions	The ratio of loan loss provision to total loans at given year.
Capital	The ratio of risk-weighted capital to total assets at given year.
Efficiency	The ratio of operating expenses to total operating income at given year.
Total assets	Natural logarithm of total assets at given year.
Financial crisis dummy	Binary variable that is 1 in financial crisis years (between 2008 and 2010).

APPENDIX TABLE 3 Money laundering, governance and bank risk: matched sample estimates

	FE estimates of the matched sample			Probit estimates for propensity score matching		
	1	2	3	1	2	3
	Default risk	Systematic risk	Systemic risk	Default risk	Systematic risk	Systemic risk
Money laundering	0.249**	0.181**	1.187*			
	(0.124)	(0.080)	(0.614)			
CEO power	0.376***	0.067*	0.288**	0.102***	0.110***	0.111***
	(0.138)	(0.034)	(0.141)	(0.020)	(0.021)	(0.023)
Board size	-0.075	-0.029*	-0.100	-0.053***	-0.052***	-0.055***
	(0.066)	(0.016)	(0.081)	(0.011)	(0.011)	(0.011)
Board independence	-0.147**	-0.001	-0.022	0.021*	0.021*	0.025**
	(0.058)	(0.014)	(0.072)	(0.011)	(0.012)	(0.012)
Capital	-0.246***	-0.038***	-0.119	-0.034***	-0.034***	-0.034***
	(0.079)	(0.012)	(0.078)	(0.006)	(0.006)	(0.005)
Liquidity	-0.031	-0.002	-0.090***	-0.004**	-0.003**	-0.002
	(0.019)	(0.004)	(0.023)	(0.002)	(0.002)	(0.002)
Loan provision	0.466	0.055	0.173	0.208***	0.216***	0.205***
	(0.174)	(0.066)	(0.190)	(0.047)	(0.047)	(0.045)
Funding	0.062***	0.003	0.047***	0.010***	0.01***	0.01***
	(0.017)	(0.006)	(0.016)	(0.002)	(0.002)	(0.002)
Efficiency	0.008**	0.001	0.012**	0.003***	0.003***	0.004***
	(0.004)	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)
Profitability	[illegible]	-0.019	-0.161***	0.020	0.016	0.021
	(0.072)	(0.019)	(0.054)	(0.016)	(0.016)	(0.016)
Size	3.889***	0.399***	1.271	0.358***	0.342***	0.338***
	(0.660)	(0.100)	(0.836)	(0.021)	(0.021)	(0.020)
Institutional ownership	0.044***	0.004*	0.008	-0.007***	-0.007***	-0.006***
	(0.013)	(0.002)	(0.014)	(0.001)	(0.001)	(0.001)
Crisis dummy	2.156	0.173***	0.227	0.008	0.002	0.030
	(0.134)	(0.048)	(0.173)	(0.043)	(0.043)	(0.042)
R^2	0.036	0.211	0.196			
Pseudo R^2				0.115	0.107	0.103
Observations	2182	2100	2320	5442	5329	5981

Notes: Columns 1 to 3 report estimates with bank and time fixed effects of the propensity score-matched sample; independent variables are lagged one period to mitigate endogeneity problems. Columns 4 to 6 provide the probit estimation results for propensity score matching to detect the likelihood of money laundering. The dependent variable (matching criteria) is bank money laundering—a binary variable that equals one if the bank is the subject of the money laundering related enforcement action, and 0 otherwise. ***, **, * indicate statistical significance at the 1, 5 and 10% levels, respectively.