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Banks as Regulated Traders

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Abstract

Banks use trading as a vehicle to take risk. Using unique high-frequency regulatory data, we estimate the sensitivity of weekly bank trading profits to aggregate equity, fixed-income, credit, currency and commodity risk factors. Our estimates imply that U.S. banks had large trading exposures to equity market risk before the Volcker Rule, which they curtailed afterwards. They also have exposures to credit and currency risk. The results hold up in a quasi-natural experimental design that exploits the phased-in introduction of reporting requirements to address identification. Heterogeneity and placebo tests further corroborate the results. Counterfactual stress-test analyses quantify the financial stability implications.

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1 Introduction

Trading has become an important part of the business model of the modern banking corporation.[1] With the traditional loan-centric model of banking in steady decline over the last two decades, the trading book has become the main alternative to loans along with securities holding. In the late 1990s and early 2000s, loans accounted for over 60% of aggregate total assets in the U.S. banking sector and trading assets were less than 1/10 the size of loans. By contrast, loans accounted for as little as 40% of total assets over the last decade, while securities holding was about 18%, and trading assets stood as high as 13%, totaling more than the aggregate value of tier 1 capital. Of course, the experience of the financial crisis serves as a harsh reminder that massive trading book losses can have a systemic impact. And bank trading remains at the center of the financial regulation agenda, with recent efforts underway to streamline the regulation of trading that was enacted under the broader framework of the Dodd-Frank Act (see Squam Lake Group, 2010; Greenwood et al. 2017a,b; Quarles, 2018 for the academic and policy debate on financial regulation). Yet, despite its importance, there has been little systematic study of the trading book in banking, with the literature having focused on more traditional assets and on the liabilities side of the bank balance sheet.[2]

In order to fill the gap in the banking literature, we use newly-available high-frequency regulatory data on the daily trading book profits and losses of U.S. banks. Trading is a powerful instrument for hedging risk, but it also allows banks to quickly and cheaply take speculative risk. If banks use trading to increase risk, then individual banks may be vulnerable to potentially large losses.[3] If all banks take similar positions, the entire banking

[1]Several recent reports by government agencies and central banks have been devoted to the bank trading book. For example, the Federal Reserve Board's Iercosan et al. (2017a,b,c) examine trading activities at U.S. systemically important banks post crisis. The BIS published a policy paper in 2013 on the Basel Committee's fundamental review of trading book capital requirements (https://www.bis.org/publ/bcbs265.pdf). And the ECB has recently increased scrutiny of the trading book of the euro zone's biggest lenders reportedly due to financial stability concerns (Bloomberg Business, June 13, 2018).

[2]For recent exceptions, see Hanson, Shleifer, Stein, and Vishny (2015) and recent work by Minton, Stulz, and Taboada (2017), who conjecture that trading assets can explain important features of bank valuation, such as the cross-sectional negative relation between bank valuation and size. Outside of banking, an influential intermediary-based asset pricing literature emphasizes the central role of banks as marginal investors to explain risk premiums in asset markets (see He and Krishnamurthy (2018) for a survey).

[3]In fact, trading losses tend to account for a large fraction of total losses projected under the severely adverse scenario in the results of the Federal Reserve's annual stress tests of U.S. banks since 2009.

sector may be vulnerable. To determine the risk exposures of banks via trading, we build on the standard approach in banking (Flannery and James (1984), Gorton and Rosen (1995)) and infer the direction of trading from bank trading profits. We estimate the sensitivity of banks' net trading profits to a broad array of aggregate risk factors, including equity markets and interest rates. We use our estimates as a key input to quantify bank trading risk exposures and empirically address two main questions: first, does trading increase or decrease systemic risk in the U.S. banking sector, in the sense of exposure to aggregate risk factors? Second, is government regulation of bank trading effective at curtailing risk?

At the end of 2017, trading assets in the U.S. banking sector stood at over 10 percent of total assets, a decline relative to the pre-crisis peak of 17 percent but still quadrupled relative to the early 1990s. Moreover, trading is concentrated within a relatively small number of big banks, with the six largest banks holding more than three quarters of the total trading assets of the banking sector and trading constituting almost 20 percent of total assets for these large banks. Because of their size and concentration, as well as the large trading losses in the financial crisis, bank trading activities have been at the center of the regulatory agenda over the last decade. The so called "Volcker Rule" was finalized in 2013 with the aim to mitigate risk taking by federally insured banks through a ban on proprietary trading.[4] The intended goal was to prevent banks from holding assets that increase the likelihood of incurring a substantial loss or pose a threat to financial stability, which is in line with the theory of bank regulation (Koehn and Santomero, 1980; Kim and Santomero, 1988). Assets held for prudent market making, underwriting, or hedging, are allowed, while those held to take directional positions aimed at profiting from price changes are not allowed. The rule relies on the supervisory process to identify prohibited assets by requiring that the agencies tasked with enforcement regularly monitor quantitative risk metrics, such as aggregate risk factor sensitivities. In summary, theory and practice suggest that the Volcker Rule should have led to a reduction in bank trading risk exposures.

We estimate the sensitivity of U.S. banks' net trading profits to an array of aggregate risk factors, which are broadly representative of the asset classes bank trading portfolios are

[4] In 2018, regulators put out for comments proposed revisions intended to streamline implementation and compliance of the rule, which have been actively debated in the press and were finalized in 2020 (see https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200625a.htm).

invested in and include seven main risk factors for equities, interest rates, credit, foreign exchange, and commodities.[5] We use this approach to document a number of stylized facts on the evolution of bank risk taking via their trading books in the post-crisis period. First, U.S. banks' trading profits displayed an economically large sensitivity to equity market risk before the Volcker Rule was finalized, which they fully curtailed afterwards. Pre-rule equity risk sensitivity holds robustly across different normalizations of trading profits and was not limited to just equity desks, but was large and significant across the board of the main asset classes, including fixed-income.[6] The decline in the sensitivity of trading book profits to the stock market after Volcker was economically large: a one standard deviation negative realization of the S&P return, which corresponds to about 2 percentage point drop, would generate a smaller trading loss relative to the Value-at-Risk (VaR) by about 14 percentage points as a consequence of the rule. This reduced loss is of the same order of magnitude as the standard deviation of banks' net profits relative to VaR in the sample. The loss reduction implied by the estimates for two other normalizations of net profit, either expressed in dollar terms or relative to trading assets, is of similar size at up to 2/5 of a standard deviation change in the respective normalization, indicating that the result is not an artifact of the way trading profits are normalized.

Second, we quantify the implied risk exposures with a stress-test calibration that uses the estimated sensitivities as one key input. The results indicate that U.S. banks' trading books had large exposures to equity market risk before the Volcker Rule was finalized, which they fully curtailed afterwards. Specifically, the estimated sensitivities to equity market risk imply that the Volcker Rule had a large impact on the total quantity of equity market risk, with the post-Volcker reduction in dollar risk exposures estimated at up to about 13 billion dollars. The effect is economically large, at about 1/4 of market risk capital, which is the capital

[5]Our bank-level sample includes 2,913 bank-week observations for 13 unique U.S. banks for which we have complete information on trading profits at the bank level between January 2013 and June 2017. We complement the bank-level analysis with a trading desk-level analysis for a sample of 20 unique U.S. banks over the same period for which we have complete information on trading profits at the more disaggregated desk-asset class level. Coverage of both samples is comprehensive. The 13 banks in the bank-level sample cover about 90% of aggregate trading assets in the U.S. banking sectors, while the 20 banks of the trading-desk sample cover virtually the universe of the U.S. banking sector's trading assets.

[6]Tabulations of sub-portfolio counts and size indicate that roughly a third of the sub-portfolios include equities, and equities are among the larger asset classes after rates together with credit, government, and foreign.

that banks are required to hold against their trading book exposures. The implied aggregate banking sector's annual losses for a 65% drop in the stock market returns, which mimics the "severely adverse scenario" of the annual regulatory stress tests conducted by the Federal Reserve, are also economically large at about 1/5 of market risk capital. The post-Volcker risk reduction is outsized for the most impacted banks, at as much as about 5 billions and over 4/5 of market risk capital. A replicating portfolio approach similar to Begenau, Piazzesi, and Schneider (2015) shows that, while both the post-Volcker decline in the size of the trading book and the decline in factor sensitivities contributed to the decline in the quantity of risk, the bulk of the reduction was due to the drop in the equity market factor loading. To help put the figures into context, from a macro-prudential regulation perspective the financial stability benefits of the Volcker Rule are equivalent to those of imposing a capital surcharge on the banks of 2% of market risk-weighted assets (1/4*mCapital=1/4*8%*mRWA) or about 1% of trading assets. Overall, our estimates indicate that the Volcker Rule had economically large financial stability benefits and that the result in not sensitive to the calculation approach and the particulars of the way trading profits are normalized.

We confirm the reduction in the quantity of risk using a variety of additional data sources and approaches. Aggregate dollar trading positions – i.e., the total value of trading assets – from the publicly-available FR Y-9C filings show a significant decline from about $2T before Volcker to as little as $1.5T after. The variability of aggregate trading revenues also declines, which are both consistent with our results. The impact on the level of revenues is relatively muted, [7] indicating that banks made up at least in part for the lost profits from risky trades with profits from other sources, such as market making fees and hedging.[8] Two additional data sources confirm the decline in risk. Aggregate banking sector's trading VaRs from hand-collected publicly-available SEC 10-Q filings show a significant decline from as much as over $1B earlier in 2013 to around $600M by late 2016. Self-reported aggregate dollar trading risk exposures from the Schedule F ("Trading") of regulatory Form FR Y-14Q filings

[7]This result is also consistent with our main regression analysis, which shows a negative but generally small and not statistically significant coefficient estimate for the non-interacted Volcker indicator, which is consistent with slightly lower to stable levels of aggregate revenues. The lower variability is consistent with the reduction in the equity factor loading.

[8]To the extent that these sources of revenues are acyclical or, if anything, countercyclical, the shift is consistent with the intended goal of the Rule to limit directional but not any other market neutral trading positions that banks can profit from.

decline markedly after Volcker.[9] Finally, two other commonly employed measures of systemic risk in the banking literature, the marginal expected shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017) and the exposure CoVaR of Adrian and Brunnermeier (2016) also show a decline of comparable magnitude to our stress-test calculations. In all, this subsidiary evidence reinforces our conclusion that Volcker was effective financial stability regulation.

We further corroborate the effect of Volcker on equity market risk with extensive robustness and sensitivity checks. The impact of Volcker on the estimated sensitivity to the equity market risk factor holds up and remains relatively stable across these tests, which include using weekly trading assets from an alternative data source, the FR 2644 collection, and using aggregate trading profits to address the concern that equally-weighting banks in our baseline regressions may understate the influence of larger banks.[10] The impact also holds up to heterogeneity tests that re-estimate our main specification sequentially for each of the banks in our sample or leaving one bank out. The estimated bank-by-bank exposures mirror closely the baseline for most of the banks in our sample (11 out of 13), with just two banks having negligible exposures both before and after Volcker, confirming that the result is not driven just by any one particular bank. That said, there is some interesting evidence of larger effects for banks with larger trading books and fewer liquid assets, which reinforces the financial stability benefits of the rule. And, when we add controls for other regulations, the effect does not appear to be driven by banks that were subjected to new or enhanced capital and liquidity requirements or banks that failed an annual stress test. In all, the results of the robustness and sensitivity analysis help to build confidence in our main estimates and solidify our interpretation that the estimates isolate an independent effect of Volcker.

Third, the evidence is more nuanced for interest rate and credit risk. While there is

[9]Self-reported equity risk exposures, which are calculated by the banks as dollar sensitivities to risk factors, declined by about $45 billion or 2.5 percent of trading assets, which is of the same order of magnitude as our estimates.

[10]These sensitivity checks include adding controls for non-linear risk factors from Fung and Hsieh (2001) to address the concern that banks may have shifted toward tail risk exposures after Volcker; not subtracting the risk-free rate from P/Ls to ensure that the result is not driven by the risk-free rate; using shorter or longer lags to calculate the Discoll-Kray standard errors; and addressing rebalancing by using an optimal changepoint regression technique to estimate time-varying risk exposures.

evidence at the desk level that banks cut back on the interest rate risk of their portfolios of government and fixed-income securities, credit risk loadings do not appear to have been affected by the rule. Finally, there is evidence of currency risk, with significant loadings on the dollar risk factor especially in commodity trading desks, in line with certain commodities and foreign exchange or currency trading being exempted from the rule. The economic significance of both credit and dollar risk loadings is much smaller compared to the pre-rule loadings on equity market risk, with a one standard deviation change in the credit (dollar) risk factor leading to a 5 (3) percentage point change in trading profits. In all, rather than hedge aggregate risk, the bank trading book tended to bet on rising stock markets pre-rule, and continued to load, though to a lesser extent, on credit risk and the dollar throughout the rest of the sample period.

Finally, we address identification with a differences-in-differences (DD) research design that exploits the staggered timing of the rule's reporting requirement, which was phased in over a period of two and half years. This design addresses potential contemporaneous confounds that are common across banks by deriving estimates for each bank relative to a control group of other banks that were not yet subject to reporting. In line with our baseline findings and, importantly, corroborating our discussion of the economic mechanism of the rule, the results indicate that the reporting requirement contributed significantly to the reduction of U.S. banks' trading book exposures to equity market risk. The size of the estimates for the reporting requirement ranges between half and 2/3 of the overall effect of Volcker, depending on the trading profit normalization used. The DD results survive several specification checks, which include using an event-time implementation similar to long-run event studies to address the concern that the bulk of statistical power of our tests comes from time-series variation, as well as using a more saturated specification that adds week fixed effects to more conservatively control for common shocks. The results hold up to just using the time–difference in a before-after analysis, confirming that the effect is indeed due to time-series variation within the treated banks. Reassuringly, when we repeat the before-after analysis just for the placebo group of banks that were exempted from reporting, this falsification test shows no decline in risk around the first reporting date (June 30, 2014), suggesting that contemporaneous confounds are unlikely to be driving the reduction in trading risk.

The additional tests are also helpful to interpret the results on credit and currency risk. Credit risk loadings in the post-Volcker period are driven by large banks and those that failed the stress tests. To the extent that these banks faced the brunt of the compression in profits from heightened regulation and the low-rate environment, their continued loading on credit risk is in line with existing evidence of reach-for-yield incentives of financial institutions in the post-crisis period (see, for example, Becker and Ivashina (2015), Di Maggio and Kacperczyk (2015)). Interestingly, the evidence indicates that reporting increased the loading on dollar risk, consistent with a migration effect toward asset classes that were exempted from the rule. Collectively, our evidence indicates that, while banning proprietary trading is an effective financial stability tool to curtail large risks, it is not a panacea, as reducing smaller risk exposures may require different, more targeted tools.

In summary, our primary contribution is to document the first comprehensive evidence on the risks that banks take in their trading. Our evidence is complementary to the existing banking literature starting with Flannery and James (1984) and Gorton and Rosen (1995), which has so far examined primarily interest rate risk exposures for measures of overall bank performance (for recent examples, see Drechsler, Savov, and Schnabl (2018), English, Van den Heuvel, and Zakrajsek (2018), Begenau, Piazzesi, and Schneider (2015), and Landier, Sraer, and Thesmar (2013)). By focusing on the performance of banks' trading books, we isolate the contribution of trading to the overall risk profile of U.S. banks – i.e., whether trading increases or decreases systemic risk in the U.S. banking sector – and how it has evolved over time since the crisis.[11] By doing so, we join a growing literature that centers around the balance-sheet positions and risks of financial institutions, either to document their properties empirically (see, for example, Adrian and Shin (2010), who examine Value-at-Risk measures of investment banks, and Bai, Krishnamurthy, and Weymuller (2018), who focus on measuring liquidity risk) or to build theoretical models (see He and Krishnamurthy (2018) for a survey). Our evidence has implications for the broader debate on whether U.S. banks have gotten safer since the crisis, which is a contentious question because, among

[11] O'Brien and Berkowitz (2007) is an earlier attempt at measuring trading book exposures for a limited number of banks (the six largest dealers) in the pre-crisis period (1998-2003).

other reasons, it is challenging to measure the riskiness of U.S. banks (see Gandhi and Lustig (2015) and Atkeson, Eisfeldt, d'Avernas, and Weill (2018) for recent related approaches that use banks' stock returns to measure their riskiness).

In addition, we contribute to the ongoing academic debate on the effectiveness of financial regulation. Agarwal, Lucca, Seru and Trebbi (2014) and Granja and Leuz (2017) exploit well-identified settings to evaluate the effectiveness of supervision. Their evidence indicates that the regulators who are entrusted with enforcing financial regulations matter for regulatory outcomes, pointing to a tension between rules and inconsistent enforcement by multiple regulators that hinders their effectiveness. While the institutional features of the Volcker Rule make our setting different from this prior work, as enforcement of the rule is not decentralized and only tasked to federal agencies, our evidence that the reporting requirement matters corroborates the broader conclusion of the literature that enforcement matters. Our analysis of the reporting requirement speaks to the heated debate on the consequences of recent efforts to streamline the post-crisis regulations of banks without compromising the safety and soundness of the U.S. financial system (Greenwood et al. (2017b) and Quarles (2018)). Our approach is also complementary to the recent literature that has sought to assess the Volcker Rule by focusing on changes in market liquidity. Duffie (2012) argues that the rule reduces the ability of banks to provide market-making services, which in turn adversely affects market liquidity in dealer-intermediated markets. Bao et al. (2016) show supporting evidence that the price impact of trades in downgraded corporate bonds increased after the rule.[12] By focusing directly on banks we sharpen identification, because we can directly control for concurrent regulatory changes and exploit the staggered introduction of the reporting requirements, thus isolating, to the best of our knowledge for the first time, the causal effect of the rule on bank risk taking.

The rest of the paper is organized as follows. Section 2 details the institutional background. Section 3 describes our data and research design. Section 4 presents our main empirical results at the "top-of-the-house" (bank) as well as at the "sub-portfolio" (desk) level,

[12] Allahrakha et al. (2018) find that transaction costs for corporate bond investors also increased. Anderson and Stulz (2017) point out that the dealers affected by the Volcker Rule were also affected by the concurrent implementation of Basel III and attribute changes in market liquidity to other regulatory reforms. Other studies find mixed to no evidence of changes in market liquidity after the crisis (Trebbi and Xiao (2017), Paddrik and Tompaidis (2018)).

and quantifies the implied risk exposures. Section 5 presents the results of our differences-in-differences tests that address identification. Section 6 concludes.

2 Institutional background

On December 10, 2013, the Federal Reserve Board along with four other U.S. agencies approved the final version of the regulations implementing the so-called "Volcker Rule." The rule is named after former Federal Reserve Chairman Paul Volcker, who led the efforts to include in the Dodd-Frank Wall Street Reform and Consumer Protection Act provisions to keep institutions like banks, that benefit from federal deposit insurance and discount-window borrowing, from taking risks that could trigger a taxpayer-funded bailout. Consequently, section 619 of the Dodd-Frank Act generally prohibits insured depository institutions and any company affiliated with an insured depository institution from engaging in "proprietary trading" and from acquiring or retaining ownership interests in, sponsoring, or having certain relationships with a hedge fund or private equity fund. These prohibitions are subject to a number of statutory exemptions, restrictions, and definitions.

The simple terms of the statute required definition and implementation by regulation. After the Dodd-Frank Act was signed into law in 2010, the Federal Reserve Board worked closely with the other agencies charged with implementing the requirements of section 619, including the Office of the Comptroller of the Currency, the Federal Deposit Insurance Corporation, the Securities and Exchange Commission, and the Commodity Futures Trading Commission. The key implementation issue was to draw the line between prohibited and permissible activities. The rule was finalized in December 2013 ("2013 final rule") when the five U.S. agencies approved regulations implementing the statute. The final rule was published on January 31, 2014 and became effective on April 1, 2014.[13] Initially, compliance was expected on a best-effort basis, with full compliance required from July 21, 2015.

The Volcker Rule, which was formally added as Section 13 of the Bank Holding Company Act of 1956, generally prohibits federally insured banking entities from engaging in

[13]The agencies provided a proposal in November 2011, which caused a lively debate reflected in 18,000 comment letters. For the text of the published final rule, see https://www.occ.gov/news-issuances/federal-register/79fr5536.pdf.

"proprietary trading," which is defined as engaging as principal for the trading account of the banking entity in the purchase or sale of a financial instrument. Explicitly excluded are repos, reverse repos, securities lending, loans, certain commodities, and foreign exchange. Additionally, the rule provides permission for certain underwriting and market-making activities, risk-mitigating hedging, and "other" permitted activities, in particular trading in U.S. government bonds (and non-U.S. government bonds within limitations), trading on behalf of a customer, trading activities of foreign banking entities, or trading by regulated insurance companies, as long as they do not pose material risks to the safety and soundness of the banking entity or the U.S. financial system.[14]

The 2013 final rule established different levels of compliance depending on the size and nature of a banking entity's trading activities, an important institutional feature that we exploit to refine identification. All banking entities with more than $10 billion in total consolidated assets have to comply with the Volcker Rule. Additionally, banking entities with $50 billion or more in consolidated assets and $10 billion or more in trading assets and liabilities are required to report quantitative trading metrics, such as position limits, risk factor sensitivities, profits and losses, and Value-at-Risk. The reporting obligation was phased in over a period of two and half years: banking entities with $50 billion or more in trading assets and liabilities were required to start reporting these metrics in June 30, 2014; banks with trading assets and liabilities between $25 and $50 billion in April 30, 2016; and banks with trading assets and liabilities between $10 and $25 billion in December 31, 2016. The timeline of the Volcker Rule's compliance and reporting requirements is summarized in Figure 1.

To help clarify the economic mechanism behind the Volcker Rule we turn to both theory and practice of bank regulation. More precisely, we discuss the implications from theories of bank regulation, and provide a summary of our conversations with several of the agencies that are tasked with the implementation and enforcement of the rule. While these conversations

[14]In March 2018, the Economic Growth, Regulatory Reform, and Consumer Protection Act made several changes to the statutory provisions of the Volcker rule, mainly to reduce compliance burden, especially for small banks or banks with limited trading activity. Separately, the five U.S. agencies that developed the 2013 final rule recently acknowledged that some revisions to the 2013 final rule are desirable with the goal to focus the application of the rule on banking entities with large trading operations and to simplify and clarify some provisions of the rule, especially those regarding impermissible activities (FRB, 2018a).

fall well short of a large-scale statistical survey, they provide useful insights into the inner workings of the rule, which reinforces the intuition provided by theory. From the standpoint of theory (Koehn and Santomero, 1980; Kim and Santomero, 1988), it is well understood that banks choose riskier portfolios because of deposit insurance and that both capital regulation via the imposition of capital ratios and explicit restrictions on asset composition are effective means to reduce bank risk. Thus, from the standpoint of theory, the Volcker Rule is best understood as a restriction on bank trading asset composition that prevents banks from holding assets on their trading book for the purpose of proprietary trading.

There are several reasons why restricting proprietary trading should be expected to lead to a reduction in the directional or systematic risk exposures of the banks that are subject to the rule. Intuitively, when banks are allowed to hold securities for proprietary trading purposes, they have an incentive to increase their exposures to market risk by making directional bets in order to profit from short-term price movements. Thus, as the value of the securities held in the trading book appreciates or depreciates with the market, so does the value of the bank trading book. Richardson (2012) contains several examples of directional trades that expose bank trading desks to systematic risk, including regulatory capital arbitrage involving certain asset-backed securities such as AAA-rated mortgage-backed securities (MBS), carry trades and the writing of out-of-the-money put options on market risk. By contrast, trading on behalf of clients is relatively more market-neutral or, as commonly referred to in the industry, it is the "moving business," not the "storage business."

Our conversations with several of the agencies that are tasked with the implementation and enforcement of the rule indicate that the line between prohibited and permissible activities is drawn based on whether trading is for prudent market making, underwriting, or hedging, which is allowed, or rather for taking systematic risk exposures from directional positions aimed at profiting from price changes, which is not allowed. Specifically, as we further detail in Appendix A.1, the final implementation of the rule prohibits any transaction or activity that would result, directly or indirectly, in a material exposure by the banking entity to high-risk assets or trading strategies, which are defined as a transaction or strategy that would substantially increase the likelihood that the banking entity would incur a substantial financial loss or would pose a threat to financial stability. The rule does not include a specific list of prohibited high-risk assets or trading strategies, but instead relies on the supervisory process to identify them. To that end, it requires that not just standard metrics of trading book size and performance, such as profits and VaR, but also market risk factor sensitivities are explicitly monitored (Federal Register, 2014, p. 5618). More broadly, to remain compliant banks are required to set and adhere to appropriate self-imposed risk limits on VaR or risk factor sensitivities in line with prudent market making, underwriting, and hedging. Assessing compliance based on the quantitative metrics involves monitoring of financial exposures to all significant market factors that drive the financial instruments in which a bank acts as a market maker or that it uses for risk management purposes (Federal Register, 2014, p. 5594). Finally, although the final rule does not require fees to be the only source of revenue from permitted market making activity, the Agencies make it clear that evaluating whether price changes are the source of profits and losses constitutes an important part of determining whether a trading activity is prohibited (Federal Register, 2014, p. 5623).[15]

In summary, both theory and practice suggest that the Volcker Rule should reduce bank trading book exposures to systematic risk. The extent to which it actually did is the focus of our empirical analysis.

3 Data and Research Design

Our primary source is newly-available regulatory reporting data collected by the Federal Reserve to monitor compliance with the U.S. Market Risk Capital Rule, which implements the market risk related provisions of the Basel III capital framework in the U.S. (Federal Register, 2012). Among other things, this rule stipulates that banks with trading assets and liabilities of at least $1 billion or 10 percent of their total assets must divide their trading book portfolios into subportfolios and calculate, for each subportfolio, (1) daily Value-at-Risk (VaR) calibrated to a one-tail 99% confidence level and (2) daily profit or loss (P/L),

[15] As such, the implementation of the Rule has followed its initial intent that, as Paul Volcker bluntly quipped in a Senate hearing on February 2010, proprietary trading is "like pornography, you know it when you see it," because it can be measured and monitored using the reported quantitative metrics of factor exposures.

that is, the net change in the value of the positions held in the subportfolio at the end of the previous business day (Federal Register, 2012, §205). Although this measure of P/L generally underestimates total profits, as banks also typically earn fees and commissions from their market making business on behalf of customers in addition to any capital gains or losses associated with their trading book positions, it is more suitable for identifying portfolio risk exposures from bank trading. We supplement this data with additional information on trading book size and more comprehensive measures of trading P/L from various other sources, including the confidential Federal Reserve quarterly FR Y-14Q[16] and weekly FR 2644,[17] as well as the publicly-available quarterly FR Y-9C and hand-collected information from SEC filings.

Starting from January 2013, the effective date of the Market Risk Capital Rule, 30 U.S. bank holding companies (BHCs) and intermediate holding companies (IHCs) report sub-portfolio risk metrics to the Federal Reserve. Given our focus on U.S. banks, we keep only domestic BHCs, which leads to a sample of 20 BHCs for which we have full reported information at the desk-asset class level, or "sub-portfolio," over the entire January 2013 to June 2017 period. For 13 of these BHCs we also have full reported information at the more aggregate bank level, or "top-of-the-house," over the period. To err on the side of caution, we opted for not including the remaining 7 BHCs in the bank-level sample because it is problematic to aggregate the desk-level VaRs into the top-of-the-house VaRs as it is well-known that VaRs are not generally additive (Artzner et al., 1999).

Coverage of our two main samples is comprehensive. The 13 banks in the bank-level sample cover about 90% of aggregate trading assets in the U.S. banking sector, while the 20 banks of the trading-desk sample cover virtually the universe of the U.S. banking sector's

[16]This additional data source is Schedule F of the Federal Reserve's Y-14Q data collection. This data collection began in June of 2012 to support the Dodd-Frank Stress Tests and the Comprehensive Capital Analysis and Review. The reporting panel includes bank holding companies exceeding US $50 billion in total assets. The dataset contains quarterly information on bank trading book exposures by asset class. Detailed documentation is publicly available at: https://www.federalreserve.gov/reportforms/forms/FR_Y-14Q20200930_i.pdf.

[17]The Federal Reserve reports the weekly aggregated balance sheet of U.S. banks at its website: https://www.federalreserve.gov/releases/h8/current/default.htm. We use the micro-data, which underlie these aggregates and were obtained through a confidential survey of depository institutions that requires confidential treatment of institution-level data and any information that identifies the individual institutions that reported the data. Detailed documentation is publicly available at: https://www.federalreserve.gov/reportforms/forms/FR_264420190327_i.pdf.

trading assets. The 13 banks in our bank-level sample include all U.S. Globally Systemically Important Banks (GSIBs) and collectively hold between $6.3 and $7.2 trillion in risk-weighted assets, which is a large fraction of the total risk-weighted assets held by U.S. banks. The banks account for an even larger share of trading assets and liabilities during our sample period. The remaining 7 banks, which did not report consistently at the bank-level, are generally small in terms of their trading activity. Their inclusion in the desk-level analysis of Section 4.3 serves as a robustness check.

Panel A of Table 1 reports summary statistics for the P/L data at the top-of-the-house level (Panel A). Although the raw data are daily, we do our analysis at the weekly frequency to mitigate the effect of high-frequency noise. Because we cannot reveal bank-specific information to preserve confidentiality, for each of the 13 banks we first calculate the time-series mean, standard deviation, 5th percentile, 95th percentile, skewness, and kurtosis of weekly dollar P/Ls. For each of these statistics, we then take the cross-sectional mean, standard deviation, minimum, and maximum across the 13 banks, which we report in turn. The average bank made trading profits of about $5 million on average per week, with a cross-sectional standard deviation of $12 million. There are large differences in trading profits across banks, as the least profitable bank in our sample lost $10 million on average per week, while the most profitable bank earned around $30 million per week. Although the average P/Ls appear relatively small, their standard deviations and extreme values are an order of magnitude higher. The second column shows that the standard deviation of trading profits for the 13 banks in our sample was $30 million, on average, and as high as $104 million. The third column shows that the 13 banks recorded a large weekly loss (bottom 5th percentile of P/Ls) of $43 million, on average, and as high as $133 million overall. Large weekly profits (top 95th percentile of P/Ls, fourth column) were $54 million, on average, and as much as $221 million. The last two columns of the table show that the distributions of the weekly P/Ls are generally asymmetric and exhibit fat tails.

The remaining panels of Table 1 report analogous statistics for the weekly VaR, which we approximate by multiplying the average daily VaR by the square root of the number of trading days within the week (Panel B), as well as quarterly and weekly trading assets from FR Y-9C and FR 2644 (Panels C-D). The bank-level average of weekly VaRs has a mean of

$73 million with a cross-sectional standard deviation of $86 million. The smallest bank in terms of average weekly VaR had an average VaR of only $851 thousand, while the largest bank had an average VaR of $221 million. Trading assets are similar across the two sources and frequencies, with the average quarterly or weekly trading assets having a mean of over $120 billion and the smallest bank in terms of average quarterly or weekly trading assets having average trading assets of $972 million, while the largest bank had average trading assets of $388 billion. Overall, the summary statistics for the weekly P/L and VaR show that while the banks in our sample tend to run fairly balanced books with a typical weekly VaR of less than $100 million, there are banks that sometimes amass large trading book exposures and experience economically significant losses.

3.1 Measuring trading book performance

Our primary outcome of interest is trading book profits. To estimate risk exposures, we consider three main measures of trading book performance, which entail different normalizations of trading book profits: dollar trading profits, either unscaled or scaled by Value-at-Risk (VaR) or trading assets. Specifically, our first outcome measure is raw dollar trading book profits:

$$P/L_{it}^{\$} = \frac{P/L_{it}}{\sigma},$$

where P/L_{it} is the weekly P/L of bank i in week t and σ is its unconditional standard deviation in the sample. We convert the dollar P/L into standard deviation units to facilitate interpretation of economic magnitudes. This measure has the benefit of providing a simple direct estimate of dollar exposures. We also consider two measures of returns relative to committed capital to provide an important sensitivity check to different normalizations of trading book profits and gauge the relative contribution of changes in the size of the trading book (or trading book "positions") vs. changes in factor exposures (or trading book "betas") to the overall quantity of risk, as further explained in the next section (see Section 4.2 and Appendix A.3). Our second measure is trading book returns relative to VaR, which we calculate by dividing the weekly P/L by the average daily VaR within the week multiplied by the square root of the number of trading days in that week:

$$P/L_{it}^{VaR} = \frac{P/L_{it}}{\sqrt{n_t} VaR_{i,t}} - r_{ft},$$

where n_t is the number of trading days in week t, $VaR_{i,t}$ is the average daily VaR of bank i in week t, and r_{ft} is the risk-free rate, which we subtract to capture returns in excess of the risk-free asset.[18] Scaling by $\sqrt{n_t}$ approximately translates a daily VaR into a weekly VaR. For this measure, we use VaR to proxy for the amount of capital committed to the trading business of each bank because VaR is an important part of the total trading-book regulatory capital (Federal Register, 2012, §204) and trading assets are not available at this level of granularity and frequency for all our banks. Under relatively mild distributional assumptions, scaling by VaR has the additional advantage of isolating innovations in P/L (see Appendix A.2 for a formal derivation). That said, one concern with this measure is that VaR is also a function of risk, because for example it increases with the volatility of P/L. Thus, the estimated exposures may be underestimated if exposures are due to banks with volatile P/L.

To address this concern, we consider an alternative measure of trading book returns that proxies for capital committed to trading using trading assets at quarterly frequency from FR Y-9C regulatory filings:

$$P/L_{it}^{TA} = \frac{P/L_{it}}{TA_{i,t}} - r_{ft},$$

where $TA_{i,t}$ is the quarterly trading assets of bank i in week t. While the FR Y-9C trading assets are available for the entire sample, the drawback is that they are at a quarterly frequency. To address this limitation, we use weekly trading assets from the FR 2466 collection. This data is only available for a sub-set of our banks and, thus, we use it as a robustness check on the results for the full sample of banks.[19] The third measure addresses the concern

[18] In additional analysis, we show that the results are robust and, in fact, little changed, if we do not subtract the risk-free rate (see Appendix Table A7).

[19] As a final robustness check, we also normalized the weekly P/L by quarterly market and book value of market risk capital and common equity tier 1 (CET1) capital. The market value of market risk capital is defined as the product of each bank's market capitalization times the proportion of trading-book risk-weighted asses (RWA):

$$r_{it} = \frac{P/L_{it}}{E_{i,t}} - r_{ft}, \quad E_{i,t} = \left(\frac{mRWA_{it}}{RWA_{it}}\right) mE_{i,t},$$

about using VaR to construct the returns by using a more direct measure of trading positions instead. We use these three measures to provide a range of estimates for the dollar trading risk exposures of banks and how they evolve over time.

Panels A-C of Table 2 report descriptive statistics for the weekly trading-book return measures (for unscaled P/Ls, see Panel A of Table 1). The mean returns tend to be close to zero, but exhibit significant variation both in the time-series and across banks. For example, the standard deviation of P/L scaled by VaR in Panel A is about 0.1 and the min-max range is about 0.4. Similar to the raw dollar P/L in Panel A of Table 1, the return distributions are asymmetric and exhibit fat tails.

3.2 Risk factors

Panel D of Table 2 reports descriptive statistics for our weekly risk factors, which are meant to measure risk for the main broad asset classes banks trade in, namely equities, fixed-income and credit, commodities, and foreign exchange. Details on the series mnemonics and data sources for each of these factors are in Appendix A.4. The market risk factor (MKT) is the weekly excess return on the value-weighted market portfolio obtained from Kenneth French's website. The volatility risk factor (VIX) is the weekly change in the CBOE VIX index. The interest rate risk factor (IR5Y) is the weekly change in the 5-year swap rate. The credit risk factor (DEF) is the weekly change in the credit spread, which is defined as the difference between a 10-year BBB-rated bond yield and the 10-year Treasury yield. The slope-of-the-yield-curve risk factor (TERM) is the weekly changes in the term spread, which is defined as the difference between the 10-year and 1-year Treasury yields. Finally, the commodity and foreign exchange risk factors are the weekly return on the Goldman Sachs Commodity Index (GSCI) and the weekly excess return on the dollar factor (DOL) introduced by Lustig et al. (2011), respectively; a positive excess return on DOL indicates US dollar depreciation.

where $mRWA_{it}$ denotes market risk-weighted assets, RWA_{it} total risk-weighted assets, and mE_{it} is the beginning-of-the-week market value of equity. Data on RWA are only available at a quarterly frequency from the FR-Y9C filings. Book value of market capital is defined in footnote 25. Summary stats for these additional denominators and scaled P/Ls are in Appendix Tables A1 and A2, respectively.

3.3 Research design

We estimate the key input to assess banks' trading risk exposures following a standard approach in banking since Flannery and James (1984) and Gorton and Rosen (1995)): how sensitive is the trading book performance of a given bank to a broad array of aggregate risk factors, including equity markets and interest rates? To that end, we examine the following main relation:

$$P/L_{it}^{X} = \beta RF_t + \lambda_i + \epsilon_{it}, \tag{1}$$

where the outcome variable, P/L_{it}^{X}, for bank i in week t is each of the three main measures of trading book performance defined in Section 3.1 ($P/L_{it}^{\$}$, P/L_{it}^{VaR}, and P/L_{it}^{TA}), in turn, and the main variable of interest, RF_t, is the vector of the seven risk factors (MKT, VIX, IR5Y, DEF, TERM, GSCI, and DOL) defined in Section 3.2. Recall that MKT and GSCI are excess returns on the market portfolio and a commodity portfolio, respectively, and we expect a positive beta if banks' trading books are exposed to these risk factors. DOL is an excess return in USD of a basket of foreign currencies, and hence an exposure of a trading book to US dollar depreciation implies a negative DOL beta. The other risk factors–VIX, IR5Y, DEF, and TERM–are changes in implied volatility, interest rates, default risk, and the slope of the yield curve, respectively, so a positive exposure to these risk factors is associated with a negative beta. To address unobserved heterogeneity, in all specifications we control for bank fixed effects by including a full set of bank-specific dummies, λ_i. The inclusion of bank effects ensures that the parameter of interest, β, which represents the risk exposures, is estimated only from within-bank time-series variation. We conduct statistical inference using the Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence.[20]

To examine whether the risk exposures changed with the introduction of the Volcker Rule, we enrich the specification in equation (1) as follows:

$$P/L_{it}^{X} = \alpha I_t + \beta RF_t + \gamma I_t RF_t + \lambda_i + \epsilon_{it}, \tag{2}$$

[20]In the main analysis, we use a lag of 4 weeks. We select the lag length for the Driscoll-Kraay standard errors using the plug-in method of Newey and West (1994) and set m = floor(4(T/100)^{2/9}), which yields 4 lags. In Appendix Table A8, we show that the standard errors are not sensitive to the choice of lag and the results are robust to using either shorter (2 weeks) or longer (6 weeks) lag structures.

where I_t is the "Volcker indicator", i.e. a variable that takes the value of one after the Volcker Rule became effective (April 1, 2014), and equals zero otherwise. The coefficient of interest is γ, which represents the change in exposures after Volcker. To isolate a causal effect of Volcker, we address two important issues with estimating equation (2), rebalancing and endogeneity. We take on rebalancing in graphical analysis that uses an optimal changepoint regression technique to estimate time-varying risk exposures and a statistical test for structural breaks in banks' equity market risk exposures similar to Bollen and Whaley (2009).

We address the main endogeneity challenge with a causal interpretation of estimates of γ, which is that contemporaneous aggregate shocks are a potential confound that may be erroneously picked up by the simple pre- vs. post-Volcker time difference, in two ways. An important type of such shocks that are common across banks is other regulatory changes. First, we estimate a richer version of equation (2) to test whether our main estimates of γ hold up to controlling for other regulations that went into effect over our sample period. Specifically, we exploit our relatively high-frequency data for a broad cross section of banks to add controls for other regulatory changes that happen within our sample period and are common across different groups of banks. Estimating γ independently even after we add these controls is feasible in our setting because other regulations, such as new or enhanced capital and liquidity requirements or the results of annual stress tests, affect different subgroups of our banks at different times within our sample period.

Second, we recognize that adding controls for other regulations helps to ameliorate but does not fully resolve the challenge of latent common shocks because, for example, these shocks may be due to common changes in the macroeconomic environment or demand conditions in securities markets, which are challenging to control for. The ideal natural experiment would randomly assign similar types of banks to the two different types of Volcker treatment status. We exploit the staggered timing of the rule's reporting requirements to design a "quasi-natural" experiment that is geared toward generating this random assignment. As we discussed in the previous section, compliance with the Volcker's reporting requirements was phased in over a period of two and half years based on arbitrary bank trading book size cutoffs: banking entities with \$50 billion or more in trading assets and liabilities were required to start reporting these metrics in June 30, 2014; banks with trading assets and liabilities between $25 and $50 billion in April 30, 2016; and banks with trading assets and liabilities between $10 and $25 billion in December 31, 2016. We exploit the staggered phase-in to implement a differences-in-differences (DD) research design. This design helps to gain traction on identification because it uses the sub-groups of banks that are not yet subject to the requirement as a control group, thus differencing out potential contemporaneous confounds that are common across banks.

Finally, we address concerns about replicability in graphical analysis based on the supplementary data sources described above, which include publicly-available quarterly P/L measures from FR Y-9C and hand-collected quarterly VaR measures from SEC filings, as well as quarterly self-reported risk exposures from regulatory FR Y-14Q.

4 Bank trading risk exposures and Volcker

In this section, we present our main stylized facts on the evolution of bank risk taking via their trading books in the post-crisis period. We start by documenting trading book performance's sensitivity to the risk factors at the bank level. We also examine the sources of risk at the trading desk level to pin down which asset classes are exposed to which risks. To measure the quantity of trading book risk – i.e., the economic magnitude of the total dollar risk exposures – and gauge the implications for financial stability, we combine our factor loadings' estimates with measures of the size of the trading book in a regression-based counterfactual exercise similar to the "stress test" commonly implemented by regulators.

4.1 Bank-level analysis

In Table 3, we summarize results from estimating equation (1) with the three main measures of trading performance as the outcome variables, dollar P/L in standard deviation units (Column 1), P/L normalized by VaR (Column 2), and P/L normalized by trading assets (Column 3), in turn, and the risk factors as the explanatory variables of interest. The coefficients on equity market risk (MKT) are not statistically significant for any of the three measures. By contrast, the coefficients on credit risk (DEF) and on the dollar (DOL) are negative and statistically significant for most measures, indicating that U.S. banks' trading tended to bet on these two types of risk over the post-crisis period. For example, the estimates in Column 2 imply that a one standard deviation change in the credit (dollar) risk factor leads to a 5 (3) percentage point change in trading profits (see Appendix Table A3 for the full set of estimates in standard deviation units). To gauge economic significance, we examine by how much a change in each risk factor moves a bank in the trading performance distribution. A one standard deviation of weekly P/L normalized by VaR ranges between 29 and 54 percentage points for banks in our sample, and is about 39 percentage points, on average. Thus, the economic significance of credit and dollar risk loadings is relatively small, with a one standard deviation change in the credit (dollar) risk factor leading to about (less than) 1/10 of a standard deviation change in trading profits. In fact, it would take a large 5%-to-95% shock to generate a loss of the same order of magnitude of one standard deviation of P/Ls. The estimates in Columns 1 and 3 imply similarly small risk loadings.[21]

Table 4 examines the evolution of risk loadings over time for the same set of trading performance measures. We report results from estimating equation (2), which tests for whether the risk factor sensitivities changed around Volcker by adding an interaction term for each risk factor with an indicator variable that takes the value of one after the introduction of the Volcker Rule in April 2014 and zero otherwise. First, robustly across the three performance measures the coefficient on the interaction term of the equity market portfolio factor and the Volcker indicator is negative and statistically significant, while the coefficient on the non-interacted factor is positive and significant, indicating that U.S. banks' trading books had significant loadings on equity market risk before the Volcker Rule was finalized, which they curtailed afterwards. The two coefficient estimates have roughly the same size, in line with the result of no significant equity market loading on average for the overall period, indicating that the pre-Volcker sensitivities were fully offset post-Volcker. The estimates imply an economically large decline in the sensitivity of trading book profits to the stock market. For example, the estimates in Column 2 imply that a one standard deviation negative re-

[21] In additional graphical analysis, we explored cross-sectional heterogeneity in the credit and dollar risk factor loadings by re-estimating equation (1) separately bank-by-bank for each of the banks in the sample. The bank-by-bank exposures estimated for the P/L scaled by VaR, which are plotted in Appendix Figure A1, indicate that there is little heterogeneity in credit exposures, with only one of the banks displaying larger exposures. Dollar exposures are relatively more heterogeneous across banks, which is in line with banks having more leeway because this asset class was exempted by the Volcker rule.

alization of the S&P return, which corresponds to about 2 percentage points drop, would generate a smaller trading loss relative to the Value-at-Risk by about 14 percentage points as a consequence of the rule (see Appendix Table A4 for the full set of estimates in standard deviation units). This reduced loss is of the same order of magnitude as the banks' standard deviation of profits relative to VaR in the sample. And the loss reduction implied by a large 5%-to-95% shock, which corresponds to about 6 percentage points drop, is about equal to a full standard deviation of P/L scaled by VaR. The loss reduction implied by the estimates for the other two trading book performance measures in Columns 1 and 3 is of similar size at up to 2/5 of a standard deviation change in the respective measure, indicating that the result is not sensitive to the way P/L is normalized. Second, there is weaker evidence of pre-Volcker sensitivity to interest rate (TERM) risk, which we revisit in the desk-level analysis.

In robustness analysis, we show that the main result on the equity market factor loading survives five batteries of important sensitivity checks. First, using aggregate P/L to address the concern that the change in average loading may be overstated because we equally-weight banks in the baseline (Appendix Table A4) or using other alternative scalings including weekly trading assets from FR 2644 to address residual measurement concerns about the baseline scalings (Appendix Table A5). Second, controlling for a standard set of five non-linear risk factors from Fung and Hsieh (2001)[22] and their interaction with the Volcker dummy to address the concern that banks may have shifted toward tail risk after Volcker (Appendix Table A6).[23] Third, not subtracting the risk-free rate from the scaled P/Ls to ensure that the result is not driven by the risk-free rate (Appendix Table A7). Fourth, using shorter or longer lags to calculate the Discoll-Kray standard errors (Appendix Table A8). Fifth, re-estimating equation (2) bank-by-bank sequentially for each of the banks in our sample (Appendix Figure A2) or leaving one bank out sequentially (Appendix Figure A3) to confirm that the result holds across the board for the majority of the banks and is not driven just by any one particular bank. The estimated bank-by-bank sensitivities mirror

[22] The five factors are as follows: the Return of PTFS Bond lookback straddle ("PTFSBD"); the Return of PTFS Currency Lookback Straddle ("PTFSFX"); the Return of PTFS Commodity Lookback Straddle ("PTFSCOM"); the Return of PTFS Short Term Interest Rate Lookback Straddle ("PTFSIR"); and the Return of PTFS Stock Index Lookback Straddle ("PTFSSTK"). The factors are downloaded from David Hsieh's data library at http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls.

[23] The results for the non-linear equity risk factor (PTFSSTK) in Appendix Table A6 indicate that, if anything, banks reduced also tail equity risk exposures after Volcker.

closely the baseline for most of the banks in our sample (11 out of 13), with just two banks having negligible equity market risk loadings both before and after Volcker.[24]

4.2 Quantifying risk exposures

Table 5 examines in more detail the financial stability implications of the Volcker Rule. The term "financial stability" is broad and has been used in the literature for different kinds of market vulnerabilities. Using our bank-level estimates as one of the key inputs, the effectiveness of Volcker as a financial stability tool can be evaluated by the extent to which it reduced pro-cyclicality of bank trading profits by reducing exposure to equity market returns. We use a counterfactual scenario to quantify the aggregate consequences of Volcker for the quantity of trading book risk – i.e., the overall reduction in total dollar risk exposures to the equity market factor. Specifically, we report the results of a stress-test exercise that consists in calculating an aggregate counterfactual for the effect on sector-wide dollar losses under two alternative adverse scenarios that vary by the size of the shock to the equity market return (30% vs. 65%).

Our estimates of the quantity of trading book risk are summarized in Table 5. We start by calculating the dollar change in exposures that is implied by our first measure of raw dollar P/L. For each bank, we multiply the estimate for the post-Volcker effect from the first column of Table 4 ("Volcker $\times$ MKT"=-22.98) by the unconditional standard deviation of P/L (σ) to convert the effect into dollar terms. We then take the sum over banks to calculate the aggregate estimate for the banking sector exposures, which is reported in the first column of Table 5 (Panel A). The estimate indicates that the Volcker Rule had a large impact on the total exposure to the equity market risk factor, with an estimated post-Volcker reduction in dollar risk exposures of about 9 billion dollars. For reference, the corresponding levels

[24]The average R^2 in these bank-level regressions is about 21%. In additional heterogeneity analysis, we explored the correlation between the equity market risk factor loading and basic bank balance sheet characteristics, including the size of the trading book (measured as trading assets), leverage (measured as the ratio of tier 1 capital to total assets), and liquidity (measured as the ratio of liquid assets to total assets, with liquid assets defined as the sum of cash plus federal funds repos plus securities). There is some evidence that banks with larger trading books and fewer liquid assets had larger loadings pre-Volcker, which they curtailed afterwards. The rank correlation coefficient between equity market betas before (after) Volcker and trading assets is 0.132 (-0.093) and that for liquid assets is -0.476 (0.566), which further corroborates the financial stability benefits of the rule.

of exposures before and after Volcker are reported in Appendix Table A9. To help gauge the economic magnitude of the effect, we consider two benchmark regulatory capital buffers, the change in overall capital buffers, measured by common-equity tier1 capital (CET1), and the level of capital buffers that banks are required to hold against trading risk, measured by market risk capital (mCapital).[25] Based on both benchmarks, the implied change in trading risk exposures after Volcker is economically large, at about 7% of the sector-wide change in CET1 and 18% of sector-wide mCapital. The implied aggregate annual losses for a 65% stock market drop, which mimics the "severely adverse scenario" of the annual regulatory stress tests (FRB, 2018b), are also economically large at about 4% of the banking sector's change of CET1 and 11% of mCapital (Panel C). Appendix Table A10 shows that the post-Volcker risk reduction is outsized for the most impacted banks in the sample, with the reduction in exposures estimated at as much as about 5 billions and 40% of the change in their CET1 and 65% of their mCapital.[26]

Next, we use a replicating portfolio approach similar to Begenau, Piazzesi, and Schneider (2015) to derive an approximate quantification of the impact of Volcker on the change in dollar value of the trading book based on the estimates for the scaled P/Ls in Table 4. Intuitively, as spelled out in more detail in Appendix A.3, this approach makes transparent that the implied change in the quantity of risk can be decomposed into two terms, one that measures the implied change in dollar positions – i.e., the part that is due to the change in size of committed capital – and another that measures the implied change in the sensitivity of the trading book to the equity market factor – i.e., the part that is due to the change in the equity factor loading. To calculate the dollar change in exposures for each bank under this approach, we combine two main inputs: 1) the estimates for the scaled P/L's pre- and post-Volcker effect from the second and third columns of Table 4 ("Volcker" and

[25] The Basel III rules introduced a standardized framework to calculate the risk weights for assets in the trading book. Under this framework, market risk capital is defined as equal to 8% of market risk-weighted assets (mRWA). And mRWA are defined as 2.5*[3*VaR+3*Stressed VaR+ Credit and equity standardized specific risk +Incremental risk charge+Comprehensive risk measure]. For more details, see the FFIEC 102 step by step calculation, which is available at https://www.ffiec.gov/pdf/FFIEC_forms/FFIEC102_201612_f.pdf.

[26] To examine the variation across banks, Appendix Table A9 uses the same calculation as Table 5 with one modification, which is to use bank-by-bank estimates of the betas from Appendix Figure A2. The implied largest reduction in exposures across banks is reported in square brackets. For reference, we also report the aggregate exposures implied by the factor loadings estimated bank-by-bank, which are similar and, if anything, somewhat larger than those in Table 5.

"Volcker × MKT"), and 2) the pre-and post-Volcker values of their respective scaling (VaR and trading assets). The change in dollar exposures associated with the market shock is then calculated for each bank as the sum of two terms (denoted as "Total" in Table 5). The first term (denoted as "ΔVaR" and "ΔTA" in Table 5) is the product of the estimated sensitivity pre-Volcker (the coefficient for "Volcker" in Table 4) times the change in dollar positions (VaR and TA). The second term (denoted as "$\Delta\beta$" in Table 5) is the product of the estimated change in the sensitivity post-Volcker (the coefficient for "Volcker × MKT" in Table 4) times the dollar positions post-Volcker (VaR and TA). We take the sum over banks to get the aggregate estimate for the banking sector exposures, which is reported in the fourth column of Table 5 (Panel A) for the calculation that uses P/L scaled by VaR and in the last column of Table 5 (Panel A) for the calculation that uses P/L scaled by trading assets.

The estimates in the fourth and in the last columns of Table 5 ("Total" in Panel A) are close to those in the first column, confirming that the Volcker Rule had a large impact on the total quantity of risk. The estimated post-Volcker reduction in dollar risk exposures ranges between about 10 and 13 billion dollars for the calculation based on P/L scaled by VaR and by trading assets, respectively. The estimates are economically large, at about 7% to 10% of the sector-wide change in common-equity tier1 capital (CET1) and 19% to 26% of market risk capital (mCapital). As shown in Appendix Table A10, the post-Volcker reduction in risk exposures is outsized for the most impacted banks in the sample at as much as about 5 billions, which corresponds to 44% of the change in their CET1 and 82% of their mCapital.[27] The implied aggregate annual losses for a 65% stock market drop are also economically large at about 5% to 6% of the banking sector's change of CET1 and 13% to 17% of mCapital (Panel C). The estimates for the decomposition in the second-to-third and fifth-to-sixth columns show that both the change in positions and the change in factor sensitivities contributed to the decline in the quantity of risk, but clearly the bulk of the effect was due to the change in the equity market factor loading.

[27] To examine the variation across banks, Appendix Table A10 uses the same calculation as Table 5 with one modification, which is to use bank-by-bank estimates of the betas from Appendix Figure A2. The implied largest reduction in exposures across banks is reported in square brackets. For reference, we also report the aggregate exposures implied by the factor loadings estimated bank-by-bank, which are similar and, if anything, somewhat larger than those in Table 5.

Overall, the relatively narrow range of estimates across trading book performance measures indicates that the rule had economically large financial stability benefits and that the result in not sensitive to the calculation approach and the particulars of the way P/L is normalized. The estimated impact on total trading book exposures is of up to about 1/4 of aggregate market risk capital and as much as 80% of market risk capital for the most impacted banks. To help put these figures into context, from a macro-prudential regulation perspective the financial stability benefits of the Volcker Rule are equivalent to those of imposing a capital surcharge on the banks of 2% of market risk-weighted assets (1/4*mCapital=1/4*8%*mRWA) or about 1% of trading assets ($13B/$13T).

4.2.1 Additional evidence from other data sources and risk measures

An important replicability concern with our results so far is whether publicly available and other data on the bank trading book is consistent with the reduction in risk exposures after Volcker. Next, we address this question using a variety of additional data sources. First, we consider quarterly information from the publicly-available regulatory FR Y-9C filings. The top panels in Figure 2 show a significant decline in aggregate dollar trading positions – i.e., the total value of trading assets – which averaged up to about $2T before Volcker and as little as $1.5T after for the 13 banks in our sample (top left panel). The top right panel shows that the change in positions after Volcker is economically significant relative to the historical range of annual variation, at about 3 standard deviations. The top panels of Figure 3 show that the decline holds also for trading positions relative to the overall size of banks as measured by their total assets. The results are in line with the decline of trading positions contributing to some extent to the reduction in the quantity of risk in our stress test exercise.

The middle panels show that aggregate trading revenues, both in dollar terms (Figure 2) and relative to total assets (Figure 3) declined slightly after Volcker, which is consistent with our regression results of a negative but generally small and not statistically significant coefficient estimate for the non-interacted Volcker indicator in the bank-level analysis (Table 4) and only weakly statistically significant in the aggregate (Appendix Table A4).[28] Consistent

[28] Y-9C data on more disaggregated revenues from equity trading shows a qualitatively similar pattern of

with our main finding of curtailed equity exposures, the variability of trading revenues also declined some. As we detailed in Section 2, the Volcker Rule is a constraint on directional positions, not on any other market neutral positions that banks can profit from, such as hedging and market making. As such, the relatively muted impact on the level of revenues despite the reduction in risk is consistent with banks making up at least in part for the lost profits from risky trades with market making fees and hedging.[29] To the extent that these sources of revenues are acyclical or, if anything, countercyclical, the shift is consistent with the intended goal of the rule.

Second, the bottom panels of Figures 2 and 3 show hand-collected quarterly information on aggregate trading VaRs from the publicly-available SEC 10-Q filings. Consistent with a decline in risk – and, under our interpretation of VaR as committed capital, with the decline in trading assets – aggregate trading VaRs show a clear decline, both in dollar terms (Figure 2) and relative to total assets (Figure 3). In dollar terms, aggregate trading VaRs were as high as over $1B earlier in 2013 and declined to around $600M by late 2016 (left panels), which correspond to a 2 to 3 standard deviation change (right panels).

Finally, we consider quarterly information from an additional regulatory data source. The Schedule F ("Trading") of Form FR Y-14Q is collected by the Federal Reserve for the purposes of capital assessment and stress testing and contains quarterly data on bank trading book risk exposures. The risk factors are similar to the ones we consider in our analysis and include equity, foreign exchange, credit, commodities, and interest rates. The exposures are self-reported as dollar P/L sensitivities to risk factors.[30] Relative to our approach, these measures are available at a lower frequency and are estimated by the banks using their internal risk-management models. As such, they provide a useful robustness check on the validity of our conclusions based on the potentially different approaches and models used by the banks to estimate their risk exposures. That said, they are also relatively more prone to judgment and potential differences in risk models and methodologies across banks. Despite these differences, Figure 4 shows that aggregate trading risk exposures from Y-14

slight decline and lower variability after Volcker.

[29]Note that trading revenues from FR Y-9C differ from our clean trading P/L in that they also include fees and commissions from market making and business on behalf of customers.

[30]See p. 86-124 of Form Y14 instructions for detailed definitions of the exposures, which is publicly available at: https://www.federalreserve.gov/reportforms/forms/FR_Y-14Q20200930_i.pdf.

were curtailed significantly after Volcker, both in dollar terms (top panel) and relative to trading assets (bottom panel). Confirming the sizable impact of Volcker on the quantity of trading risk, bank curtailed trading risk exposures by about $80B, on average, after Volcker or about 4.5 percent of their trading assets. Self-reported equity risk exposures, which are calculated by the banks as the change in total trading book value for each dollar change in the price of their equity assets, declined by about $45 billion, or 2.5 percent of trading assets. These figures are of the same order of magnitude as those in Panel A of Table 5, corroborating our conclusion that Volcker had sizable financial stability benefits.[31]

To further build confidence in the financial stability impact of Volcker, we examine the implications of our findings for other commonly employed measures of systemic risk in the banking literature.[32] We consider two such measures, the marginal expected shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017), which in our context is defined as the expected P/L conditional on the equity market return being equal to the 5th percentile of its distribution, and the exposure CoVaR of Adrian and Brunnermeier (2016), which is defined as the quantile of the P/L distribution conditional on the equity market return being equal to its 95% VaR. To implement the calculations, we build on Loeffer and Raupach (2018), who show that in our linear risk factor setting there is a tight connection between estimated risk factor loadings and the two systemic risk measures. Specifically, we take the same approach as in Table 5 and use their closed form expressions (see Loeffer and Raupach (2018), equations 6 and 7 on p.276-7) to calculate the implied bank trading book MES and exposure CoVaR as a function of the baseline estimates of the equity factor loading before and after Volcker.[33] The results are shown in Figure 5 in dollar terms (top panel) and relative to market risk capital (bottom panel). For both MES and CoVaR, risk exposures declined significantly after Volcker and the magnitude of the risk reduction is comparable to Panels B and C of Table 5, offering further reassurance about our conclusion that Volcker was effective

[31] Interestingly, the timing of the decline lines up well with the timeline of the Volcker rule rollout, as exposures start declining after the rule went into effect in 2014Q2 and fully abate after compliance is required in mid-2015.

[32] We thank Philipp Schnabl for suggesting this analysis.

[33] The other inputs are the standard deviation of the equity risk factor, which we take from the data, and the distributional parameter for the tail of returns, α, which we set at 5% as it is standard in the literature. We use the estimated equity factor loadings for P/L_{it}^{VaR} in Table 4. We have repeated the analysis using the estimated loadings for $P/L_{it}^{\$}$ and P/L_{it}^{TA}, which deliver qualitatively similar results.

financial stability regulation.

4.3 Desk-level analysis

Next, we examine more closely the sources of risk by repeating the analysis at the desk level. The Market Risk Capital Rule requires banks to divide their portfolios into a number of subportfolios, which have to be granular enough to allow the supervising agency to assess the adequacy of the VaR models used by the banks to satisfy market-risk capital requirements (Federal Register, 2012).[34] For each of their subportfolios, banks have to report the daily P/L and VaR calibrated to a one-tail 99% confidence level for each business day over the previous two years. In addition to these metrics, banks report the types of assets that comprise each subportfolio. The different asset types that comprise each broad asset class are listed in the first column of Table 6, where we report the number of subportfolios in our sample by asset class. For each asset class, we calculate the total number of subportfolios containing assets within this class (first row) and the number of subportfolios that also contain a specific asset type (subsequent rows). For example, there are 246 subportfolios that contain equities, and 97 out of these subportfolios also contain corporate bonds.[35] Table 7 reports the total Value-at-Risk ($ million) at the desk level by asset class. Both in terms of number and VaR size, roughly a third of the sub-portfolios contain equities, and equities are among the larger asset classes after rates together with credit, government, and foreign.

Table 8 summarizes results from estimating equation (2) at the desk level by broad asset class, with trading performance (P/L) normalized by its standard deviation (Panel A), VaR (Panel B), and trading assets (Panel C) as the outcome variables, in turn, and each risk factor interacted with the Volcker indicator to test for whether exposures changed around Volcker. Each column shows results for a given asset class – equities, rates, government, credit, securities, forex, and commodities, in turn. First, for the equity desks we confirm

[34] While from a reporting perspective sub-portfolios do not necessarily correspond to trading desks, we have used an additional internal data source with information on trading desks to verify that sub-portfolios can be plausibly interpreted as trading desks. Specifically, in our sample there are 763 unique sub-portfolios and 790 unique trading desks. On average, there are about 85 sub-portfolios per bank and about 90 trading desks per bank. In addition, at the bank-by-bank level, sub-portfolio counts line up closely with desk counts.

[35] In brackets, we report the total number of subportfolios within each asset class that only contain assets within their own class and no other asset types. For example, there are 26 subportfolios that include no asset type other than equities.

our earlier finding that robustly across all P/L measures in Panels A to C the coefficient on the interaction term of equity market portfolio factor and the Volcker indicator is negative and statistically significant, while the coefficient on the non-interacted factor is positive and significant. Interestingly, the result also holds for fixed-income and credit desks, suggesting that the sources of equity risk exposure pre-Volcker were not limited to just equity desks.[36] There is no robust effect for forex and commodities desks, consistent with these asset classes being exempt from Volcker. Second, there is evidence at the equities and fixed-income desks' level that banks also cut back on their interest rate exposures, with a positive and significant coefficient on the interaction term of the interest rate risk factor (TERM) and the Volcker indicator and a negative and significant coefficient on the non-interacted factor (see Appendix Table A11 for the coefficient estimates).[37]

5 Refining identification

The challenge with interpreting the baseline OLS estimates of the effect of Volcker on equity market risk is to distinguish the effect of the rule from the other broad aggregate shocks that happened over the post-crisis period, especially the new regulations that were rolled out and changes in the macroeconomic environment and financial markets. This section builds confidence on the internal validity of the effect of Volcker on equity market risk and bolsters a causal interpretation using tests that add controls for other regulations and a quasi-experiment. First, we consider tests that explicitly control for the effect of other regulatory changes that happened over our sample period. Second, we exploit the phased-in introduction of the Volcker Rule's reporting requirements to implement a quasi-natural differences-in-differences (DD) experimental design.

[36] While not robust to the other P/L measures (Panels B-C), there is weak evidence of partial risk migration as the sensitivity of dollar P/Ls to the equity market risk factor increases for commodities desks (Panel A), which is consistent with this asset class being exempt.

[37] In a final battery of additional robustness checks, we repeat both our analysis at the bank and desk level to address rebalancing by using an optimal changepoint regression technique to estimate time-varying risk exposures (see Appendix A.5 for details).

5.1 Controlling for other regulations

The Volcker Rule was part of the broader regulatory overhaul of banks in the aftermath of the financial crisis. Capital requirements were strengthened, new liquidity requirements introduced, and annual stress tests conducted. Some of these new regulations were enacted or phased in during our sample period. The Supplementary Leverage Ratio (SLR), which serves as a backstop to risk-based capital requirements, became effective in January 2018, but public disclosure requirements related to SLR were mandatory from January 2015 and all U.S. banks subject to the SLR were compliant with the rule during this period. The Liquidity Coverage Ratio (LCR), which requires banks to hold a sufficient amount of liquid assets to be able to withstand a significant outflow of deposits, is being phased in and as of January 2015 the threshold was set to 80% of the final liquidity requirement.

A concern with attributing the change over time in equity exposures to Volcker is that these other regulations may have also impacted the way banks conduct their trading activities, for example, by increasing the balance sheet cost of market making (Duffie, 2016, Adrian et al., 2017). Additionally, some banks failed the Comprehensive Capital Analysis and Review (CCAR) – an annual stress test conducted by the Federal Reserve since 2011 – during our sample period, which may have impacted their ability and willingness to engage in market making and risk taking. To examine whether the Volcker effect on equity risk exposures can be explained by other regulations, we enrich our baseline specification in equation (2) as follows:

$$P/L_{it}^{X} = \alpha_v I_t + \alpha_d d_i + \beta RF_t + \gamma_v I_t RF_t + \gamma_d d_i RF_t + \epsilon_{it}, \tag{3}$$

where d_i is the "other regulation" indicator that takes the value of one if bank i is in the treatment group of banks that are affected by the other regulations. We consider two other regulations that cover the two main other regulatory changes that happened within our sample period: one, where a bank is subject to SLR or LCR, and the other where a bank failed CCAR in the post-Volcker period. This richer specification adds a control term for other regulations, $\gamma_d d_i RF_t$, which allows us to implement a first simple robustness test of whether Volcker affected trading risk factor loadings over and above any effects that these other regulations may have also had. The key coefficient of interest is γ_d, which captures the effect of these other regulations, and the robustness test is whether the coefficient estimate on the interaction with the Volcker indicator, γ_v, remains negative and statistically significant.

Table 9 summarizes results from estimating equation (3) at the bank level with trading performance (P/L) normalized by its standard deviation, VaR, and trading assets as the outcome variable, in turn. The estimate of the Volcker indicator, γ_v, remains strongly statistically significant and relatively stable for the equity market factor robustly across trading book performance measures, thus confirming our baseline findings that banks curtailed their exposures to equity market risk after Volcker. By contrast, the coefficient estimate of interest, γ_d, is not statistically significant for either of the two other regulations. In fact, Appendix Table A12 shows that γ_d is generally insignificant for all other factors, with the notable exception of credit risk (DEF), for which there is some evidence of a significant interaction effect with CCAR results.

In all, these findings indicate that our main result on the change in equity exposures does not appear to be driven by banks that either were subjected to new or enhanced capital and liquidity requirements or failed annual stress tests, all suggesting that our estimates isolate an independent effect of Volcker. The analysis is also helpful to interpret our earlier finding of an overall loading on credit risk over the post-crisis period in Table 3, as it suggests that the loading on credit risk is driven by banks that failed the stress tests. To the extent that these banks faced the brunt of the compression in profits from heightened regulation and the low-rate environment, their continued long credit-risk exposure is also in line with existing evidence of reach-for-yield incentives of financial institutions in the post-crisis period (see, for example, Becker and Ivashina (2015), Di Maggio and Kacperczyk (2015)).

5.2 Analysis of the reporting requirement

In our final analysis, we exploit the staggered phase-in of the Volcker Rule's reporting requirement to implement a quasi-experimental differences-in-differences (DD) design. In addition to compliance, the rule also included a requirement that banks report quantitative trading metrics, such as position limits, risk factor sensitivities, profits and losses, and Value-at-Risk to regulators. The reporting obligation was phased in over a period of two and half years:

banking entities with \$50 billion or more in trading assets and liabilities were required to start reporting these metrics in June 30, 2014; banks with trading assets and liabilities between \$25 and \$50 billion in April 30, 2016; and banks with trading assets and liabilities between \$10 and \$25 billion in December 31, 2016. Using this important institutional feature of the rule, we estimate the following differences-in-differences (DD) specification:

$$P/L_{it}^{X} = \alpha I_{it}^{m} + \beta RF_t + \gamma I_{it}^{m} RF_t + \lambda_i + \epsilon_{it}, \tag{4}$$

where I_{it}^{m} is the "metrics indicator" that takes the value of one if bank i has to report metrics at time t, and equals zero otherwise. The key difference between this design and our baseline equation (2) is that we can now exploit quasi-random variation around the arbitrary size thresholds of the reporting requirement to estimate the change in risk factor loadings over time for any given bank as the within-bank effect relative to a control group of other banks that were relatively similar and also subject to compliance with Volcker but that were not yet subject to reporting. Using these banks as a control group addresses potential contemporaneous confounds that are common across banks over our sample period. To address unobserved heterogeneity, we include bank fixed effects, λ_i. The coefficient of interest is γ, which represents the effect of the treatment on the treated – i.e., the change in risk factor loading after the Volcker reporting requirement is phased in relative to the control group of other banks that are not subject to the requirement.

The first three columns of Table 10 summarize results from estimating equation (4) at the bank level with trading performance (P/L) normalized by its standard deviation, VaR, and trading assets as the outcome variable, in turn. In line with our baseline findings, robustly across the three trading book performance measures the coefficient estimate for the interaction term of the reporting indicator and the equity market factor is negative and statistically significant, while the coefficient on the non-interacted factor is positive and significant, indicating that the reporting requirement reduced U.S. banks' trading book loading on equity market risk. While smaller than our baseline estimates in Table 4, the estimates for the reduction in equity market risk loadings when banks are subject to the reporting requirement remain economically large. For example, the estimate of -5.599 implies that a one standard deviation negative realization of the S&P return would generate an about 9 percentage point smaller trading loss relative to the Value-at-Risk (VaR) as a consequence of the requirement. This loss reduction is sizable at about 1/4 of the unconditional standard deviation of P/L relative to VaR.[38]

The last three columns of Table 10 show results of robustness analysis. We address the concern that, while the bulk of statistical power to estimate our factor loadings comes from time-series variation, the DD estimates also rely on cross-sectional comparison of relatively small sub-groups of banks that are required to report at each time. As such, the results may be driven by and sensitive to the small size of the comparison groups. To focus more directly on time-series variation, we use a different implementation of the estimator and, similar to the methodology of long-run event studies (see, for example, Barber and Lyon, 1997), for each bank in our sample construct a "benchmark" of P/Ls, $\overline{P/L}_{-i,t}$, for the portfolio of control banks. The control banks for the benchmark include banks that in week t are not subject to reporting. We then repeat the baseline analysis for "excess" P/Ls relative to the average P/L in the benchmark group, $P/L_{i,t} - \overline{P/L}_{-i,t}$.[39] This approach aggregates across banks in the control group to construct the benchmark P/L. The estimates for the "excess" P/L normalized by VaR, shown in the fourth column of Table 10, are little changed relative to the baseline (second column). We also repeat the analysis of the reporting requirement just for the before-after effect within the treatment group – i.e., without subtracting the benchmark adjustment for the controls. The estimates, shown in Appendix Table A14, are again similar to the baseline, indicating that the decline in the equity risk factor loading is mainly driven by time-series variation within treated banks.

The fifth column of Table 10 shows that the main result is also robust to using a more saturated specification that adds week fixed effects to more conservatively control for common shocks. The last column of Table 10 shows that the result is also robust to using the broader cross-section of 20 banks. Finally, in Appendix Table A14 we summarize results of a

[38]Appendix Table A13 shows that the requirement increased exposure to the dollar, consistent with a risk migration toward asset classes that were exempted from the rule. There is also some mixed evidence of weakly significant and relatively smaller reductions in exposures to equity market volatility (VIX), interest rate (TERM), and credit (DEF) risk, but these results do not hold up across our range of robustness checks.

[39]As a further robustness check, for this part of the analysis we cluster the standard errors at the reporting-wave level, as recommended by Bertrand, Duflo, and Mullainathan (2004).

falsification test, which repeats the before-after analysis just for the placebo group of banks that were exempted from reporting. Reassuringly, there was no decline in risk around the first reporting date (June 30, 2014) for exempted banks, suggesting that contemporaneous confounds are unlikely to be driving the decline in risk.

6 Conclusion

The bank trading book has attracted increasing attention in the wake of the 2008-09 financial crisis and the ensuing new regulatory landscape for banks. In order to better understand the sources of risk that emanate from the trading book and, more broadly, whether banks use trading as a vehicle for adding risk, we have used novel regulatory data on bank trading profits and a transparent measurement approach to assess risk exposures. We have documented several stylized facts on the evolution of bank risk taking via their trading books in the post-crisis period, including robust evidence that U.S. banks had large trading exposures to equity market risk before the introduction of the Volcker Rule in 2014 and that they curtailed these exposures afterwards. The approach developed in this paper offers a first step toward assessing risk for the modern banking corporation, which had not yet been the subject of systematic empirical testing despite the growth of the bank trading book. There are several venues along which our approach can be extended.

First, we took a step in the direction of measuring risk exposures, but clearly more can be done to extend the framework for policy evaluation of alternative financial stability tools. It would be particularly interesting to integrate the loan book in the analysis and examine the interplay between exposures across different bank activities as highlighted, for example, in the model of Froot and Stein (1998). Second, it would be interesting to study risk exposures in a more explicit structural setting, which would allow for a more quantitative evaluation of policy counterfactual such as the stress testing scenarios that regulators use for banks. Third, our high-frequency data and approach could be extended to study in more detail the link between bank trading, financial regulation, and several documented pricing anomalies and deviations from arbitrage in forex and fixed-income markets. Finally, extending the analysis to an international setting by examining risk exposures of intermediate holding companies

(IHCs) would allow for an analysis of the effect of foreign regulations and help to understand the extent to which they interact with domestic ones.

References

Acharya, V., Pedersen, L.H., Philippon, T., Richardson, M., 2017, Measuring Systemic Risk, *Review of Financial Studies*, 30, 2-47.

Adrian, T., N. Boyarchenko, and O. Shachar, 2017, Dealer Balance Sheets and Bond Liquidity Provision, *Journal of Monetary Economics*, 89, 92–109.

Adrian, T., and Brunnermeier, M. K., 2016, CoVaR, *American Economic Review*, 106, 1705-1741.

Adrian, T. and H. Shin, 2010, Liquidity and Leverage, *Journal of Financial Intermediation*, 19(3), 418–437.

Agarwal, S., D. Lucca, A. Seru, and F. Trebbi, 2014, Inconsistent Regulators: Evidence from Banking, *Quarterly Journal of Economics*, 129(2), 889–938.

Allahrakha, M., J. Cetina, B. Munyan, and S. Watugala, 2018, The Effects of the Volcker Rule on Corporate Bond Trading: Evidence from the Underwriting Exemption, Working Paper, Office of Financial Research.

Anderson M., and R. M. Stulz, 2017, Is Post-Crisis Bond Liquidity Lower? NBER Working Paper No. 23317.

Andrews, D.W.K., I. Lee, and W. Ploberger, 1996, Optimal Changepoint Tests for Normal Linear Regressions, *Journal of Econometrics*, 70, 9–38.

Artzner, P., F. Delbaen, J.-M. Eber, and D. Heath, 1999, Coherent Measures of Risk, *Mathematical Finance*, 9(2), 203–228.

Atkeson, A., A. Eisfeldt, A. d'Avernas, and P. O. Weill, 2018, Government Guarantees and the Valuation of American Banks, NBER Macroeconomics Annual, forthcoming.

Bai J., A. Krishnamurthy, C-H. Weymuller, 2018, Measuring Liquidity Mismatch in the Banking Sector, *Journal of Finance*, 73(1), 51–93.

Bao, J., M. O'Hara, and X. Zhou, forthcoming, The Volcker Rule and Corporate Bond Market-making in Times of Stress, *Journal of Financial Economics.*

Barber, B.M., and J.D. Lyon, 1997, Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics, Journal of Financial Economics, 43, 341-372.

Becker, B. and V. Ivashina, 2015, Reaching for Yield in the Bond Market, *Journal of Finance*, 70(5), 1863- 1902.

Begenau, J., M. Piazzesi, and M. Schneider, 2015, Banks' Risk Exposures, Working Paper, Stanford University.

Bertrand M., E. Duflo, and S. Mullainathan, 2004, "How Much Should We Trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics*, 119(1), 249-275.

Bessembinder, H., S. E. Jacobsen, W. F. Maxwell, and K. Venkataraman, forthcoming, Capital commitment and illiquidity in corporate bonds, *Journal of Finance*,

Bollen, N.P.B. and R.E. Whaley, 2009, Hedge Fund Risk Dynamics: Implications for Performance Appraisal, *Journal of Finance*, 64(2), 985–1035.

Bond, P. and I. Goldstein, 2015, Government Intervention and Information Aggregation by Prices, *Journal of Finance*, 70(6), 2777–2815.

Choi, J. and Y. Huh, 2017, Customer Liquidity Provision: Implications for Corporate Bond Transaction Costs, Finance and Economics Discussion Series 2017-116, Board of Governors of the Federal Reserve System.

Di Maggio, M. and M. Kacperczyk, 2017, The Unintended Consequences of the Zero Lower Bound Policy, *Journal of Financial Economics*, 123, 59–80.

Drechsler, I., A. Savov, and P. Schnabl, 2018, Banking on Deposits: Maturity Transformation without Interest Rate Risk, NBER Working Paper No. 24582.

Driscoll, J. C. and A. C. Kraay, 1998, Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data, *Review of Economics and Statistics*, 80(4), 549–560.

Duffie, D., 2012, Market Making Under the Proposed Volcker Rule, Duffie, Darrell, Market Making Under the Proposed Volcker Rule, mimeo, Stanford University.

Duffie, D., 2016, Financial Regulatory Reform After the Crisis: An Assessment, ECB Forum on Central Banking, June 27-29, 2016.

English, W. B., S. J. Van den Heuvel, and E. Zakrajsek, 2018, Interest Rate Risk and Bank Equity Valuations, *Journal of Monetary Economics*, 98, 80–97.

Federal Register, 2012, Regulatory Capital Rules: Advanced Approaches Risk-Based Capital Rule; Market Risk Capital Rule, Vol. 77, No. 169, August 30, 2012.

Federal Register, 2013, Regulatory Capital Rules: Regulatory Capital, Implementation of Basel III, Capital Adequacy, Transition Provisions, Prompt Corrective Action, Standardized Approach for Risk-weighted Assets, Market Discipline and Disclosure Requirements, Advanced Approaches Risk-Based Capital Rule, and Market Risk Capital Rule, Vol. 78, No. 198, October 11, 2013.

Flannery, M. J. and C. M. James. 1984, The Effect of Interest Rate Changes on the Common Stock Returns of Financial Institutions, *Journal of Finance*, 39(4), 1141–1153.

FRB, 2018a, Draft Proposed Revision to Rules Implementing the Proorietary Trading and Hedge and Private Equity Fund Restrictions of Section 13 of the Bank Holding Company Act, Board of Governors of the Federal Reserve System, May 25, 2018, Washington, D.C.

FRB, 2018b, Dodd-Frank Act Stress Test 2018: Supervisory Stress Test Methodology and Results, Board of Governors of the Federal Reserve System, June 2018, Washington, D.C.

Froot, K. A, and J. C. Stein, 1998, Risk Management, Capital Budgeting and Capital Structure Policy for Financial Institutions: An Integrated Approach. *Journal of Financial Economics*, 47, 55–82.

Fung, W. and D. A. Hsieh, 2001, "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," The Review of Financial Studies, 14 (2), 313-341.

Gandhi, P. and H. Lustig, 2015, Size Anomalies in U.S. Bank Stock Returns, *Journal of Finance*, 70(2), 733–768.

Granja, J. and C. Leuz, 2017, The Death of a Regulator: Strict Supervision, Bank Lending and Business Activity, Working Paper, Chicago Booth.

Greenwood, R., S. G. Hanson, J. C. Stein, and A. Sunderam, 2017a, The Financial Regulatory Reform Agenda in 2017, Working Paper, Harvard Business School.

Greenwood, R., S. G. Hanson, J. C. Stein, and A. Sunderam, 2017b, Strengthening and Streamlining Bank Capital Regulation, *Brookings Papers on Economic Activity*, September 2017.

Gorton, G. and R. Rosen, 1995, Banks and Derivatives, in: Bernanke and Rotemberg, eds., NBER Macroeconomics Annual 1995, Volume 10, 1995.

Hanson, S. G., A. Shleifer, J. C. Stein, and R. W. Vishny, 2015, "Banks as patient fixed-income investors, *Journal of Financial Economics*, 117(3), 449–469

He, Z. and A. Krishnamurthy, 2018, Intermediary Asset Pricing and the Financial Crisis, NBER WP 24415.

Iercosan, D., A. Kumbhat, M. Ng, and J. Wu, 2017a, Trading Activities at Systemically Important Banks, Part 1: Recent Trends in Trading Performance, FEDS Notes 2017-07-10. Board of Governors of the Federal Reserve System .

Iercosan, D., A. Kumbhat, M. Ng, and J. Wu, 2017b, Trading Activities at Systemically Important Banks, Part 2: What Happened during Recent Risk Events?" FEDS Notes 2017-07-10. Board of Governors of the Federal Reserve System.

Iercosan, D., A. Kumbhat, M. Ng, and J. Wu, 2017c. Trading Activities at Systemically Important Banks, Part 3: What Drives Trading Performance?" FEDS Notes 2017-07-10. Board of Governors of the Federal Reserve System.

Kim, D. and A.M. Santomero, 1988, Risk in Banking and Capital Regulation, *Journal of Finance*, 43, 1219-1233.

Koehn, M. and A.M. Santomero, 1980, Regulation of Bank Capital and Portfolio Risk, *Journal of Finance*, 35, 1235-1244.

Landier, A., D. Sraer, and D. Thesmar, 2013. Banks Exposure to Interest Rate Risk and the Transmission of Monetary Policy, NBER Working Paper 18857.

Lustig, H., N. Roussanov, and A. Verdelhan, 2011, Common Risk Factors in Currency Markets, *Review of Financial Studies*, 24(11), 3731–3777.

Minton, B., R. M. Stulz, and A. G. Taboada, 2017, Are Larger Banks Valued More Highly? NBER WP 23212.

Newey, W. K., and K. D. West, 1994, Automatic Lag Selection in Covariance Matrix Estimation, *The Review of Economic Studies*, 61 (4), 631-653.

O'Brien, J.M. and J. Berkowitz, 2007, Estimating bank trading risk: A factor model approach, In: The Risks of Financial Institutions, M. Carey and R.M. Stulz (eds.), University of Chicago Press.

Paddrik, M. and S. Tompaidis, 2018, CDS Market Structure: Before and After the Volcker Rule, Working Paper, Office of Financial Research, U.S. Department of the Treasury.

Quarles, R. K., 2018, Early Observations on Improving the Effectiveness of Post-Crisis Regulation, Remarks at the American Bar Association Banking Law Committee Annual Meeting, Washington, D.C.

Sarin, N. and L. H. Summers, 2016, Understanding Bank Risk through Market Measures, *Brookings Papers on Economic Activity*, Fall 2016.

Richardson, M. 2012. Why the Volcker Rule Is a Useful Tool for Managing Systemic Risk, White Paper, SEC.

Thakor, A. V., 2012, The Economic Consequences of the Volcker Rule, Working Paper, Olin School of Business.

Trebbi, F. and K. Xiao, forthcoming, Regulation and Market Liquidity, *Management Science*.

Tables and Figures

Table 1: This table presents summary statistics for weekly dollar profits/losses (P/L), weekly dollar Value-at-Risk (VaR), weekly dollar trading assets obtained from FR 2644, and quarterly dollar trading assets obtained from FR Y-9C, all at the top-of-the-house level for our 13 banks, 1/2013 – 6/2017. For each bank, we first calculate the time-series mean, standard deviation, 5th percentile, 95th percentile, skewness, and curtosis, and report in the table the cross-sectional average, standard deviation, minimum, and maximum separately for each of these statistics.

	Mean	Std. dev.	5th Pct	95th Pct	Skew	Kurt
A. Weekly P/L ($)						
Obs.	13	13	13	13	13	13
Mean	5,217,239	30,217,884	-43,282,288	54,497,247	-0.04	1.98
Std. dev.	11,958,301	37,042,113	52,560,209	71,821,157	0.51	1.63
Min	-10,128,222	218,949	-133,286,131	485,949	-0.70	0.29
Max	30,302,113	103,905,747	-97,659	221,338,340	0.90	6.35
B. Weekly VaR ($)						
Obs.	13	13	13	13	13	13
Mean	73,040,899	23,467,791	45,753,841	119,121,650	0.80	0.72
Std. dev.	85,651,303	32,765,046	53,722,399	148,852,495	0.60	2.13
Min	850,719	268,760	304,997	1,337,954	-0.17	-0.85
Max	220,946,575	113,594,931	144,568,979	466,021,961	1.99	7.19
C. Trading assets (FR Y-9C) ($ thousand)						
Obs.	13	13	13	13	13	13
Mean	125,657,103	10,967,847	109,655,089	145,147,209	0.26	-0.58
Std. dev.	148,652,698	11,727,027	133,140,419	167,877,724	0.46	0.68
Min	972,414	119,060	464,132	1,200,748	-0.57	-1.51
Max	387,751,450	38,248,645	350,728,160	430,931,000	0.87	0.42
D. Weekly trading assets (FR 2644) ($ thousand)						
Obs.	11	11	11	11	11	11
Mean	122,752,313	10,206,550	108,258,893	141,448,529	0.36	-0.46
Std. dev.	131,901,389	11,563,820	117,659,084	151,836,499	0.37	0.50
Min	997,132	181,419	336,671	1,573,053	-0.35	-1.21
Max	329,269,497	39,053,121	280,091,844	409,166,828	0.79	0.41

Table 2: Panels A-C of this table present summary statistics for weekly dollar P/L scaled by weekly dollar Value-at-Risk (VaR), quarterly dollar trading assets obtained from FR Y-9C or weekly dollar trading assets obtained from FR 2644, all at the top-of-the-house level for our 13 banks, 1/2013 – 6/2017. For each bank, we first calculate the time-series mean, standard deviation, 5th percentile, 95th percentile, skewness, and kurtosis, and report in the table the cross-sectional average, standard deviation, minimum, and maximum separately for each of these statistics. To ease comparison, Panels B and C show quarterly rates (QR) in percent, that is, the dollar P/L divided by the dollar trading assets is multiplied by the number of weeks per quarter (12) times 100.

	Mean	Std. dev.	5th Pct	95th Pct	Skew	Kurt
A. Weekly P/L divided by VaR						
Obs.	13	13	13	13	13	13
Mean	0.047	0.391	-0.552	0.657	-0.10	4.32
Std. dev.	0.132	0.067	0.231	0.206	1.13	4.53
Min	-0.140	0.293	-0.944	0.389	-1.58	0.23
Max	0.286	0.535	-0.072	1.028	2.79	15.3
B. Weekly P/L divided by trading assets (FR Y-9C) (QR, percent)						
Obs.	13	13	13	13	13	13
Mean	0.040	0.405	-0.587	0.693	-0.08	2.05
Std. dev.	0.221	0.286	0.584	0.404	0.53	1.37
Min	-0.478	0.197	-2.428	0.230	-0.86	0.15
Max	0.540	1.271	-0.083	1.484	0.85	3.96
C. Weekly P/L divided by trading assets (FR 2644) (QR, percent)						
Obs.	11	11	11	11	11	11
Mean	0.101	0.440	-0.590	0.824	0.04	1.73
Std. dev.	0.170	0.208	0.368	0.459	0.43	1.63
Min	-0.074	0.239	-1.136	0.347	-0.94	0.01
Max	0.552	0.829	-0.096	1.826	0.47	5.09

cont. on next page

Table 2: Panel D of this table reports summary statistics for our weekly risk factors, 1/2013 – 6/2017. MKT denotes the market return (decimal; Kenneth French's website), VIX is the change in CBOE implied volatility index (percentage points; Bloomberg), IR5Y is the change in the five-year swap rate (percentage points; Bloomberg), TERM is the change in the term spread, which is defined as the difference between the 10-year and 1-year US Treasury zero coupon yield (percentage points; Federal Reserve), DEF is the change in the default factor, which is defined as the difference between a 10-year BBB-rated corporate bond and the 10-year Treasury yield (percentage points; ICE BofAML and Federal Reserve), SPGSCI is the return on the S&P GSCI commodity index (decimal; Bloomberg), and DOL is the return on the Lustig et al. (2011) dollar factor (decimal; Bloomberg and own calculations). See Appendix A.4 for details on the series mnemonics.

	Mean	Std. dev.	5th Pct	95th Pct	Skew	Kurt
D. Weekly risk-factors						
Obs	225	225	225	225	225	225
MKT	0.00	0.02	-0.03	0.03	-0.58	1.42
VIX (ppt)	-0.00	2.71	-3.79	4.19	1.00	6.25
IR5Y (ppt)	0.00	0.10	-0.14	0.18	0.71	1.49
TERM (ppt)	-0.00	0.09	-0.12	0.15	0.78	1.14
DEF (ppt)	-0.00	0.05	-0.07	0.07	-0.00	1.67
SPGSCI	-0.00	0.02	-0.05	0.04	-0.15	0.15
DOL	-0.00	0.01	-0.02	0.01	-0.24	0.12

Table 3: This table reports panel regression results of P/L on our risk factors. We report results for weekly dollar profits/losses (P/L) in standard-deviation units ($), P/L scaled by Value-at-Risk (VaR), and P/L scaled by FR Y-9C trading assets (TA). All specifications include bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	$P/L_{\$}$		P/L_{VaR}		P/L_{TA}	
MKT	4.835	(3.362)	1.259	(1.305)	1.089	(1.322)
DVIX	0.033*	(0.020)	0.009	(0.008)	0.008	(0.007)
IR5Y	0.404	(0.698)	0.061	(0.290)	0.339	(0.309)
TERM	-1.112	(0.708)	-0.184	(0.274)	-0.584**	(0.295)
DEF	-2.970***	(1.045)	-1.049***	(0.387)	-1.058**	(0.447)
SPGSCI	0.036	(1.413)	-0.130	(0.570)	0.024	(0.569)
DOL	-9.293*	(5.044)	-3.692*	(2.084)	-1.748	(2.013)
R^2	0.022		0.018		0.012	
N	2,913		2,913		2,913	
Economic significance						
SD LHS	1.000		0.391		0.405	
1-SD (DEF)	-0.137		-0.048		-0.039	
1-SD (DOL)	-0.072		-0.028		-0.040	
5%-95% (DEF)	-0.384		-0.134		-0.110	
5%-95% (DOL)	-0.216		-0.084		-0.120	

Table 4: This table reports panel regression results of P/L on our risk factors interacted with the Volcker indicator variable, which takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. We report results for weekly dollar profits/losses (P/L) in standard-deviation units ($), P/L scaled by Value-at-Risk (VaR), and P/L scaled by FR Y-9C trading assets (TA). All specifications include bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	$P/L_{\$}$		P/L_{VaR}		P/L_{TA}	
Volcker	-0.077	(0.137)	−0.038	(0.044)	-0.018	(0.061)
MKT	20.59**	(8.547)	6.883***	(2.571)	7.568*	(3.863)
DVIX	0.131	(0.081)	0.041*	(0.023)	0.059	(0.037)
IR5Y	1.661	(1.718)	0.505	(0.505)	0.480	(0.777)
TERM	-3.359**	(1.537)	−0.850*	(0.465)	-1.155*	(0.683)
DEF	-1.606	(2.389)	−0.385	(0.768)	-0.710	(0.924)
SPGSCI	3.206	(3.046)	0.899	(0.966)	2.287*	(1.213)
DOL	-13.14	(12.21)	−4.283	(3.943)	-5.107	(4.865)
Volcker × MKT	-22.98**	(9.130)	−8.371***	(2.928)	-9.433**	(4.012)
Volcker × DVIX	-0.130	(0.083)	−0.044*	(0.024)	-0.066*	(0.038)
Volcker × IR5Y	-1.425	(1.888)	−0.499	(0.613)	-0.107	(0.848)
Volcker × TERM	2.907*	(1.676)	0.787	(0.555)	0.743	(0.731)
Volcker × DEF	-2.159	(2.552)	−1.090	(0.871)	-0.612	(0.990)
Volcker × SPGSCI	-3.942	(3.361)	−1.289	(1.143)	-2.719**	(1.358)
Volcker × DOL	1.347	(13.23)	−0.731	(4.565)	3.239	(5.300)
R^2	0.040		0.033		0.023	
N	2,913		2,913		2,913	
Economic significance						
SD LHS	1.000		0.391		0.405	
1-SD (MKT)	0.333		0.111		0.122	
1-SD (Vlckr × MKT)	-0.371		-0.135		-0.152	
5%-95% (MKT)	1.000		0.333		0.366	
5%-95% (Vlckr × MKT)	-1.113		-0.405		-0.456	

Table 5: This table reports a quantification of the post-Volcker change in dollar risk exposures to the equity market factor (MKT). For P/L scaled by VaR or TA, using our estimates of the sensitivity to the market portfolio pre- and post-Volcker reported in Table 4 as an input, we calculate the predicted change in the P/L associated with the market shock as the sum of two terms (denoted as Total): The first term (denoted as "ΔVaR" and "ΔTA") is the product of the estimated sensitivity pre-Volcker (the coefficient for "Volcker" in Table 4) times the change in dollar positions (VaR and TA). The second term (denoted as "$\Delta\beta$") is the product of the estimated change in the sensitivity post-Volcker (the coefficient for "Volcker MKT" in Table 4) times the dollar positions post-Volcker (VaR and TA). We take the sum over banks to get the aggregate estimate for the banking sector exposures, which is reported in the second to fourth columns (Panel A) for the calculation that uses P/L scaled by VaR and in the fifth to seventh columns (Panel A) for the calculation that uses P/L scaled by trading assets. For dollar P/L, we calculate the predicted change in the P/L associated with the market shock as the change in the market beta post-Volcker also using the respective estimates reported in Table 4. For each, we also report in Panels B and C the implied annual gains/losses under two alternative adverse scenarios, a stock market drop of 35% or 65%, which mimics the "severely adverse scenario" of the annual regulatory stress tests. We report all estimates both in dollar terms and relative to two regulatory capital buffers, the change in overall capital buffers, measured by common-equity tier1 capital (CET1), and the level of capital buffers that banks are required to hold against trading risk, measured by market risk capital (mCapital), which equals 8% of market risk-weighted assets. See Appendix A.3 for additional details on the decomposition of the change in dollar exposures.

	$P/L_{\$}$	P/L_{VaR}			P/L_{TA}		
	Total	ΔVaR	$\Delta\beta$	Total	ΔTA	$\Delta\beta$	Total
A. Δ*Exposures*							
Dollar (mn)	-9,027	-2,993	-6,970	-9,963	-837	-12,488	-13,324
% ΔCET1	-6.51	-2.16	-5.03	-7.19	-0.60	-9.01	-9.61
% mCapital	-17.5	-5.80	-13.5	-19.3	-1.62	-24.2	-25.8
B. Δ*Gain/loss*: 30% shock							
Dollar (mn)	-2,708	-898	-2,091	-2,989	-251	-3,746	-3,997
% ΔCET1	-1.95	-0.65	-1.51	-2.16	-0.18	-2.70	-2.88
% mCapital	-5.25	-1.74	-4.05	-5.79	-0.49	-7.26	-7.75
C. Δ*Gain/loss*: 65% shock							
Dollar (mn)	-5,867	-1,945	-4,531	-6,476	-544	-8,117	-8,661
% ΔCET1	-4.23	-1.40	-3.27	-4.67	-0.39	-5.86	-6.25
% mCapital	-11.3	-3.77	-8.78	-12.5	-1.05	-15.7	-16.8

Table 6: This table reports the number of subportfolios in our sample by asset class. For each asset class, we calculate the total number of subportfolios containing assets within this class (first row) and the number of subportfolios that also contain a specific asset type (subsequent rows). For example, there are 246 subportfolios that contain equities and out of these subportfolios, 88 also contain sovereign bonds, 97 also contain corporate bonds, and so on. In brackets, we report the total number of subportfolios within each asset class that only contain assets within this class and no other asset types. For example, there are 26 subportfolios that include no asset type other than equities. The total number of unique subportfolios in our sample equals 763, and there are 85 unique subportfolios per bank, on average.

	Equities	Rates	Gov't	Credit	Securit.	FX	Comm.
Total	246 [26]	508 [40]	358 [12]	354 [14]	84 [3]	399 [49]	85 [33]
Sovereign bonds	88	285	336 [8]	200	43	167	22
Corporate bonds	97	159	168	234 [9]	14	138	18
Municipal bonds	11	40	53 [3]	42	9	22	1
Agency MBS	7	57	64 [1]	27	41	11	1
Non-agency MBS	10	43	31	46	61 [3]	17	1
CMO	7	40	42	28	47 [0]	8	1
Index CDS	69	151	127	224 [2]	44	118	10
Single-name CDS	87	176	141	247 [3]	39	146	19
Tranched	27	63	39	92 [0]	23	56	3
Linear equities	218 [24]	121	77	94	9	144	33
Nonlinear equities	174 [1]	109	68	84	5	124	27
Exotic equities	57 [1]	41	32	36	1	43	16
Interest rates	142	508 [40]	303	241	64	306	48
FX	162	306	170	188	18	399 [49]	49
Commodities	34	48	22	22	1	49	85 [33]
Other products	84	175	135	152	32	132	27

Table 7: This table reports the total Value-at-Risk ($ million) of subportfolios by asset class. For each asset class, we calculate the total VaR of subportfolios containing assets within this class (first row) and the total VaR of subportfolios that also contain a specific asset type (subsequent row), and report their respective averages in the sample. For example, the subportfolios in the Equities class have a total VaR of $1,322.29 million and out of these subportfolios, those that also contain sovereign bonds have a VaR of $653.11 million. In brackets, we report the total VaR of subportfolios within each asset class that only contain assets within this class and no other asset types. For example, the total VaR of all subportfolios that include no asset type other than equities is $86.24 million. The total VaR across portfolios in our sample equals 3,374 ($ million)

	Equities	Rates	Gov't	Credit	Securit.	FX	Comm.
Total	1322.29	2397.28	1840.96	1576.39	447.41	1772.89	562.08
	[86.24]	[124.36]	[23.94]	[6.14]	[13.45]	[71.51]	[132.09]
Sovereign bonds	653.11	1569.77	1728.60	1020.77	239.20	1022.06	251.28
			[21.81]				
Corporate bonds	576.92	807.50	843.97	1063.88	51.93	760.82	152.98
				[4.99]			
Municipal bonds	103.63	229.36	244.31	201.87	23.75	156.51	11.75
			[1.08]				
Agency MBS	69.47	366.46	376.51	144.03	233.19	98.49	18.22
			[1.05]				
Non-agency MBS	76.71	259.02	204.99	289.11	341.44	109.01	18.22
					[13.45]		
CMO	45.43	235.68	227.85	133.15	241.04	66.32	18.22
					[0.00]		
Index CDS	451.82	795.12	705.78	1104.01	274.19	622.84	78.27
				[0.87]			
Single-name CDS	569.55	904.79	798.04	1201.04	249.86	747.85	142.91
				[0.27]			
Tranched credit	155.19	285.79	212.25	412.29	111.16	246.21	7.33
				[0.00]			
Linear equities	1163.62	792.37	599.21	570.37	55.01	859.73	350.94
	[83.36]						
Nonlinear equities	920.98	627.87	486.48	531.08	47.69	667.90	175.48
	[2.28]						
Exotic equities	351.83	245.14	208.24	241.67	3.54	257.79	113.18
	[0.59]						
Interest rates	916.00	2397.28	1680.27	1179.81	364.59	1569.32	404.04
	[124.36]						
FX	956.16	1569.32	1055.98	953.84	112.55	1772.89	420.18
						[71.51]	
Commodities	351.34	404.04	251.28	164.96	18.22	420.18	562.08
							[132.09]
Other products	619.17	1042.21	808.51	867.47	200.63	851.45	254.21

Table 8: This table reports panel regression results for the P/L with alternative normalizations at the subportfolio level. We report results for weekly dollar profits/losses (P/L) in standard-deviation units ($), P/L scaled by Value-at-Risk (VaR), and P/L scaled by FR Y-9C trading assets (TA). For each asset class, we regress the normalized subportfolio P/L on our risk factors interacted with the Volcker indicator variable, which takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. For readability, we report the main estimates for the MKT factor and omit the estimates for the other factors, which are reported in Appendix Table A11. All specifications include bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	Equities	Rates	Gov't	Credit	Securit.	FX	Comm.
A. $P/L_{\$}$							
Volcker	-0.107***	-0.052	-0.018	-0.093*	-0.118	-0.100***	-0.054
	(0.035)	(0.037)	(0.061)	(0.054)	(0.082)	(0.025)	(0.048)
MKT	5.326***	3.105*	5.971**	3.833*	-0.654	3.092**	-6.429***
	(1.509)	(1.599)	(2.342)	(2.063)	(3.025)	(1.534)	(2.470)
Volcker × MKT	-4.063**	-2.367	-5.277**	-3.945*	0.124	-2.431	5.840**
	(1.804)	(1.765)	(2.512)	(2.278)	(3.146)	(1.755)	(2.790)
R^2	0.004	0.001	0.002	0.003	0.002	0.002	0.002
N	39,747	74,905	54,951	51,262	11,815	59,888	12,152
B. P/L_{VaR}							
Volcker	-0.025	-0.020	0.003	-0.013	-0.039	-0.044*	-0.029
	(0.023)	(0.026)	(0.019)	(0.020)	(0.120)	(0.026)	(0.023)
MKT	4.474***	6.557**	3.705**	2.442*	23.79	7.010**	-0.373
	(1.512)	(3.101)	(1.469)	(1.452)	(15.25)	(3.476)	(1.302)
Volcker × MKT	-4.128**	-6.998**	-4.231***	-2.807*	-25.66*	-6.981*	2.461
	(1.705)	(3.187)	(1.612)	(1.614)	(15.54)	(3.598)	(1.957)
R^2	0.002	0.001	0.002	0.001	0.002	0.001	0.004
N	39,747	74,905	55,000	51,311	11,815	59,888	12,152
C. P/L_{TA}							
Volcker	-0.133***	-0.095**	-0.013	-0.204***	-0.150*	-0.151***	-0.200**
	(0.030)	(0.037)	(0.085)	(0.063)	(0.090)	(0.042)	(0.085)
MKT	5.414***	1.921	7.359*	5.911**	0.801	2.460	-5.437
	(2.035)	(1.774)	(4.367)	(2.526)	(2.613)	(2.022)	(3.814)
Volcker × MKT	-6.493**	-2.454	-8.071*	-5.324*	-0.702	-2.295	3.980
	(2.567)	(2.070)	(4.534)	(2.767)	(3.082)	(2.306)	(4.074)
R^2	0.015	0.001	0.001	0.008	0.004	0.001	0.006
N	5,218	16,575	14,021	8,687	1,571	10,069	2,447

Table 9: This table reports panel regression results of P/L on our risk factors interacted with the Volcker indicator variable ("Volcker") controlling for an indicator variable ("Treated") for SLR/LCR banks (SLR/LCR) or CCAR banks (CCAR). We report results for weekly dollar profits/losses (P/L) in standard-deviation units ($), P/L scaled by Value-at-Risk (VaR), P/L scaled by FR Y-9C trading assets (TA). The Volcker indicator takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. The Treated indicator takes the value of one if a bank was subject to SLR/LCR or CCAR, and zero otherwise. For readability, we report the main estimates for the MKT factor and omit the estimates for the other factors, which are reported in Appendix Table A12. All specifications include bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	SLR/LCR			CCAR		
	$P/L_{\$}$	P/L_{VaR}	P/L_{TA}	$P/L_{\$}$	P/L_{VaR}	P/L_{TA}
Volcker	-0.095	-0.035	0.032	-0.046	-0.024	-0.002
	(0.155)	(0.054)	(0.077)	(0.140)	(0.046)	(0.066)
Treated	0.061	0.006	-0.079*	-0.152	-0.065	-0.085**
	(0.105)	(0.049)	(0.044)	(0.103)	(0.047)	(0.037)
MKT	20.585**	6.882***	7.569*	20.654**	6.919***	7.519*
	(8.561)	(2.574)	(3.869)	(8.532)	(2.564)	(3.868)
Volcker × MKT	-19.763**	-6.957**	-9.608**	-22.536**	-8.112***	-9.382**
	(9.352)	(3.015)	(4.580)	(9.160)	(2.909)	(4.054)
Treated × MKT	-5.106	-2.396	-0.037	-2.805	-1.610	-0.169
	(5.145)	(2.339)	(2.691)	(4.983)	(1.993)	(1.557)
R^2	0.052	0.042	0.040	0.045	0.039	0.025
N	2,913	2,913	2,913	2,913	2,913	2,913

Table 10: This table reports panel regression results of P/L on our risk factors interacted with the Reporting indicator variable, which takes the value of one if a bank is subject to the Volcker-related metrics reporting obligation and zero otherwise. We report results for weekly dollar profits/losses (P/L) in standard-deviation units ($), P/L scaled by Value-at-Risk (VaR), P/L scaled by FR Y-9C trading assets (TA). In addition to the baseline panel regression results, we report results of robustness analysis using an event-time specification for a 24-month window around each reporting date (Event time) as well as to including controls for weekly dummies (Week FE) and the full sample of 20 banks (Extended). For readability, we report the main estimates for the MKT factor and omit the estimates for the other factors, which are reported in Appendix Table A13. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	Baseline			Event time		
	$P/L_{\$}$	P/L_{VaR}	P/L_{TA}	Baseline	Week FE	Extended
Reporting	-0.178	-0.094*	-0.097***	-0.071**		-0.084***
	(0.136)	(0.053)	(0.037)	(0.028)		(0.031)
MKT	9.423***	2.749**	2.493	4.069***		4.003***
	(3.365)	(1.234)	(1.564)	(1.139)		(1.375)
Report. × MKT	-15.47***	-5.599**	-4.602**	-6.615***	-4.274***	-5.764***
	(5.955)	(2.614)	(2.119)	(1.443)	(1.002)	(1.354)
R^2	0.041	0.043	0.023	0.047	0.385	0.051
N	2,913	2,913	2,913	1,405	1,405	1,405

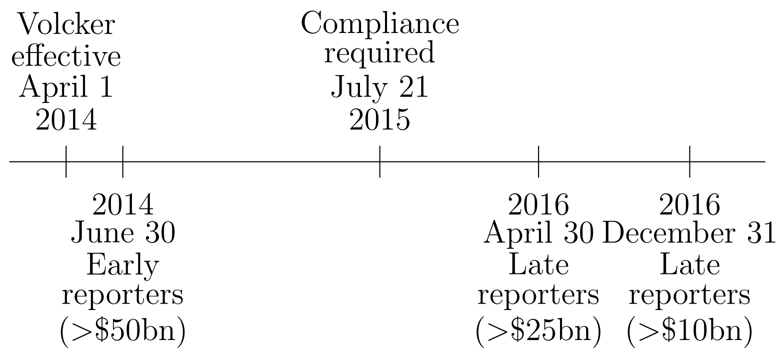

Figure 1: Timeline of the Volcker Rule.

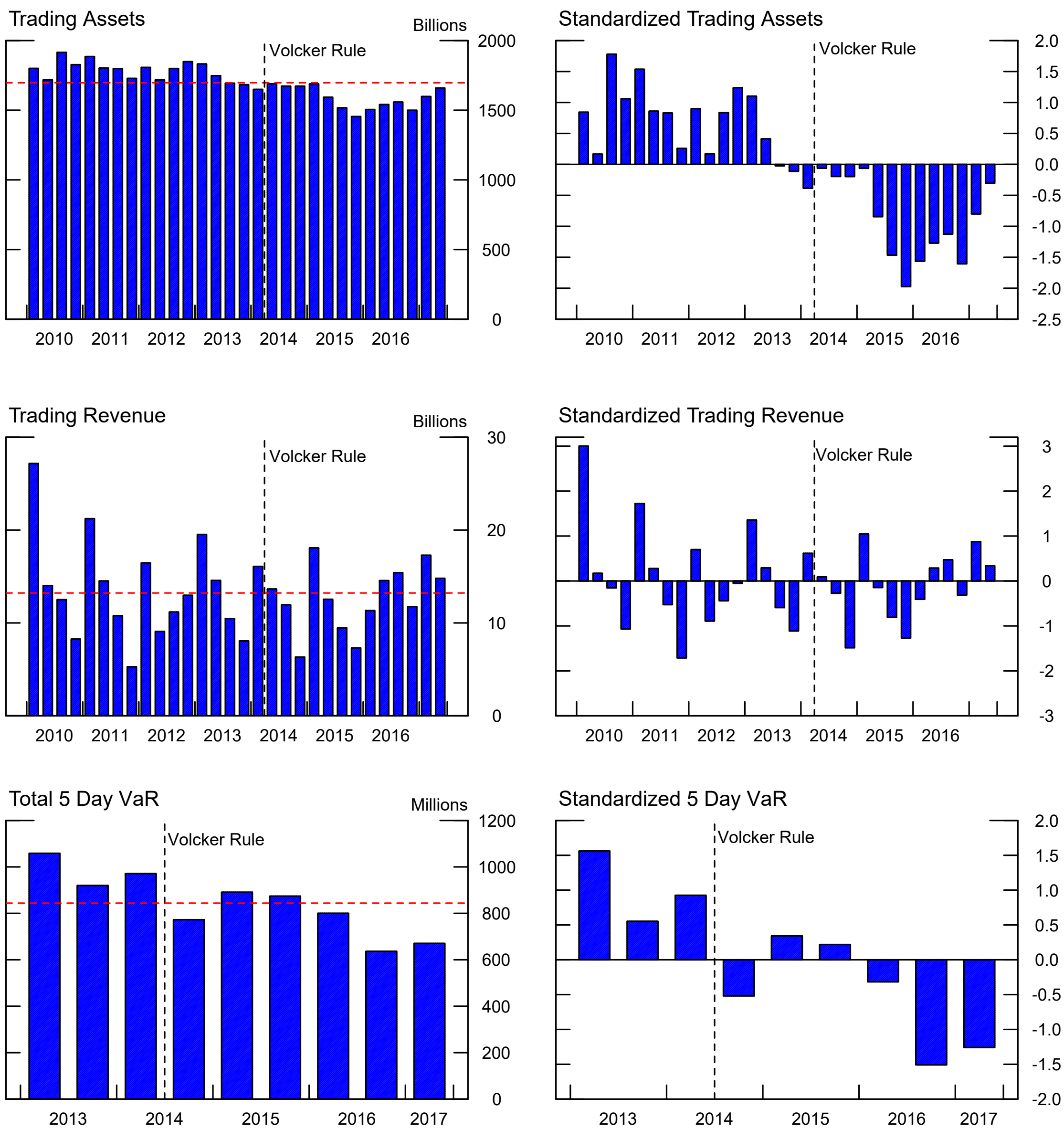

Figure 2: This figure shows the evolution of aggregate trading assets and trading revenue (quarterly) and aggregate 5-day Value-at-Risk (semi-annual) for the 13 banks in our sample. The left panels show these variables expressed in dollars (the horizontal dashed line denotes the sample mean). To help gauge economic significance, the right panels plot the corresponding standardized variables, that is, the dollar variables de-meaned and normalized by their own standard deviation. The trading asset and revenue data are obtained from FR Y-9C and the 5-day Value-at-Risk from SEC 10-Q. Since the SEC 10-Qs are not filed in Q4, for ease of exposition, we only show Q1 and Q3 data for each year.

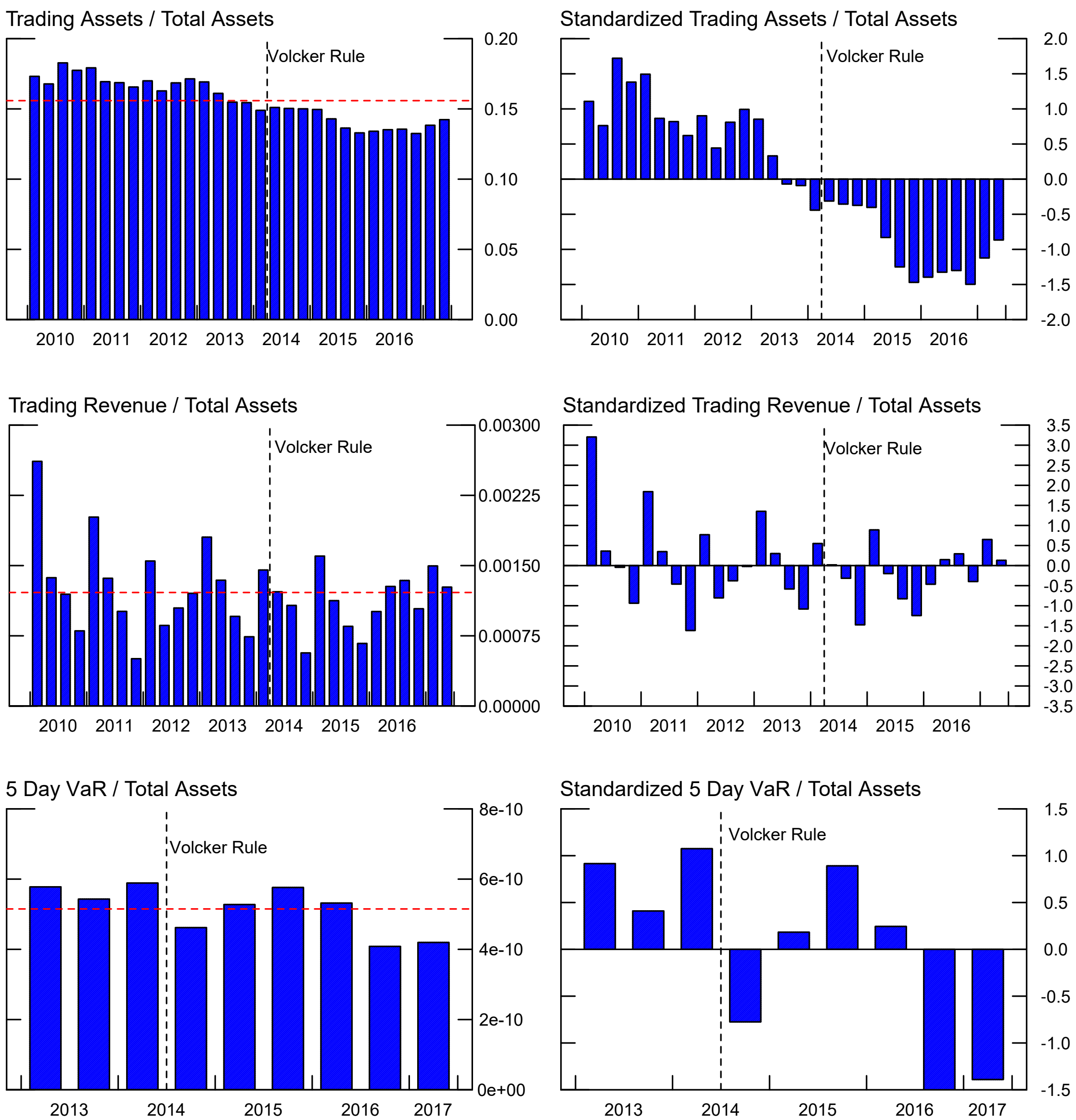

Figure 3: This figure shows the evolution of aggregate trading assets and trading revenue (quarterly) and aggregate 5-day Value-at-Risk (semi-annual) as a fraction of total assets for the 13 banks in our sample. The left panels show these variables expressed as decimals (the horizontal dashed line denotes the sample mean). To help gauge economic significance, the right panels plot the corresponding standardized variables, that is, the variables de-meaned and normalized by their own standard deviation. The total asset, trading asset, trading revenue data are obtained from FR Y-9C and the 5-day Value-at-Risk from SEC 10-Q. Since the SEC 10-Qs are not filed in Q4, for ease of exposition, we only show Q1 and Q3 data for each year.

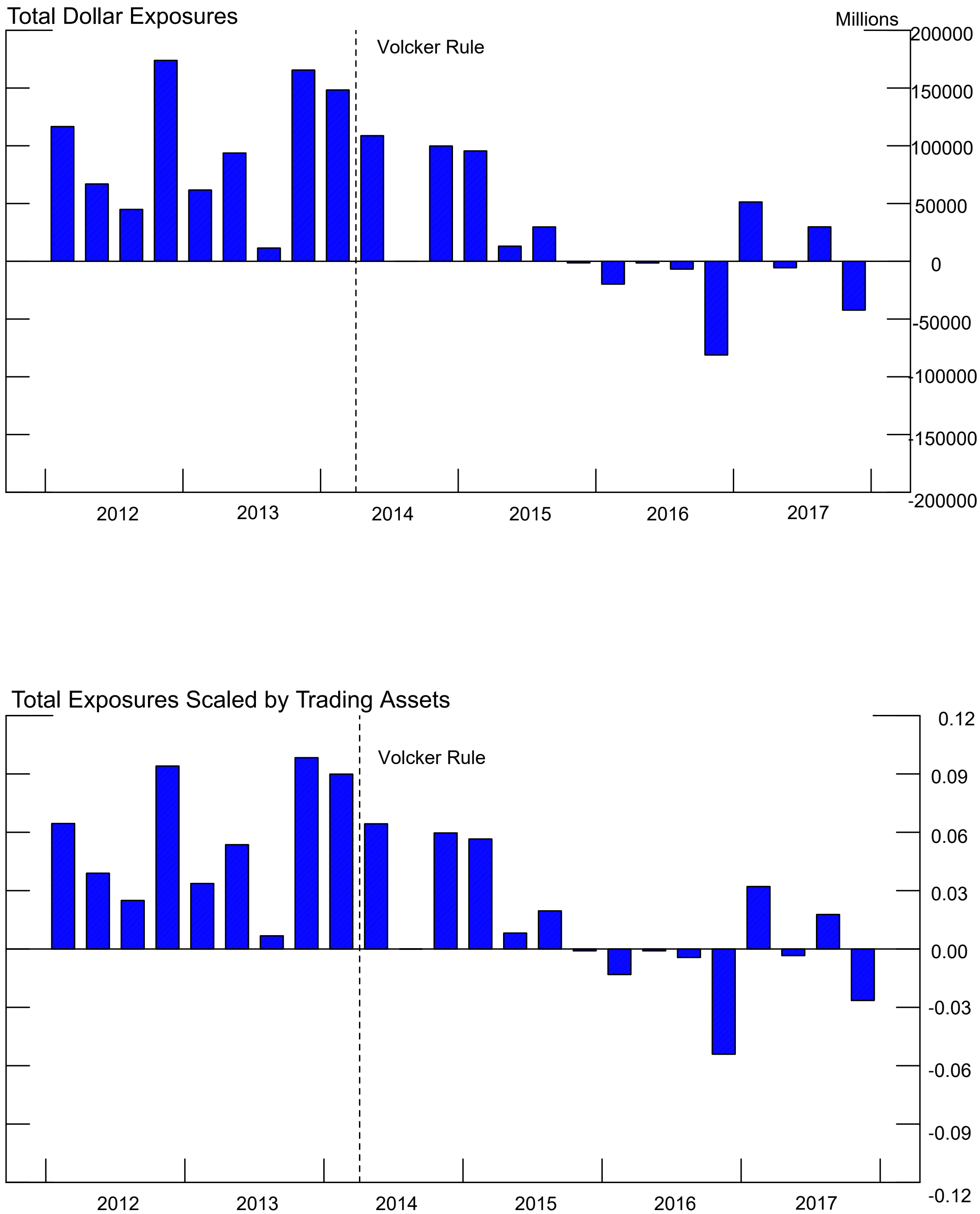

Figure 4: This figure shows the evolution of the dollar trading risk exposures of banks in our sample for which the information on self-reported exposures is available from the supervisory FR Y-14 data. The top panel shows exposures expressed in dollars, while the bottom panel shows dollar exposures as a fraction of total trading assets, both at the quarterly frequency. The trading asset data are from FR Y-9C. See Section 3 (footnote 16) and Section 4.2 (footnote 30) for details on the FR Y-14 data.

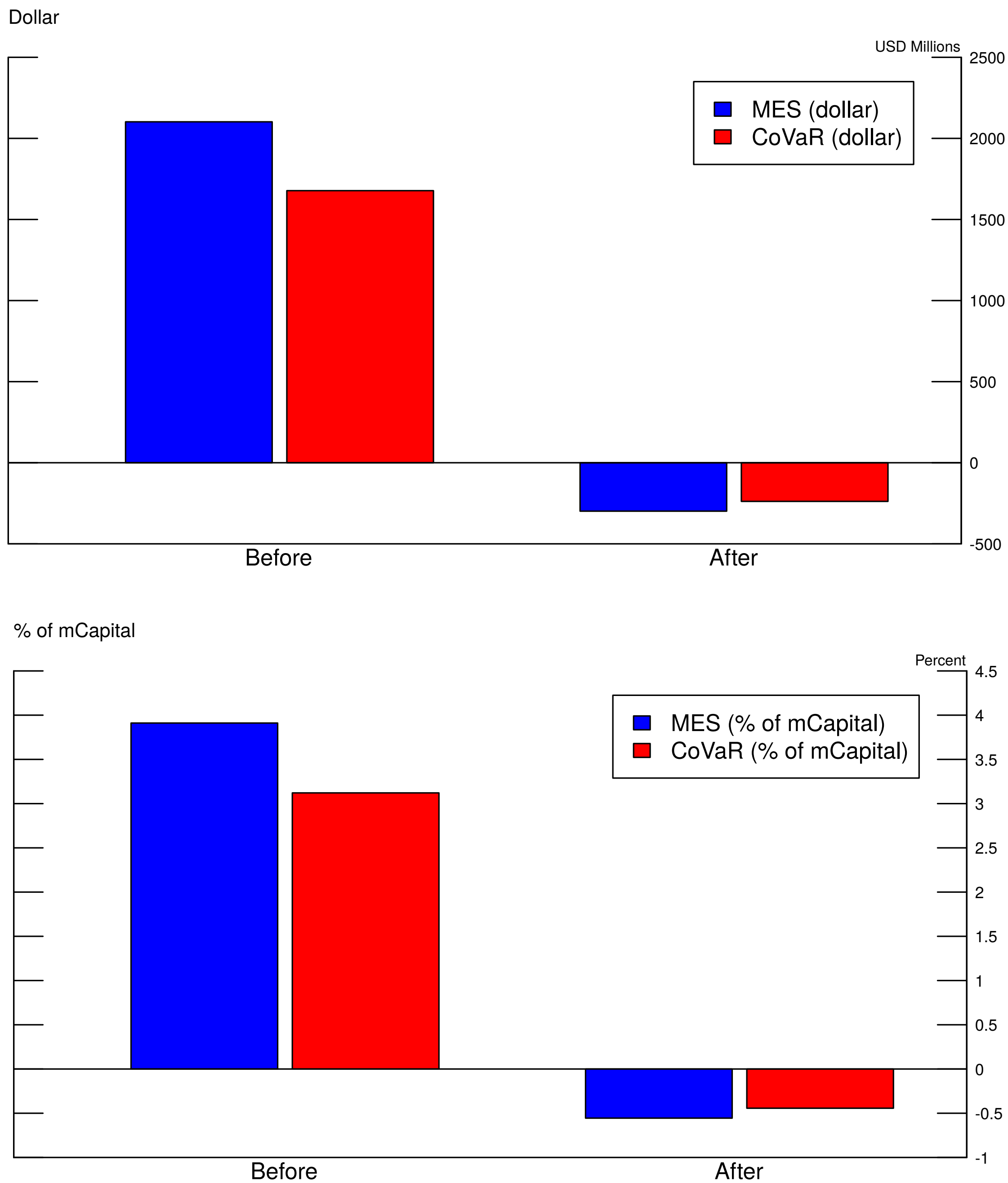

Figure 5: This figure shows the aggregate Marginal Expected Shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017) and CoVaR of Adrian and Brunnermeier (2016) before and after the implementation of the Volcker rule. MES is defined as the expected P/L conditional on the equity market return being equal to the 5th percentile of its distribution. CoVaR is defined as the quantile of the P/L distribution conditional on the equity market return being equal to its 95% VaR. We calculate the systemic risk measure for each bank using our estimates of the sensitivity of the P/L scaled by VaR to the market portfolio pre- and post-Volcker reported in Table 4 and report the sum across banks. The MES and CoVaR are calculated using the formulae in Loeffler and Raupach (2018). The top panel shows these exposures expressed in dollars, while the bottom panel plots dollar exposures as a fraction of market risk capital (mCapital), which equals 8% of market risk-weighted assets.

Internet Appendix for "Banks as Regulated Traders"

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A.1 Volcker rule, market making exemption, and risk exposures: Additional details on institutional background

The Volcker rule generally prohibits any insured depositary institution, or a company that controls an insured depositary institutions, from engaging in proprietary trading and investing in certain investment funds, such as private equity and hedge funds (Federal Register, 2014, §3 and 10, pp. 5781–5796). The rule exempts certain activities from the proprietary trading prohibition. The permitted activities include underwriting, market making, risk-mitigating hedging, and some other activities such as proprietary trading in government securities, trading on behalf of customers, trading by insurance companies and certain foreign banking entities (Federal Register, 2014, §4-6, pp. 5783–5786). Below, we discuss the elements of the rule that are relevant for our analysis of banks trading book exposures, namely the market making exemptions, the compliance requirements and metrics reporting, and the nature of financial exposures the rule intends to curb.

The market making exemption allows covered banking entities to engage in market-making related activities that are genuinely client-facing and designed not to exceed the reasonable expected near-term demands of clients, customers, and counterparties (Federal

Register, 2014, §4(b), pp. 5783–5784). Specifically, the rule requires banking entities invoking the market making exemptions to routinely stand ready to buy or sell one or more types of financial instruments for its own account in commercially reasonable amounts and throughout market cycles, reflecting the market liquidity and maturity of the instruments traded (Federal Register, 2014, §4(b)(2)(i)). The banking entity has to ensure that the amount, types, and risk of the financial instruments in the trading desks market making inventory do not exceed, on an ongoing basis, the reasonably expected near-term demands of clients, customers, and counterparties, based on the market liquidity and maturity and demonstrable analysis of historical and projected customer demand (Federal Register, 2014, §4(b)(2)(ii)). The banking entity has to establish and comply with written policies and procedures that include describing the financial instruments in which it is trading, actions taken to manage the risks associated with its financial exposures, limits on its market-making inventory, financial exposures, allowable risks, and hedging activities, procedures for dealing with breaches of these limits, and appropriate internal controls and monitoring of compliance at the trading desk level (Federal Register, 2014, §4(b)(2)(iii-iv)).

Banking entities that engage in trading or investment activities covered by the rule have to develop a reasonably designed compliance program that allows for continued monitoring of compliance with the rule (Federal Registers, 2014, §20-21, pp. 5796–5797). This compliance program includes reporting and record keeping requirements designed to allow regulators to identify and detect prohibited proprietary trading and high-risk trading strategies (Federal Register, 2014, Appendix A, pp. 5797–5800). Specifically, banking entities subject to the reporting requirement, discussed in the paper, have to periodically furnish to the relevant Agency a set of quantitative measurements, including risk and positions limits and usage; risk factor sensitivities; Value at Risk and stressed Value at Risk; comprehensive profit and loss attribution; inventory turnover; inventory aging; and customer-facing trade ratio (Federal Register, 2014, Appendix A(III)(a), p. 5798). These metrics have to be reported for each trading day (Federal Register, 2014, Appendix A(III)(b), p. 5798).

Although the final implementation of the rule does not impose specific limits for individual metrics, it makes it clear that monitoring of compliance includes making sure the firms set and adhere to appropriate self-imposed limits in line with their market making and hedging activity. As such, the rule does not require that overall risk, as measured by volatility or VaR, necessarily decrease. Rather, the nature of risk that firms are permitted to take on under the rule is expected to be consistent with prudent market making, underwriting, or hedging, profits or losses of which generally exhibit little correlation with aggregate risk factors. Importantly, financial exposure is understood to be exposure to all significant market factors driving the financial instruments in which a firm act as a market maker or that it uses for risk management purposes (Federal Register, 2014, p. 5594). The idea is that risk factor sensitivities are more suitable for detecting prohibited activities than simple risk measures, because speculative trading is typically characterized by taking directional positions aimed at profiting from price changes (Federal Register, 2014, p. 5618), that is, features that volatility or VaR cannot generally detect. The trading activities that are exempt from the proprietary trading prohibition, such as market making, while still being able to generate considerable volatility and VaR, nonetheless typically exhibit less directional exposures to common risk factors, as these strategies typically hedge the associate market risk and derive profit from bid-ask spreads, commissions, and other fees. Although the final rule does not require these fees to be the only source of revenue from permitted market making activity, the Agencies make it clear that evaluating the source of profits and losses will constitute an important part of determining whether a trading activity constitutes prohibited proprietary trading (Federal Register, 2014, p. 5623).

A.2 Scaling by VaR: Additional details on measurement

Consider a stylized location-scale model, where the profits (P/L) are given by

$$P/L_t = \mu_{t-1} + \sigma_{t-1} Z_t,$$

where μ_{t-1} is the conditional mean and σ_{t-1} is the conditional volatility of P/L_t at time $t-1$ and Z_t is a sequence of independently and identically distributed innovations with zero mean and unit variance. Because we are modelling the clean P/L at weekly frequency, which has a mean close to zero, we can safely assume that $\mu_t = 0$ for all t; this is a standard assumption in the literature when modeling high-frequency asset returns (e.g. Christofferesen, 2012, Section 1.7). Then, the Value-at-Risk (VaR) at the confidence level α is given by (e.g. McNeil et al., 2005, Section 4.4)

$$VaR_{t-1} = F^{-1}(\alpha)\sigma_{t-1},$$

where F is the cumulative distribution function of Z_t. Even if we do not observe σ_t, we can back out Z_t, up to a constant, if we observe the VaR, since:

$$Z_t = F^{-1}(\alpha) \times \frac{P/L_t}{VaR_{t-1}}.$$

Thus, scaling P/L by VaR isolates the unexpected component of P/L.

A.3 Stress test variables: Additional details on dollar risk exposures

Consider the case when committed capital is proxied by trading assets, TA. Let β_B and β_A be the market beta before and after Volcker, and let TA_B and TA_A be the trading assets before and after Volcker. The change in dollar positions is

$$\Delta Positions = TA_A - TA_B, \tag{1}$$

Following the definition of dollar risk exposures of Begenau et al. (2015), the change in dollar risk exposures due to Volcker is given by

$$\Delta Exposures = \beta_A TA_A - \beta_B TA_B = \beta_B \Delta TA + TA_A \Delta\beta, \tag{2}$$

where we write $\beta_A = \beta_B + \Delta\beta$; in the notation of equation (2) in the paper, β_B corresponds to β and $\Delta\beta$ corresponds to γ. In the tables, we report the results of this decomposition to show the contribution of the change in trading assets vs. the change in beta to $\Delta Exposures$.

The change in the dollar gain/loss associated with a market shock is given by

$$\Delta Gain/Loss = \Delta Exposures \times shock, \tag{3}$$

where *shock* is the market shock, for which we consider two scenarios, a 35% and a 65% stock market drop.

A.4 List of risk factors and corresponding data sources

Variable	Description	Source	Mnemonic(s)
MKT	market return	K. French's website	Mkt-RF
VIX	CBOE Volatility Index	Bloomberg	VIX
IR5Y	5Y swap rate	Bloomberg	USSW5
TERM	1Y Treasury yield	Federal Reserve Board	SVENPY0100
	10Y Treasury yield	Federal Reserve Board	SVENPY1000
DEF	10Y Corporate BBB Yield	ICE BofAML	own calculations
	10Y Treasury yield	Federal Reserve Board	SVENPY1000
SPGSCI	commodity index return	Bloomberg	SPGSCI
DOL	dollar factor return	Datastream	see Lustig et al. (2011)

A.5 Additional Robustness

Finally, we repeat both our analysis at the bank and desk level to address rebalancing by using an optimal changepoint regression technique to estimate time-varying risk exposures. If banks rebalanced their portfolios at some point in our sample period irrespective of the Volcker rule, our OLS regression with the Volcker indicator may erroneously attribute the structural change to the effect of Volcker. The optimal changepoint technique treats the precise timing of the structural change as unknown and thus serves as a useful robustness check.

Our implementation of the changepoint regression closely follows Bollen and Whaley

(2009). In particular, for each portfolio and each π, $0 < \pi < 1$, we run the regressions

$$r_{it} = \alpha_{0i} + \beta_{i0} RF_t + \epsilon_{it}, \quad t = 1, ..., \pi T,$$
$$r_{it} = \alpha_{0i} + \alpha_{1i} + (\beta_{0i} + \beta_{1i}) RF_t + \epsilon_{it}, \quad t = \pi T + 1, ..., T,$$

and calculate the F-statistic, $F(\pi)$, for the null hypothesis that $\alpha_{1i} = \beta_{1i} = 0$. The test for a structural break at an unknown date is then based on the average F-statistic, $\sum_{\pi} F(\pi)$. Following Bollen and Whaley (2009), we approximate the critical values for this statistic by bootstrap and estimate the date of the structural break by minimizing (over π) the sum of squared residuals in the model above. The additional benefit of this approach is that we can implement a statistical test for structural breaks in banks' and desks' equity market risk exposures similar to Bollen and Whaley (2009), who show that the optimal changepoint method is superior to a stochastic parameter model in detecting time-varying exposures.

The results are reported in Figure A4, which plots the cumulative frequencies of banks (right axis) and trading desks (left axis) that experience a significant structural break in their equity market beta in any given quarter over our sample period. In line with our OLS results, about half (40%) of the banks (desks) experienced a break in equity risk exposure in the quarters after the rule became effective in April 2014 and before full compliance was required in July 2015, and over 80% (70%) of the banks (desks) experienced a break within a quarter after the full compliance date.

Additional References

Christofferesen, P. F., 2012, *Elements of Financial Risk Management*, 2nd Edition, Academic Press.

McNeil, A. J., R. Frey, and P. Embrechts, 2005, *Quantitative Risk Management: Concepts, Techniques, Tools*, Princeton University Press.

Appendix Tables and Figures

Table A1: This table presents summary statistics for the dollar market and book values of market risk capital and for common equity Tier 1 capital at the top-of-the-house level for our 13 banks, 1/2013–6/2017. For each bank, we first calculate the time-series mean, standard deviation, 5th percentile, 95th percentile, skewness, and kurtosis, and report in the table the cross-sectional averages, standard deviations, minima, and maxima for these statistics.

	Average	5th Percentile	95th Percentile	Skew	Kurt
A. Market value of market risk capital ($)					
Obs.	13	13	13	13	13
Mean	8,568,414,782	5,227,244,802	12,026,268,725	-0.09	0.23
St. dev.	8,918,207,543	6,046,018,931	11,990,015,654	0.79	1.52
Min	35,255,796	25,360,829	62,030,493	-1.32	-1.50
Max	25,064,879,637	19,598,227,518	31,441,788,329	1.22	2.78
B. Book value of market risk capital ($)					
Obs.	13	13	13	13	13
Mean	8,424,464,287	6,197,411,705	11,386,386,909	0.05	0.12
St. dev.	9,888,496,851	7,440,989,824.000	13,220,133,750	0.76	1.69
Min	27,068,219	18,981,813	39,743,442	-1.65	-1.59
Max	24,947,310,423	20,622,487,268	35,754,177,201	0.86	3.79
C. Common equity Tier 1 capital ($)					
Obs.	13	13	13	13	13
Mean	7,066,365,240	5,236,059,429	9,473,918,159	0.06	0.10
St. dev.	8,377,165,788	6,348,609,089	11,123,217,740	0.71	1.72
Min	22,474,525	15,636,251	36,299,560	-1.65	-1.64
Max	21,050,728,229	17,915,814,331	29,949,563,208	0.82	3.76

Table A2: This table presents summary statistics for weekly dollar profits/losses (P/L) scaled by market and book value of market risk capital and common equity Tier 1 (CET1) capital at the top-of-the-house level for our 13 banks (Panels A-C) and for aggregate weekly dollar P/L (Panel D), 1/2013–6/2017. For each bank, we first calculate the time-series mean, standard deviation, 5th percentile, 95th percentile, skewness, and excess kurtosis and report in the table the cross-sectional average, standard deviation, minimum, and maximum for these statistics. To ease comparison, we show quarterly rates (QR) in percent, that is, the dollar P/L divided by the dollar trading assets is multiplied by the number of weeks per quarter (12) times 100. For the aggregate dollar P/L reported in Panel D, we simply report the time-series mean, 5th and 95th percentiles, and the skewness and kurtosis.

	Average	5th Percentile	95th Percentile	Skew	Kurt
A. P/L divided by market equity (QR, percent)					
Obs.	13	13	13	13	13
Mean	0.012	-0.065	0.099	0.53	6.90
St. dev.	0.022	0.038	0.063	1.36	6.50
Min	-0.011	-0.146	0.009	-1.62	0.73
Max	0.061	-0.006	0.260	3.12	22.1
B. P/L divided by book equity (QR, percent)					
Obs.	13	13	13	13	13
Mean	0.012	-0.088	0.124	0.40	5.36
St. dev.	0.026	0.059	0.088	1.16	5.90
Min	-0.018	-0.238	0.036	-1.42	0.31
Max	0.076	-0.007	0.339	2.88	20.9
C. P/L divided by CET1 (QR, percent)					
Obs.	13	13	13	13	13
Mean	0.015	-0.103	0.145	0.40	5.22
St. dev.	0.032	0.066	0.105	1.16	5.74
Min	-0.018	-0.276	0.049	-1.41	0.36
Max	0.094	-0.008	0.418	3.01	20.2
D. Aggregate P/L (Weekly, USD million)					
Obs.	225	225	225	225	225
Aggr. P/L	68.3	-385.1	551.6	0.136	0.589

Table A3: This table reports additional panel regression results of P/L on our risk factors. We use the same baseline specification for overall exposures as in Table 3, but express each factor in standard-deviation units by dividing it by its respective standard deviation, to help gauge economic significance and ease comparison across factors. All specifications include bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	$P/L_{\$}$	P/L_{VaR}	P/L_{TA}	Aggregate P/L
MKT	0.078	0.020	0.022	0.050
	(0.054)	(0.021)	(0.021)	(0.035)
DVIX	0.090*	0.024	0.031	0.047
	(0.053)	(0.021)	(0.020)	(0.035)
IR5Y	0.040	0.006	0.013	-0.016
	(0.069)	(0.029)	(0.027)	(0.040)
TERM	-0.099	-0.016	-0.029	0.019
	(0.063)	(0.024)	(0.026)	(0.037)
DEF	-0.137***	-0.048***	-0.039**	-0.039
	(0.048)	(0.018)	(0.018)	(0.029)
SPGSCI	0.001	-0.003	-0.011	0.002
	(0.035)	(0.014)	(0.014)	(0.020)
DOL	-0.072*	-0.028*	-0.040***	-0.070***
	(0.039)	(0.016)	(0.015)	(0.022)
R^2	0.022	0.018	0.013	0.088
N	2,913	2,913	2,913	225

Table A4: This table reports additional panel regression results of P/L on standardized risk factors interacted with the Volcker indicator variable, which takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. We use the same baseline specification for the change in exposures after Volcker as in Table 4, but express each factor in standard-deviation units by dividing it by its respective standard deviation, to help gauge economic significance and ease comparison across factors. All specifications includes bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	P/L$_{\$}$	P/L$_{\text{VaR}}$	P/L$_{\text{TA}}$	Aggregate P/L
Volcker	-0.077	-0.038	-0.018	-0.116*
	(0.137)	(0.044)	(0.061)	(0.070)
MKT	0.333**	0.111***	0.122*	0.167**
	(0.138)	(0.042)	(0.062)	(0.079)
DVIX	0.354	0.110*	0.160	0.129
	(0.219)	(0.062)	(0.100)	(0.102)
IR5Y	0.164	0.050	0.047	-0.009
	(0.170)	(0.050)	(0.077)	(0.084)
TERM	-0.300**	-0.076*	-0.103*	-0.054
	(0.137)	(0.041)	(0.061)	(0.071)
DEF	-0.074	-0.018	-0.033	0.001
	(0.110)	(0.035)	(0.043)	(0.064)
SPGSCI	0.079	0.022	0.056*	0.040
	(0.075)	(0.024)	(0.030)	(0.058)
DOL	-0.101	-0.033	-0.039	-0.107**
	(0.094)	(0.030)	(0.038)	(0:052)
Volcker × MKT	-0.371**	-0.135***	-0.152**	-0.196**
	(0.148)	(0.047)	(0.065)	(0.086)
Volcker × DVIX	-0.352	-0.118*	-0.178*	-0.136
	(0.224)	(0.066)	(0.102)	(0.106)
Volcker × IR5Y	-0.141	-0.049	-0.011	0.003
	(0.186)	(0.060)	(0.084)	(0.095)
Volcker × TERM	0.260*	0.070	0.066	0.085
	(0.150)	(0.050)	(0.065)	(0.081)
Volcker × DEF	-0.099	-0.050	-0.028	-0.062
	(0.118)	(0.040)	(0.046)	(0.069)
Volcker × SPGSCI	-0.097	-0.032	-0.067**	-0.046
	(0.083)	(0.028)	(0.033)	(0.061)
Volcker × DOL	0.010	-0.006	0.025	0.017
	(0.102)	(0.035)	(0.041)	(0.056)
R^2	0.040	0.033	0.023	0.189
N	2,913	2,913	2,913	225

Table A5: This table reports additional panel regression results of P/L on our risk factors interacted with the Volcker indicator variable, which takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. We use the same baseline specification for the change in exposures after Volcker as in Table 4, but report results for four alternative scalings of P/L, market and book value of market risk capital (ME and BE), common equity Tier 1 (CET1) capital, and weekly trading assets from FR 2644 (FR). The specification includes bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	PL_{ME}	PL_{BE}	PL_{CET1}	PL_{FR}
Volcker	-0.001*	-0.001	-0.001	-0.054
	(0.001)	(0.001)	(0.001)	(0.051)
MKT	0.104**	0.118**	0.142**	6.865**
	(0.041)	(0.048)	(0.056)	(3.105)
DVIX	0.001	0.001	0.001	0.044
	(0.0004)	(0.0004)	(0.0005)	(0.029)
IR5Y	0.007	0.011	0.013	0.579
	(0.010)	(0.012)	(0.014)	(0.595)
TERM	-0.012	-0.017	-0.019	-1.297**
	(0.008)	(0.011)	(0.012)	(0.590)
DEF	0.008	0.004	0.005	-0.814
	(0.015)	(0.016)	(0.018)	(0.797)
SPGSCI	0.024	0.027	0.030	1.184
	(0.019)	(0.019)	(0.022)	(1.293)
DOL	-0.064	-0.080	-0.092	-9.783**
	(0.059)	(0.065)	(0.076)	(4.473)
Volcker × MKT	-0.118***	-0.129**	-0.154***	-8.088**
	(0.043)	(0.051)	(0.059)	(3.457)
Volcker × DVIX	-0.001	-0.001	-0.001	-0.045
	(0.0004)	(0.0004)	(0.0005)	(0.030)
Volcker × IR5Y	-0.004	-0.008	-0.009	-0.466
	(0.010)	(0.012)	(0.014)	(0.681)
Volcker × TERM	0.010	0.012	0.015	1.219*
	(0.009)	(0.011)	(0.013)	(0.666)
Volcker × DEF	-0.021	-0.020	-0.025	-0.045
	(0.016)	(0.016)	(0.019)	(0.884)
Volcker × SPGSCI	-0.030	-0.036*	-0.040*	-1.879
	(0.019)	(0.020)	(0.023)	(1.410)
Volcker × DOL	0.017	0.049	0.056	3.782
	(0.063)	(0.069)	(0.082)	(4.980)
R^2	0.031	0.017	0.018	0.026
N	2,913	2,913	2,913	2,452

Table A6: This table reports panel regression results of P/L on linear and nonlinear risk factors interacted with the Volcker indicator variable, which takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. The non-linear risk factors are from Fung and Hsieh (2001). The specification includes bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	$PL_{\$}$		PL_{VaR}		PL_{TA}	
Volcker	-0.082	0.230	-0.041	0.042	-0.017	0.096
	(0.135)	(0.183)	(0.043)	(0.060)	(0.059)	(0.072)
MKT	17.61*	15.38**	5.800*	5.093**	5.620	5.805*
	(10.38)	(6.857)	(3.162)	(2.395)	(4.802)	(3.004)
DVIX	0.199**	0.071	0.063**	0.022	0.091**	0.038
	(0.092)	(0.052)	(0.027)	(0.018)	(0.042)	(0.024)
IR5Y	1.771	3.095*	0.530	0.940*	0.466	1.017
	(1.570)	(1.632)	(0.452)	(0.520)	(0.773)	(0.689)
TERM	-3.579** *	-4.198***	-0.912**	-1.132**	-1.200*	-1.392**
	(1.478)	(1.431)	(0.442)	(0.479)	(0.677)	(0.612)
DEF	-1.496	0.117	-0.346	0.050	-0.646	0.111
	(2.306)	(1.262)	(0.739)	(0.422)	(0.907)	(0.576)
SPGSCI	3.399	2.789	0.978	0.845	2.463*	2.086
	(3.168)	(3.375)	(0.997)	(1.078)	(1.268)	(1.390)
DOL	-13.99	-7.724	-4.608	-2.657	-5.751	-3.134
	(12.09)	(10.71)	(3.854)	(3.653)	(5.085)	(4.172)
PTFSBD		0.300		0.106		-0.057
		(0.643)		(0.212)		(0.242)
PTFSFX		-0.870		-0.231		-0.297
		(0.641)		(0.257)		(0.251)
PTFSCOM		-0.991**		-0.313*		-0.412**
		(0.476)		(0.170)		(0.168)
PTFSIR		-2.241***		-0.632***		-0.809***
		(0.792)		(0.236)		(0.289)
PTFSSTK		1.184**		0.367*		0.269
		(0.561)		(0.193)		(0.219)

cont. on next page

Volcker × MKT	-24.34**	-16.57**	-8.844**	-6.060**	-8.707*	-7.418**
	(11.40)	(7.668)	(3.791)	(2.843)	(5.032)	(3.230)
Volcker × DVIX	-0.167*	-0.062	-0.053*	-0.022	-0.088**	-0.042*
	(0.095)	(0.056)	(0.029)	(0.020)	(0.043)	(0.025)
Volcker × IR5Y	1.577	-2.884	0.539	-0.954	-0.105	-0.585
	(1.749)	(1.794)	(0.566)	(0.619)	(0.843)	(0.759)
Volcker × TERM	3.139*	3.887**	0.856	1.138**	0.792	0.937
	(1.615)	(1.562)	(0.532)	(0.561)	(0.722)	(0.659)
Volcker × DEF	-2.177	-3.623**	-1.047	-1.403**	-0.645	-1.528**
	(2.484)	(1.609)	(0.854)	(0.622)	(0.989)	(0.691)
Volcker × SPGSCI	-4.048	-3.646	-1.295	-1.281	-2.866**	-2.577*
	(3.502)	(3.666)	(1.182)	(1.238)	(1.419)	(1.525)
Volcker × DOL	1.616	-3.965	-0.687	-2.379	3.713	1.425
	(13.12)	(11.71)	(4.485)	(4.222)	(5.508)	(4.613)
Volcker × PTFSBD		-0.413		-0.163		0.319
		(0.750)		(0.283)		(0.295)
Volcker × PTFSFX		0.925		0.244		0.210
		(0.700)		(0.288)		(0.284)
Volcker × PTFSCOM		0.722		0.215		0.343*
		(0.531)		(0.200)		(0.187)
Volcker × PTFSIR		2.282***		0.657**		0.744**
		(0.834)		(0.262)		(0.312)
Volcker × PTFSSTK		-1.512**		-0.515**		-0.353
		(0.593)		(0.213)		(0.237)
R^2	0.045	0.063	0.036	0.046	0.026	0.040
N	2,913	2,913	2,913	2,913	2,913	2,913

Table A7: This table reports additional panel regression results of P/L on risk factors interacted with the Volcker indicator variable, which takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. We use the same baseline specification for the change in exposures after Volcker as in Table 4, but do not subtract the risk free rate from P/L. The specification includes bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	PL_{VaR}	PL_{TA}
Volcker	-0.038	0.009
	(0.044)	(0.062)
MKT	6.883***	7.530*
	(2.571)	(3.890)
DVIX	0.041*	0.059
	(0.023)	(0.037)
IR5Y	0.505	0.498
	(0.505)	(0.788)
TERM	-0.850*	-1.189*
	(0.465)	(0.694)
DEF	-0.385	-0.741
	(0.768)	(0.931)
SPGSCI	0.899	2.268*
	(0.966)	(1.224)
DOL	-4.283	-5.184
	(3.943)	(4.923)
Volcker × MKT	-8.371***	-9.213**
	(2.928)	(4.040)
Volcker × DVIX	-0.044*	-0.064*
	(0.024)	(0.038)
Volcker × IR5Y	-0.499	-0.110
	(0.613)	(0.859)
Volcker × TERM	0.787	0.686
	(0.555)	(0.744)
Volcker × DEF	-1.090	-0.777
	(0.871)	(0.987)
Volcker × SPGSCI	-1.289	-2.551*
	(1.143)	(1.362)
Volcker × DOL	-0.732	2.509
	(4.565)	(5.336)
R^2	0.033	0.026
N	2,913	2,913

Table A8: This table reports additional panel regression results of P/L on risk actors interacted with the Volcker indicator variable, which takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. We use the same baseline specification for the change in exposures after Volcker as in Table 4, but report results for two alternative choices of shorter vs. longer numbers of lags for the Driscoll and Kraay (1998) standard errors (in paretheses). The specification includes bank fixed effects. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

		DK Standard Errors		
	Coefficient	2 lags	4 lags	6 lags
Volcker	-0.038	(0.039)	(0.044)	(0.047)
MKT	6.883	(2.560)	(2.571)	(2.662)
DVIX	0.041	(0.022)	(0.023)	(0.023)
IR5Y	0.505	(0.512)	(0.505)	(0.494)
TERM	-0.850	(0.470)	(0.465)	(0.471)
DEF	-0.385	(0.696)	(0.768)	(0.795)
SPGSCI	0.899	(1.009)	(0.966)	(1.034)
DOL	-4.283	(4.080)	(3.943)	(3.731)
Volcker × MKT	-8.371	(2.917)	(2.928)	(3.013)
Volcker × DVIX	-0.044	(0.024)	(0.024)	(0.025)
Volcker × IR5Y	-0.499	(0.603)	(0.613)	(0.611)
Volcker × TERM	0.787	(0.552)	(0.555)	(0.565)
Volcker × DEF	-1.090	(0.799)	(0.871)	(0.897)
Volcker × SPGSCI	-1.289	(1.170)	(1.143)	(1.203)
Volcker × DOL	-0.731	(4.616)	(4.565)	(4.434)
R^2	0.033			
N	2,913			

Table A9: This table reports additional estimates for the main quantification of the dollar risk exposures to the equity market factor (MKT) before and after Volcker. The approach is the same as in Table 5, to which we refer for details. While Table 5 reports the implied changes, the additional estimates reported in this table are the corresponding levels of exposures before and after Volcker for each of the metrics considered in Table 5.

	$P/L_{\$}$		P/L_{VaR}		P/L_{TA}	
	Before	After	Before	After	Before	After
A. $\Delta Exposures$						
Dollar (mn)	8,088	-938	8,724	-1,239	10,856	-2,469
% ΔCET1	5.83	-0.68	6.29	-0.89	7.83	-1.78
% mCapital	15.7	-1.82	16.9	-2.40	21.0	-4.78
B. $\Delta Gain/loss$: 30% shock						
Dollar (mn)	2,427	-281	2,617	-372	3,257	-741
% ΔCET1	1.75	-0.20	1.89	-0.27	2.35	-0.53
% mCapital	4.70	-0.55	5.07	-0.72	6.31	-1.44
C. $\Delta Gain/loss$: 65% shock						
Dollar (mn)	5,257	-610	5,671	-805	7,056	-1,605
% ΔCET1	3.79	-0.44	4.09	-0.58	5.09	-1.16
% mCapital	10.2	-1.18	11.0	-1.56	13.7	-3.11

Table A10: This table reports additional estimates of the post-Volcker change in dollar risk exposures to the equity market factor (MKT). The approach is the same as in Table 5, to which we refer for details, with one modification: instead of using the baseline estimates of the risk factor loadings in Table 4, we now use the bank-by-bank estimates of the loadings that are plotted in Figure A2. We report banking sector totals and minima across banks (in brackets).

	$PL_{\$}$	PL_{VaR}			PL_{TA}		
	Total	ΔVaR	$\Delta\beta$	Total	ΔTA	$\Delta\beta$	Total
A. $\Delta Exposures$							
Dollar (mn)	-12,620	-3,758	-8,861	-12,618	-887	-11,653	-12,540
	[-5,136]	[-2,254]	[-2,982]	[-5,095]	[-543]	[-4,726]	[-5,045]
% ΔCET1	-9.10	-2.71	-6.39	-9.10	-0.64	-8.41	-9.05
	[-40.5]	[-10.1]	[-33.5]	[-43.6]	[-6.10]	[-33.3]	[-39.4]
% mCapital	-24.5	-7.28	-17.2	-24.5	-1.72	-22.6	-24.3
	[-64.7]	[-28.4]	[-108]	[-80.2]	[-9.89]	[-72.3]	[-82.2]
B. $\Delta Gain/loss$: 30% shock							
Dollar (mn)	-3,786	-1,127	-2,658	-3,786	-266	-3,496	-3,762
	[-1,541]	[-676]	[-894]	[-1,529]	[-163]	[-1,418]	[-1,514]
% ΔCET1	-2.73	-0.81	-1.92	-2.73	-0.19	-2.52	-2.71
	[-12.2]	[-3.04]	[-10.1]	[-13.1]	[-1.83]	[-10.0]	[-11.8]
% mCapital	-7.34	-2.18	-5.15	-7.34	-0.52	-6.77	-7.29
	[-19.4]	[-8.53]	[-32.4]	[-24.1]	[-2.97]	[-21.7]	[-24.7]
C. $\Delta Gain/loss$: 65% shock							
Dollar (mn)	-8,203	-2,442	-5,760	-8,202	-577	-7,574	-8,151
	[-3,338]	[-1,465]	[-1,938]	[-3,312]	[-353]	[-3,072]	[-3,279]
% ΔCET1	-5.92	-1.76	-4.15	-5.92	-0.42	-5.46	-5.88
	[-26.3]	[-6.59]	[-21.8]	[-28.4]	[-3.97]	[-21.6]	[-25.6]
% mCapital	-15.9	-4.73	-11.2	-15.9	-1.12	-14.7	-15.8
	[-42.1]	[-18.5]	[-70.3]	[-52.1]	[-6.43]	[-47.0]	[-53.5]

Table A11: This table reports the full estimates for panel regression analysis of P/L normalized by VaR at the subportfolio level in Table 8. For each asset class, we regress the subportfolio P/L normalized by VaR on our risk factors interacted with the Volcker indicator variable, which takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. All specifications include bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	Equities	Rates	Gov't	Credit	Securit.	FX	Comm.
Volcker	−0.025	−0.020	0.003	−0.013	−0.039	−0.044*	−0.029
	(0.023)	(0.026)	(0.019)	(0.020)	(0.120)	(0.026)	(0.023)
MKT	4.474***	6.557**	3.705**	2.442*	23.79	7.010**	−0.373
	(1.512)	(3.101)	(1.469)	(1.452)	(15.25)	(3.476)	(1.302)
DVIX	−0.006	0.032	0.002	0.009	0.152	0.035	0.001
	(0.011)	(0.027)	(0.011)	(0.010)	(0.138)	(0.030)	(0.009)
IR5Y	0.068	−0.542	0.309	0.286	−4.233	−0.896	0.018
	(0.381)	(0.790)	(0.337)	(0.329)	(3.833)	(0.799)	(0.165)
TERM	−0.467	0.596	−0.562*	−0.559*	5.071	1.160	0.034
	(0.362)	(0.747)	(0.339)	(0.300)	(3.423)	(0.738)	(0.151)
DEF	0.032	−0.327	−0.335	−0.201	−0.795	−0.241	0.430**
	(0.463)	(0.423)	(0.327)	(0.324)	(2.037)	(0.462)	(0.160)
SPGSCI	−1.530	0.496	−1.132	−0.443	6.195	0.931	−0.960
	(1.128)	(1.075)	(0.803)	(0.864)	(4.385)	(1.035)	(0.791)
DOL	−3.463	−4.582	−1.519	−1.800	−2.949	−3.806	−4.734***
	(2.716)	(6.878)	(1.871)	(2.114)	(38.85)	(7.891)	(1.701)
Volcker × MKT	−4.128**	−6.998**	−4.231***	−2.807*	−25.66*	−6.981*	2.461
	(1.705)	(3.187)	(1.612)	(1.614)	(15.54)	(3.598)	(1.957)
Volcker × DVIX	0.006	−0.031	−0.003	−0.007	−0.143	−0.031	0.007
	(0.012)	(0.027)	(0.011)	(0.011)	(0.139)	(0.030)	(0.011)
Volcker × IR5Y	−0.293	0.454	−0.371	−0.426	4.846	0.887	−0.376
	(0.402)	(0.797)	(0.351)	(0.346)	(3.960)	(0.829)	(0.341)
Volcker × TERM	0.809**	−0.431	0.693*	0.806**	−5.701	−1.045	0.333
	(0.385)	(0.766)	(0.354)	(0.322)	(3.621)	(0.782)	(0.338)
Volcker × DEF	−0.439	−0.181	−0.205	−0.312	−0.323	−0.322	−0.356
	(0.490)	(0.440)	(0.367)	(0.383)	(2.084)	(0.497)	(0.300)
Volcker × SPGSCI	1.673	−0.668	1.020	0.367	−6.569	−1.149	0.627
	(1.168)	(1.080)	(0.839)	(0.899)	(4.365)	(1.055)	(0.931)
Volcker × DOL	2.764	2.748	0.354	0.558	6.052	1.355	−0.570
	(2.832)	(6.891)	(1.989)	(2.209)	(38.99)	(7.913)	(2.794)
R^2	0.002	0.001	0.002	0.001	0.002	0.001	0.004
N	39,747	74,905	55,000	51,311	11,815	59,888	12,152

Table A12: This table reports full estimates of panel regression analysis of P/L on our risk factors interacted with the Volcker indicator variable (Volcker") controlling for an indicator variable (Treated") for SLR/LCR banks (SLR/LCR) or CCAR banks (CCAR) in Table 9. We report results for weekly dollar profits/losses (P/L) in standard-deviation units ($), P/L scaled by Value-at-Risk (VaR), P/L scaled by FR Y-9C trading assets (TA). The Volcker indicator takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. The Treated indicator takes the value of one if a bank was subject to SLR/LCR or CCAR, and zero otherwise. All specifications include bank fixed effects. Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	SLR/LCR			CCAR		
	$PL_{\$}$	PL_{VaR}	PL_{TA}	PL_{σ}	PL_{VaR}	PL_{TA}
Volcker	-0.095	-0.035	0.032	-0.046	-0.024	-0.002
	(0.155)	(0.054)	(0.077)	(0.140)	(0.046)	(0.066)
MKT	20.59**	6.882***	7.569*	20.65**	6.919***	7.519*
	(8.561)	(2.574)	(3.869)	(8.532)	(2.564)	(3.868)
DVIX	0.131	0.041*	0.059	0.131	0.041*	0.059
	(0.081)	(0.023)	(0.037)	(0.081)	(0.023)	(0.037)
IR5Y	1.660	0.505	0.480	1.663	0.505	0.484
	(1.720)	(0.506)	(0.778)	(1.723)	(0.507)	(0.780)
TERM	-3.358**	-0.849*	-1.155*	-3.364**	-0.851*	-1.162*
	(1.539)	(0.465)	(0.685)	(1.542)	(0.466)	(0.687)
DEF	-1.609	-0.385	-0.709	-1.591	-0.378	-0.705
	(2.390)	(0.768)	(0.925)	(2.396)	(0.770)	(0.928)
SPGSCI	3.205	0.899	2.288*	3.206	0.897	2.306*
	(3.050)	(0.967)	(1.214)	(3.052)	(0.968)	(1.216)
DOL	-13.132	-4.282	-5.108	-13.202	-4.313	-5.109
	(12.223)	(3.948)	(4.871)	(12.218)	(3.943)	(4.877)
Treated	0.061	0.006	-0.079*	-0.152	-0.065	-0.085**
	(0.105)	(0.049)	(0.044)	(0.103)	(0.047)	(0.037)
Volcker × MKT	-19.76**	-6.96**	-9.61**	-22.54**	-8.112***	-9.382**
	(9.352)	(3.015)	(4.580)	(9.160)	(2.909)	(4.054)
Volcker × DVIX	-0.109	-0.036	-0.061	-0.129	-0.044*	-0.066*
	(0.084)	(0.025)	(0.040)	(0.083)	(0.024)	(0.038)
Volcker × IR5Y	-0.288	-0.269	0.869	-1.409	-0.529	-0.041
	(2.164)	(0.741)	(1.088)	(1.903)	(0.610)	(0.870)
Volcker × TERM	3.459*	1.225*	0.316	3.211*	0.948*	0.710
	(1.878)	(0.652)	(0.880)	(1.672)	(0.543)	(0.748)
Volcker × DEF	-2.178	-0.885	-1.943*	-1.132	-0.575	-0.503
	(2.638)	(0.894)	(1.140)	(2.512)	(0.830)	(0.989)
Volcker × SPGSCI	-2.710	-0.820	-2.229	-3.578	-1.047	-2.619*
	(3.700)	(1.277)	(1.819)	(3.329)	(1.106)	(1.384)
Volcker × DOL	10.265	1.801	8.868	0.739	-0.939	3.197
	(15.070)	(5.371)	(6.842)	(13.100)	(4.450)	(5.389)

Treated × MKT	-5.106	-2.396	-0.037	-2.805	-1.610	-0.169
	(5.145)	(2.339)	(2.691)	(4.983)	(1.993)	(1.557)
Treated × DVIX	-0.028	-0.010	-0.006	-0.008	0.001	0.004
	(0.025)	(0.012)	(0.014)	(0.025)	(0.010)	(0.007)
Treated × IR5Y	-1.309	-0.216	-1.405**	-0.156	0.107	-0.362
	(1.286)	(0.583)	(0.661)	(0.738)	(0.387)	(0.268)
Treated × TERM	-1.270	-0.818	0.550	-1.340	-0.723*	0.210
	(1.168)	(0.527)	(0.512)	(0.901)	(0.430)	(0.301)
Treated × DEF	-0.083	-0.347	1.782**	-4.754***	-2.378***	-0.525
	(1.631)	(0.750)	(0.850)	(1.441)	(0.814)	(0.426)
Treated × SPGSCI	-2.344	-0.813	-0.611	-1.423	-0.997	-0.438
	(2.234)	(0.992)	(1.309)	(1.416)	(0.819)	-0.438
Treated × DOL	-9.185	-2.563	-8.198*	2.427	0.860	-0.169
	(8.738)	(3.812)	(4.247)	(7.898)	(3.532)	(2.189)
R^2	0.052	0.042	0.040	0.045	0.039	0.025
N	2,913	2,913	2,913	2,913	2,913	2,913

Table A13: This table reports the full estimates for the diff-in-diff analysis of the reporting requirement in Table 10. Specifically, we report panel regression results of P/L on our risk factors interacted with the Reporting indicator variable, which takes the value of one if a bank is subject to the Volcker-related metrics reporting obligation and zero otherwise. We report results for weekly dollar profits/losses (P/L) in standard-deviation units ($), P/L scaled by Value-at-Risk (VaR), P/L scaled by FR Y-9C trading assets (TA). In addition to the baseline panel regression results, we report results of robustness analysis using an event-time specification for a 24-month window around each reporting date (Event time) as well as to including controls for weekly dummies (Week FE) and the full sample of 20 banks (Extended). Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	Baseline			Event time		
	$PL_{\$}$	PL_{VaR}	PL_{TA}	Baseline	Week FE	Extended
Reporting	-0.178	-0.094*	-0.097***	-0.071**		-0.084***
	(0.136)	(0.053)	(0.037)	(0.028)		(0.031)
MKT	9.423***	2.749**	2.493	4.069***		4.003***
	(3.365)	(1.234)	(1.564)	(1.139)		(1.375)
DVIX	0.053**	0.013*	0.013	0.004		-0.001
	(0.021)	(0.007)	(0.009)	(0.006)		(0.008)
IR5Y	1.090*	0.266	0.655*	-0.336*		-0.256
	(0.661)	(0.234)	(0.383)	(0.186)		(0.283)
TERM	-1.924***	-0.445*	-1.009***	0.251		-0.038
	(0.720)	(0.238)	(0.380)	(0.373)		(0.408)
DEF	-2.553**	-0.779*	-1.135**	0.856**		0.717*
	(1.253)	(0.409)	(0.565)	(0.352)		(0.382)
SPGSCI	-0.730	-0.510	-0.033	-0.233		-0.030
	(1.482)	(0.510)	(0.759)	(0.261)		(0.303)
DOL	-0.753	0.517	0.246	-1.858		-3.370
	(5.500)	(2.087)	(2.565)	(2.650)		(3.344)

	Baseline			Event time		
	$PL_{\$}$	PL_{VaR}	PL_{TA}	Baseline	Week FE	Extended
Rep. × MKT	-15.47***	-5.599**	-4.602**	-6.615***	-4.274***	-5.764***
	(5.955)	(2.614)	(2.119)	(1.443)	(1.002)	(1.354)
Rep. × DVIX	-0.064**	-0.018	-0.019*	-0.010	-0.0002	-0.009
	(0.029)	(0.012)	(0.011)	(0.007)	(0.005)	(0.007)
Rep. × IR5Y	-1.676	-0.492	-0.762*	-0.202	-0.187	-0.108
	(1.113)	(0.513)	(0.403)	(0.313)	(0.304)	(0.474)
Rep. × TERM	2.301*	0.748	1.171***	0.189	0.508	0.241
	(1.187)	(0.529)	(0.447)	(0.402)	(0.375)	(0.528)
Rep. × DEF	-1.125	-0.743	0.400	-0.699**	-0.408	-0.604*
	(1.795)	(0.784)	(0.707)	(0.328)	(0.711)	(0.342)
Rep. × SPGSCI	1.927	0.941	0.316	1.366	1.535	1.063
	(1.958)	(0.854)	(0.806)	(1.010)	(1.218)	(0.959)
Rep. × DOL	-29.25***	-14.34***	-8.917***	-5.849**	-6.444*	-7.497**
	(7.741)	(3.273)	(2.778)	(2.953)	(3.618)	(3.551)
R^2	0.041	0.043	0.023	0.047	0.385	0.051
N	2,913	2,913	2,913	1,405	1,405	1,405

Table A14: The first three columns of this table report additional panel regression results of P/L on our risk factors interacted with the Reporting indicator variable, which takes the value of one if a bank is subject to the Volcker-related metrics reporting obligation and zero otherwise. We report results for weekly dollar profits/losses (P/L) in standard-deviation units ($), P/L scaled by Value-at-Risk (VaR), P/L scaled by FR Y-9C trading assets (TA). The specification is otherwise the same as in Table 10 but for the fact that the control group of non-reporters is excluded from the sample. The last three columns repeat the baseline analysis using only the non-reporters and a Placebo reporting indicator, which takes value of one after the Early reporters date (June 30, 2014). Driscoll and Kraay (1998) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence are reported in parentheses. Levels of significance are indicated by *, **, and *** for 10%, 5%, and 1% respectively.

	w/o control			Placebo test		
	$PL_{\$}$	PL_{VaR}	PL_{TA}	$PL_{\$}$	PL_{VaR}	PL_{TA}
Reporting	-0.116*	-0.065	-0.092***	0.119*	0.081	0.054
	(0.060)	(0.043)	(0.031)	(0.061)	(0.055)	(0.043)
MKT	5.899**	4.502**	4.298***	0.536	0.752	0.313
	(2.435)	(2.018)	(1.543)	(1.624)	(1.685)	(2.128)
Reporting×MKT	-9.731***	-7.320***	-5.795***	-0.480	2.422	6.665*
	(2.863)	(2.592)	(1.803)	(3.752)	(2.439)	(3.887)
N	1,405	1,405	1,405	950	950	950
R^2	0.081	0.056	0.050	0.034	0.038	0.040

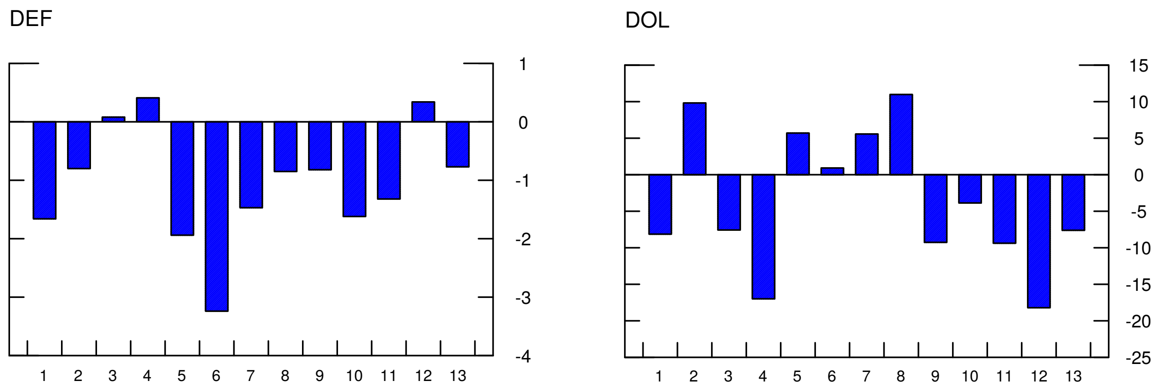

Figure A1: This figure shows the estimated bank-by-bank beta coefficients (β) for DEF and DOL from a regression of banks' P/L scaled by Value-at-Risk on our risk factors (equation (1), estimated bank by bank).

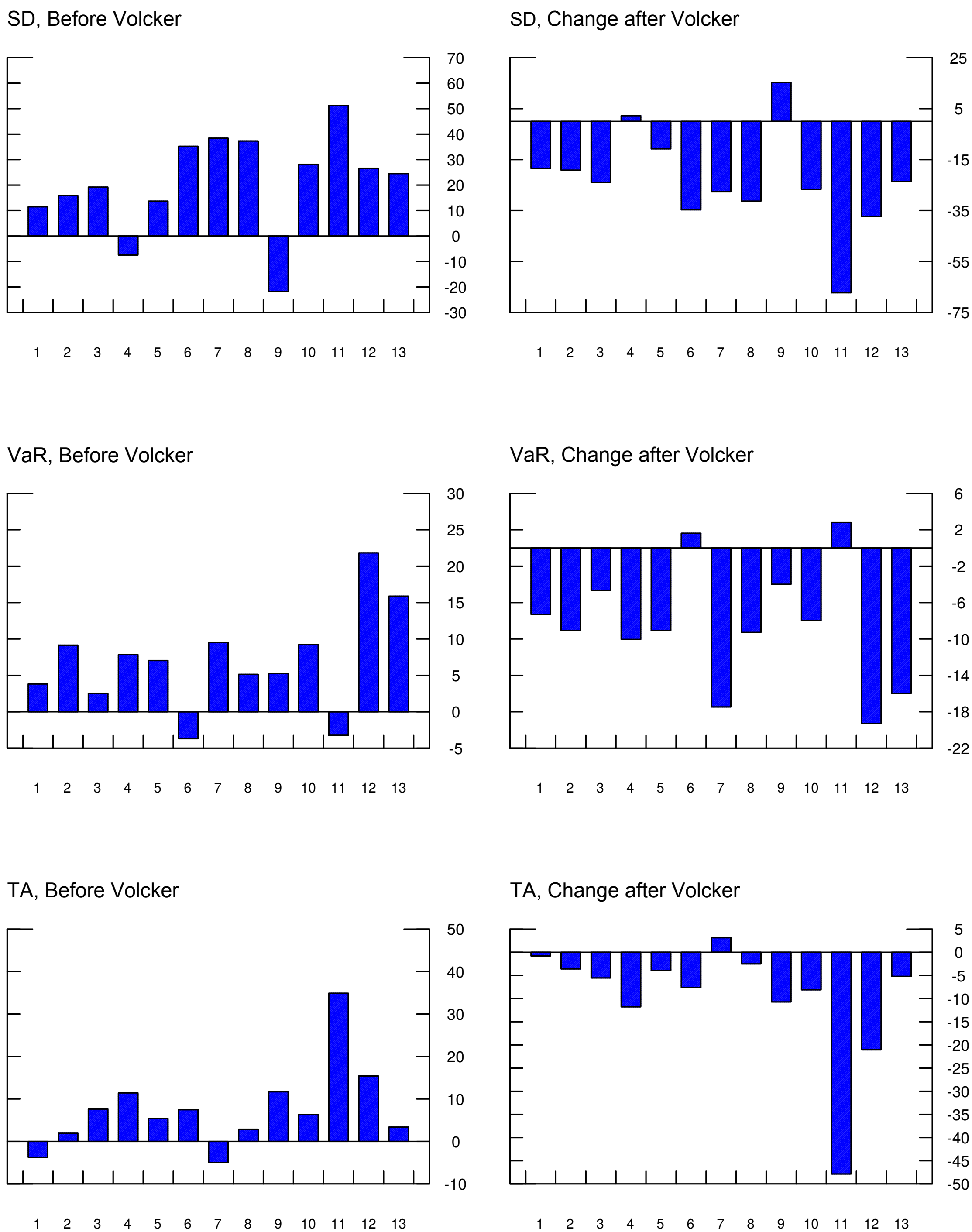

Figure A2: This figure shows the estimated bank-by-bank pre-Volcker market beta coefficients (β, left column) and post-Volcker change in the market beta coefficients (γ, right column) from our baseline regression of banks' P/L on our risk factors (equation (2), estimated bank by bank). The P/L is scaled by its own standard deviation (top panel), Value-at-Risk (VaR) (middle panel), and trading assets (bottom panel).

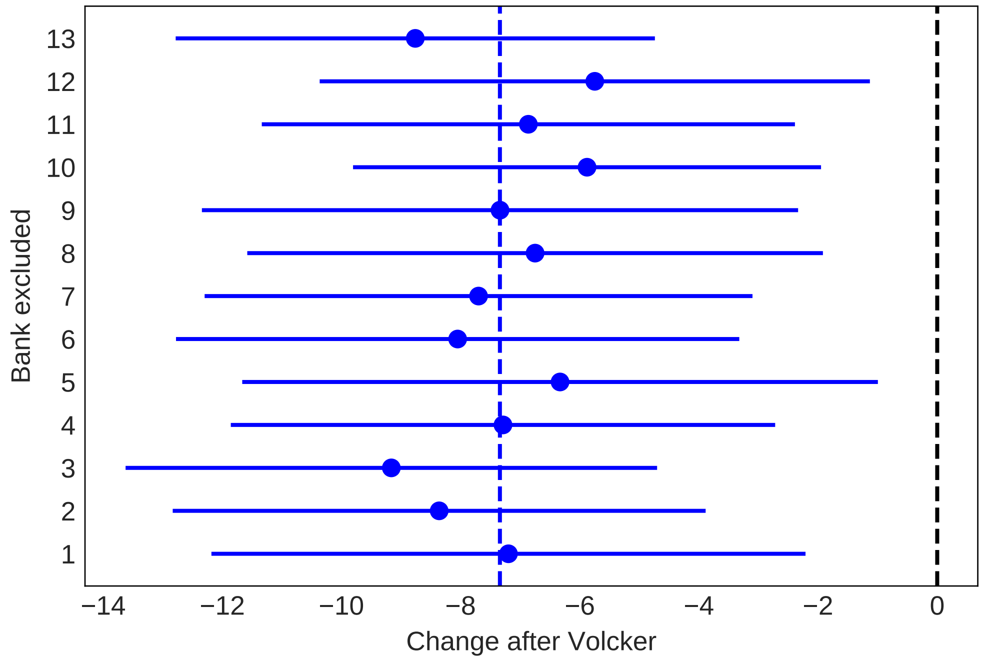

Figure A3: This figure shows the estimated post-Volcker change in the market beta coefficient (γ) together with the associated 99% confidence band from our baseline regression of banks' P/L scaled by VaR in equation (2), where we exclude one bank from the sample at a time.

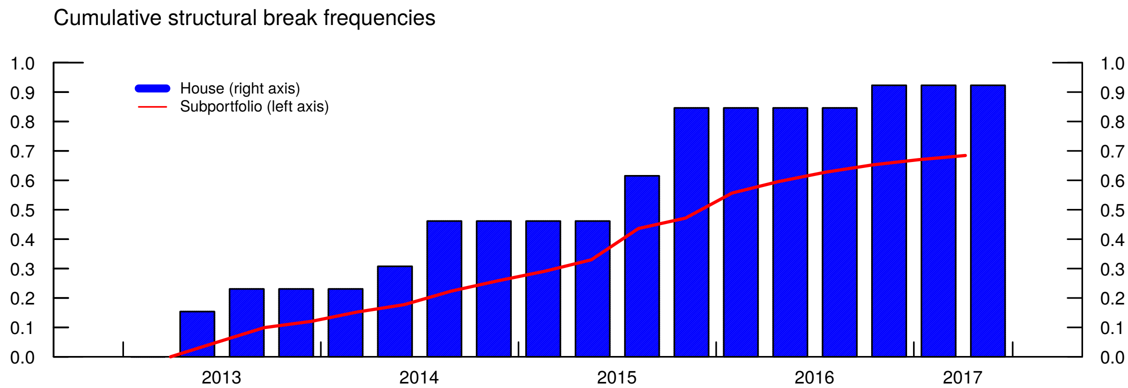

Figure A4: This figure plots the cumulative frequency of structural brakes in the sensitivity of the P/L normalized by VaR to the market return (MKT). We report results at the top-of-the-house level (line) and at the subportfolio level (bars). See Appendix A.5 for details.