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. 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. Timing, heterogeneity, and placebo tests further corroborate the results. Counterfactual and 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.

[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).

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 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 to 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 totaled about $2 trillion, after peaking at around $3 trillion in 2007 (Figure 2, left panel). As a fraction of total assets, they stood at around 10 percent (Figure 2, right panel), a decline relative to the pre-crisis peak (17 percent) but still quadrupled relative to the early 1990s (2.5 percent) and doubled relative to the late 1990s and early 2000s (5.0 percent). 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 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 and investing in hedge funds and private equity. In 2018, regulators put out for comments proposed revisions intended to streamline

[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.

implementation and compliance of the rule, which have been actively debated in the press.

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 invested in and include seven main risk factors for equities, interest rates, credit, foreign exchange, and commodities.[4] 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 books had large exposures to equity market risk before the Volcker Rule was finalized, which they fully curtailed afterwards. Pre-rule equity risk exposures were not limited to equity desks, but were large and significant across the board of the main asset classes, including fixed-income. The decline in trading book value when the stock market declines was economically large: a one standard deviation negative realization of the S&P return, which corresponds to a 2 percentage points drop, would have generated a 14 percentage point trading loss relative to the Value-at-Risk (VaR). This loss is of the same order of magnitude as the banks' average net profits relative to VaR in the sample and about half of its standard deviation. A stress-test calibration indicates that, pre-regulation, a 5% drop in stock market returns would have led to large aggregate losses, up to about 3% (1.5%) of the banking sector's market risk weighted assets (tier 1 common equity capital).

Second, the evidence is more nuanced for interest rate and credit risk. While there is evidence at the desk level that banks cut back on their interest rate exposures of their portfolios of government and fixed-income securities, exposures to credit risk do

[4]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.

not appear to have been affected by the rule. Third, there is evidence of exposure to currency risk, with the dollar risk factor significant 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 exposures is much smaller compared to the pre-rule exposure to 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 exposures, the bank trading book tended to also 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.

We corroborate the effect of Volcker on equity market risk with a battery of additional tests that address two main issues with our baseline analysis, rebalancing and identification. First, the effect is robust to addressing rebalancing by using 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). Second, the effect is also robust to using a differences-in-differences (DD) research design that refines identification by exploiting 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. Third, the effect also holds up to falsification and heterogeneity tests. 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. Finally, it holds across the board of our cross-section of banks, with no evidence of heterogeneity by bank or trading book size, all suggesting that our estimates isolate an independent effect of Volcker.

The additional tests are also helpful to interpret the results on credit and currency risk. Credit risk exposures 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 blunt of the compression in profits from heightened regulation and the low-rate environment, their continued credit-risk exposure 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 exposure to the dollar, 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 exposures, it is not a panacea, as reducing smaller 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.[5] 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 (2011), 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

[5] 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).

U.S. banks have gotten safer since the crisis, which is a contentious question because, among 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 surpervision. Their evidence indicates that the regulators who are entrusted with enforcing financial regulations matter for regulatory outcomes, pointing to a tension betweeen rules and inconsistent enforcement by multiple regulators that hinders their effectivess. 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.[6] 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

[6] 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)).

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 provides an 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. Section 5 presents the results of our falsification and 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 lead 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 lines between prohibited and permissible activities. The rule was finalized in December 2013 ("2013 final rule") when 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.[7] 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 "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 U.S. financial stability.

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 asset 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

[7]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.

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.

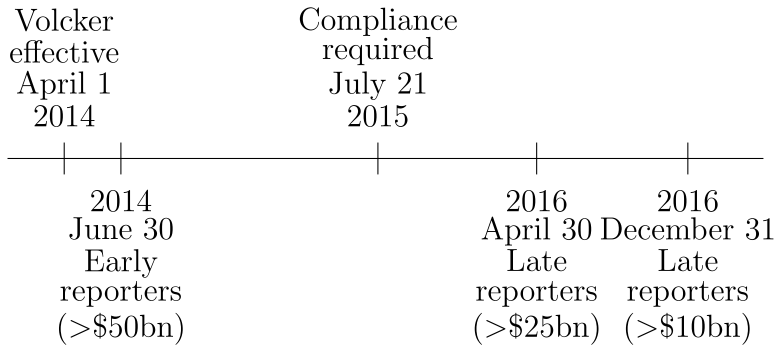

Figure 1: Timeline of the Volcker Rule.

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).

3 Data and Research Design

We use 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 revised 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 \$1.0 billion or 10 percent of their total assets must divide its trading book portfolio 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) for its portfolio, that is, the net change in the value of the positions held in the subportfolio at the end of the previous business day (§205). Although this measure of P/L generally underestimates total profits, as banks also typically earn fees and commissions from their market making and 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.

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, or "sub-portfolio," level 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 sectors, while the 20 banks of the trading-desk sample cover virtually the universe of the U.S. banking sector's trading assets. The 13 firms 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, holding \$1.5–\$1.8 trillion in trading assets and \$625–\$760 billion in trading 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 4.2 serves as a robustness check.

Table 1, Panel A, reports some summary statistics for the P/L data at the top-of-the-house level. Although the raw data are available daily, we do our analysis at the weekly frequency to mitigate the effect of high-frequency noise. For confidentiality reasons, we cannot present firm-specific statistics, so we report cross-sectional statistics for banks' time-series mean, minimum, and maximum weekly P/L. The average bank made around \$5 million on average per week, with a standard deviation of \$12 million. The least profitable firm in our sample lost \$10 million on average per week, while the most profitable firm earned around \$30 million per week. Although the average P/Ls appear relatively small, their extreme values are an order of magnitude higher. Starting with losses, the second column of Table 1 shows that the 13 banks in our sample recorded a maximum weekly loss of \$84 million on average and \$247 million overall. Maximum weekly profits (third column) are even larger, with an average of \$117 million and a maximum of \$477 million. The last two columns of the table show that the distributions of the weekly P/L are generally asymmetric and exhibit uniformly fat tails.

Panel B of Table 1 reports analogous statistics for the weekly VaR, which we approximate by multiplying the average daily VaR by the number of trading days within the week. The average weekly VaR has a mean of \$73 million with a standard deviation of \$85 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. The maximum weekly VaR recorded for any week or bank in our sample was \$505 million. Overall, the summary statistics for the weekly P/L and VaR show that while on average 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 exposures, we scale trading profits by Value-at-Risk (VaR), which is an important part of the total trading-book regulatory capital (Federal Register, 2012, §204). Specifically, we construct our main measure of scaled trading profits by dividing the weekly P/L by the average daily VaR within the week multiplied by the number of trading days in that week and subtracting the risk-free rate:

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

where P/L_{it} is the sum of daily P/L of bank i in week t, n_t is the number of trading days in week t, and $VaR_{i,t}$ is the average daily VaR of bank i in week t; scaling by $\sqrt{n_t}$ approximately translates a daily VaR into a weekly VaR.

The intuition behind this measure is that weekly trading-book returns are defined as the weekly P/L divided by the amount of capital committed to the trading business of each bank at the beginning of the week. We use VaR to proxy for committed capital because the latter is not available at this level of granularity and frequency. In robustness analysis we also consider an alternative measure of scaled trading profits that proxies for capital committed to trading using the product of each bank's market capitalization times the proportion of trading-book risk-weighted asses (RWA):

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

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. The clear drawback of this measure is that data on RWA are only available at a quarterly frequency.

Thus, we set the within quarter RWA equal to the beginning of quarter RWA. The RWA data are obtained from the FR-Y9C regulatory filings.[8]

Table 2 reports some descriptive statistics for the weekly trading-book returns for each firm in our baseline sample. The mean returns tend to be close to zero with standard deviations between 0.3 and 0.5%. The minimum weekly returns range from -0.75% to -2.74% and the maximum weekly return from 0.60% to 2.93%. Similar to the raw P/L, the weekly return distributions are asymmetric and exhibit fat tails.

3.2 Risk factors

Table 3 reports descriptive statistics for our weekly risk factors, which are meant to measure risk by the main broad asset classes banks trade in, equities, fixed-income and credit, commodities, and foreign exchange. Our market risk factor (MKT) is the weekly excess return on the value-weighted market portfolio obtained from Kenneth French's website. Our volatility risk factor (VIX) is the weekly change in the CBOE VIX index. Our interest rate risk factor (IR5Y) is the weekly change in the 5-year swap rate. Our 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. Our 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, our 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. Except for the Treasury yields, which are obtained from the Federal Reserve, all the other data are from Bloomberg.

[8]As a final robustness check, we also normalized the weekly P/L by quarterly trading assets, which leads to qualitatively similar results (not reported).

3.3 Research design

We 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:

$$r_{it} = \beta RF_t + \lambda_i + \epsilon_{it}, \tag{1}$$

where the outcome variable, r_{it}, for bank i in week t is the trading book return defined in Section 3.1, 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 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.

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

$$r_{it} = \alpha I_t + \beta RF_t + \gamma I_t RF_t + \lambda_i + \epsilon_{it}, \tag{2}$$

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 falsification and heterogeneity tests. Specifically, we exploit our relatively high-frequency data for a broad cross section of banks to add controls for and interactions with 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 sub-groups 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 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.

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. After documenting trading books' exposures at the bank level, we examine more closely the sources of risk at the trading desk level. This finer analysis allows us to pin down which asset classes are exposed to which risks. To offer additional insight on the economic magnitude of the risk exposures and gauge the implications for financial stability, we use our estimates in a regression-based counterfactual exercise similar to the "stress test" commonly implemented by regulators.

4.1 Bank-level analysis

In Table 4, we summarize results from estimating equation (1) with trading performance (P/L) normalized by VaR as the outcome variable, and with our risk factors sequentially by broad asset class, equities (Columns 1 and 2), fixed-income and credit (Column 3), commodities (Column 4) and foreign exchange (Column 5), in turn, and all together (Column 6) as the explanatory variables of interest, respectively. The coefficients on equity market risk (MKT and VIX) are not statistically significant. By contrast, the coefficients on credit risk (DEF) and on the dollar (DOL) are negative and statistically significant, indicating that U.S. banks' trading tended to bet on these two types of risk over the post-crisis period. The estimates imply that a one standard deviation change in the credit (dollar) risk factor leads to a 5 (3) percentage point change in trading profits. 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 change in trading profits ranges between 36 and 53 percentage points for banks in our sample, and is about 30 percentage points on average (Table 2). Thus, the economic significance of credit and dollar risk exposures is relatively small, with a one standard deviation change in the credit (dollar) risk factor leading to about 1/6 (1/10) of a standard deviation change in trading profits.

Table 5 examines the evolution of risk exposures over time. We report results from estimating equation (2), which tests for whether exposures 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, 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 exposures to 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 exposure on average for the overall period, indicating that the pre-Vocker exposures were fully offset post-Volcker. The estimates for the pre-Volcker period imply an economically large decline in trading book value when the stock market declines: a one standard deviation negative realization of the S&P return, which corresponds to a 2 percentage points drop, would have generated a 14 percentage point trading loss relative to the

Value-at-Risk (VaR). This loss is of the same order of magnitude as the banks' average net profits relative to VaR in the sample and about half of its standard deviation. Second, there is weaker evidence of pre-Volcker exposure to equity market volatility (VIX) and interest rate (TERM) risk, which we revisit in the desk-level analysis.

Tables 6 and 7 examine 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 many different kinds of market vulnerabilities. Based on our bank-level estimates, 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. The extent to which pre-Volcker exposures hindered financial stability depends both on the estimated sensitivity to the equity risk factor and the size of the bank trading books. We use a counterfactual scenario to quantify the aggregate consequences of Volcker. Specifically, we report the results of a stress-test exercise that consists in calculating an aggregate counterfactual for the effect on sector-wide losses as a percentage of aggregate market risk weighted assets (RWA) or common equity tier 1 capital (CET1) for several alternative adverse scenarios that vary by the size of the shock to the equity market return (5% vs. 10% vs. 20% for weekly losses in Table 6, and 5% vs. 30% vs. 65% for annual losses in Table 7). For the calculation, we use the estimated pre-Volcker exposure in Table 5. Even a 5% drop in stock market returns would have led to large aggregate annual losses, up to about 3% (1.5%) of the banking sector's market risk weighted assets (tier 1 common equity capital). Losses are outsized at about 40% (20%) of the banking sector's market risk weighted assets (tier 1 common equity capital) for a 65% stock market drop, which mimics the "severely adverse scenario" of the annual regulatory stress tests (FRB, 2018b), indicating that Volcker had economically large financial stability benefits.

4.2 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). 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, our data also identify 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 8, 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 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. By way of additional descriptive statistics, Table 9 reports the total Value-at-Risk ($ million) at the desk level by asset class.

Table 10 summarizes results from estimating equation (2) at the desk level by broad asset class, with trading performance (P/L) normalized by VaR as the outcome variable, each risk factor interacted with the Volcker indicator to test for whether exposures changed around Volcker, and each column reporting results for a given asset class, equities, rates, government, credit, securities, forex, and commodities, in turn. First, both for the equities desks and across the board of other asset classes including fixed-income, we confirm our earlier findings that 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, suggesting that the sources of equity risk exposure pre-Volcker were not limited to equity desks. 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.

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.[9] The additional benefit of this approach is that we can implement a statistical test for structural breakes 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 3, 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

[9] 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

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

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.

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.

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 heterogeneity tests and a quasi-experiment. First, we consider heterogeneity tests that explicitly control and allow for variation of the effect with other regulatory changes that happened over our sample period as well as with bank size. 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.

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 (1) as follows:

$$r_{it} = \alpha_v I_t + \alpha_d d_i + \beta RF_t + \gamma_v I_t RF_t + \gamma_d d_i RF_t + \delta d_i I_t RF_t + \epsilon_{it}, \tag{3}$$

where d_i is the "placebo treatment" indicator that takes the value of one if bank i is in the placebo treatment. We consider two different placebo treatments 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, $\alpha_d d_i$, which allows us to implement a first simple falsification test of whether other regulations affected trading risk exposures by examining whether the coefficient estimate, α_d, is statistically significant. The specification also adds an interaction term of the Volcker indicator with the other regulations, $d_i I_t RF_t$. By doing so, we can implement a second falisication test of whether the estimated effect of Vocker is larger for any particular subset of banks that are subject to other regulations. If this were the case, it would spell doubt on attributing the effect to Volcker. As such, the key coefficients of interest are α_d and δ, and the falsification test is whether these coefficient estimates are statistically significant.

Table 11 summarizes results from estimating equation (3) at the bank level with trading performance (P/L) normalized by VaR as the outcome variable. The estimate of the Volcker indicator, α_v, remains strongly statistically significant and relatively stable for the equity market factor, thus confirming our baseline findings that banks curtailed their exposures to equity market risk after Volcker. By contrast, neither coefficient estimate of interest, α_d or δ, is statistically significant for either of the two other regulations. In fact, these coefficient estimates are generally insignificant for all other factors, with the notable exception of credit risk (DEF), for which there is evidence of a significant interaction effect of Volcker with CCAR results. The results are confirmed by Table 12, which repeats the falsification analysis to examine if the change in risk exposures post-Volcker varies with bank size. In this version of the analysis, the "placebo treatment" indicator, Top, takes the value of one if a bank belongs to the top quartile of bank or trading book size, as proxied by total (Column 1) or market (Column 2) risk weighted assets, respectively. Neither coefficient estimate of interest, α_d or δ, is statistically significant for either size proxy, again with the exception of the credit risk factor (DEF), for which there is evidence that large banks had a larger post-Volcker exposure. Interestingly, in line with our desk-level results, there is weak evidence of a reduction in interest rate risk exposures (IR5Y and TERM) after Volcker for smaller banks.

In all, these findings indicate that our main result on the change in equity exposures holds up to the falsification and heterogeneity tests, because the effect 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. And it holds across the board of our cross-section of banks, with no evidence of heterogeneity by bank or trading book size, all suggesting that our estimates isolate an independent effect of Volcker. The analysis is also helpful to interpret our earlier finding of an overall credit risk exposure over the post-crisis period in Table 4, as it suggests that credit risk exposure in the post-Volcker period is driven by large banks and those that failed the stress tests. To the extent that these banks faced the blunt of the compression in profits from heightened regulation and the low-rate environment, their continued long credit-risk exposure 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)).

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 Federal Reserve). 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:

$$r_{it} = \alpha I_{it}^{m} + \beta RF_t + \gamma I_{it}^{m} RF_t + \lambda_i + \epsilon_{it}, \tag{4}$$

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 exposures 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, and again conduct statistical inference using the Driscoll and Kraay (1998) standard errors which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence. The coefficient of interest is γ, which represents the effect of the treatment on the treated – i.e., the change in exposures after the Volcker reporting requirement is phased in relative to the control group of other banks that are not subject to the requirement.

Table 13 summarizes results from estimating equation (4) at the bank level with trading performance (P/L) normalized by VaR as the outcome variable. In line with our baseline findings, 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 exposures to equity market risk. While smaller than our baseline estimate in Table 5, the estimate for the reduction in equity market risk exposures when banks are subject to the reporting requirement remains economically large. The estimate of -4.437 implies that a one standard deviation negative realization of the S&P return would have generated about 9 percentage point smaller trading loss relative to the Value-at-Risk (VaR) as a consequence of the requirement. This loss is of the same order of magnitude as the pre-Volcker exposures. Second, relative to the baseline analysis there is stronger evidence of an economically significant reduction in exposures to equity market volatility (VIX) risk. The estimate of -0.028 implies that a one standard deviation increase in the VIX would have generated about 7.5 percentage point smaller trading gains relative to the Value-at-Risk (VaR) as a consequence of the requirement. Finally, there is evidence that the requirement increased exposure to the dollar, consistent with a risk migration toward asset classes that were exempted from the rule.

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 counterfactuals 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.

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Tables

Table 1: This table presents cross-sectional summary statistics for weekly dollar profits/losses (P/L) and weekly dollar Value-at-Risk (VaR) 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, minimum, and maximum, and report in the table the cross-sectional averages (column 1), minima (column 2), maxima (column 3), skewness (column 4), and excess kurtosis (column 5) for these statistics.

	Average	Minimum	Maximum	Skew	Kurt
A. Weekly P/L ($)					
Obs.	13	13	13	13	13
Mean	5,217,239	−84,345,157	117,047,668	-0.04	1.98
St. dev.	11,958,301	97,820,374	155,162,710	0.51	1.63
Min	−10,138,322	−247,052,444	708,441	-0.70	0.29
Max	30,302,113	−629,335	477,400,093	0.90	6.35
B. Weekly VaR ($)					
Obs.	13	13	13	13	13
Mean	73,040,899	38,954,458	138,937,035	0.80	0.72
St. dev.	85,651,303	45,871,041	164,206,641	0.60	2.13
Min	850,719	179,790	1,697,901	-0.17	-0.85
Max	220,946,575	113,594,931	504,850,069	1.99	7.19

Table 2: This table presents summary statistics for weekly profits/losses (P/L) normalized by Value-at-Risk (VaR) for our 13 banks 1/2013 – 6/2017. For each bank, the table reports the time-series mean, median, standard deviation, skewness, excess kurtosis, minimum, and maximum.

Firm	Obs	Mean	Med	StD	Skew	Kurt	Min	Max
1	225.00	-0.14	-0.12	0.36	-1.36	5.59	-2.07	0.60
2	225.00	0.05	0.03	0.40	0.02	0.98	-1.11	1.61
3	225.00	0.20	0.19	0.42	0.14	1.36	-1.30	1.89
4	224.00	-0.05	-0.01	0.41	-1.40	7.33	-2.74	1.22
5	225.00	0.06	0.07	0.53	-0.23	0.23	-1.36	1.66
6	225.00	-0.00	0.02	0.37	-0.06	1.09	-1.40	1.29
7	225.00	-0.14	-0.11	0.37	-0.83	6.60	-2.37	1.25
8	225.00	-0.01	0.02	0.29	-1.58	9.67	-2.05	0.68
9	225.00	0.19	0.14	0.37	2.79	15.32	-0.75	2.93
10	214.00	-0.07	-0.07	0.39	0.07	0.81	-1.13	1.32
11	225.00	0.29	0.25	0.30	0.07	5.00	-1.37	1.39
12	225.00	0.14	0.14	0.49	0.39	0.64	-1.09	2.04
13	225.00	0.08	0.07	0.37	0.66	1.52	-0.88	1.49

Table 3: This table reports summary statistics for our weekly risk factor returns/changes 1/2013 – 6/2017. MKT denotes the market return, VIX is the change in CBOE implied volatility index, IR5Y is the change in the five-year swap rate, 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, 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, SPGSCI is the return on the S&P GSCI commodity index, and DOL is the return on the Lusting et al. (2011) dollar factor.

Factor	Obs	Mean	Med	StD	Skew	Kurt	Min	Max
MKT	225.00	0.00	0.00	0.02	-0.58	1.42	-0.06	0.05
VIX	225.00	-0.00	-0.24	2.71	1.00	6.25	-10.99	15.20
IR5Y	225.00	0.00	-0.00	0.10	0.71	1.49	-0.24	0.43
TERM	225.00	-0.00	-0.02	0.09	0.78	1.14	-0.23	0.36
DEF	225.00	-0.00	-0.00	0.05	-0.00	1.67	-0.16	0.17
SPGSCI	225.00	-0.00	-0.00	0.02	-0.15	0.15	-0.09	0.06
DOL	225.00	-0.00	-0.00	0.01	-0.24	0.12	-0.03	0.02

Table 4: This table reports panel regression results of P/L normalized by VaR on our risk 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.

	(1)	(2)	(3)	(4)	(5)	(6)
MKT	1.018					1.259
	(0.730)					(1.305)
DVIX		-0.004				0.009
		(0.005)				(0.008)
IR5Y			0.208			0.061
			(0.289)			(0.290)
TERM			-0.253			-0.184
			(0.274)			(0.274)
DEF			-0.939***			-1.049***
			(0.321)			(0.387)
SPGSCI				0.284		-0.130
				(0.494)		(0.570)
DOL					-3.472**	-3.692*
					(1.764)	(2.084)
R^2	0.002	0.001	0.013	0	0.005	0.018

Table 5: This table reports panel regression results of 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. 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.

	Coeff.	(Std. err.)
Volcker	-0.038	(0.044)
MKT	6.883^{***}	(2.571)
DVIX	0.041^{*}	(0.023)
IR5Y	0.505	(0.505)
TERM	-0.850^{*}	(0.465)
DEF	-0.385	(0.768)
SPGSCI	0.899	(0.966)
DOL	-4.283	(3.943)
Volcker $\times$ MKT	-8.371^{***}	(2.928)
Volcker $\times$ DVIX	-0.044^{*}	(0.024)
Volcker $\times$ IR5Y	-0.499	(0.613)
Volcker $\times$ TERM	0.787	(0.555)
Volcker $\times$ DEF	-1.090	(0.871)
Volcker $\times$ SPGSCI	-1.289	(1.143)
Volcker $\times$ DOL	-0.731	(4.565)
R^2	0.033	
N	2913	

Table 6: This table reports the reduction in weekly predicted losses post-Volcker in response to a shock to the market portfolio (MKT). Based on our estimates of the change in the sensitivity to the market portfolio post-Volcker reported in Table 5, we calculate the predicted change in the P/L normalized by VaR and then multiply this change by the Mean VaR (top panel) or Maximum VaR (bottom panel) to obtain the decline in dollar losses associated with the market shock. We also report the losses expressed as a percentage of market risk weighted assets (RWA) or common equity Tier 1 capital (CET1).

	Mean VaR								
	USD million			% of market RWA			% of CET1		
shock	total	min	max	total	min	max	total	min	max
5%	397.43	0.36	92.48	0.06%	0.04%	0.18%	0.04%	0.00%	0.11%
10%	794.85	0.71	184.95	0.12%	0.09%	0.36%	0.09%	0.00%	0.22%
20%	1,589.71	1.42	369.91	0.25%	0.18%	0.71%	0.17%	0.01%	0.44%
	Maximum VaR								
	USD million			% of market RWA			% of CET1		
shock	total	min	max	total	min	max	total	min	max
5%	755.98	0.71	211.30	0.12%	0.08%	0.45%	0.08%	0.00%	0.20%
10%	1,511.95	1.42	422.61	0.23%	0.17%	0.89%	0.16%	0.01%	0.40%
20%	3,023.91	2.84	845.22	0.47%	0.34%	1.79%	0.33%	0.02%	0.79%

Table 7: This table reports the reduction in annual predicted losses post-Volcker in response to a shock to the market portfolio (MKT). Based on our estimates of the change in the sensitivity to the market portfolio post-Volcker reported in Table 5, we calculate the predicted change in the P/L normalized by VaR and then multiply this change by the Mean VaR (top panel) or Maximum VaR (bottom panel) to obtain the decline in dollar losses associated with the market shock. We also report the losses expressed as a percentage of market risk weighted assets (RWA) or common equity Tier 1 capital (CET1).

	Mean VaR								
	USD million			% of market RWA			% of CET1		
shock	total	min	max	total	min	max	total	min	max
5%	2,865.88	2.57	666.86	0.44%	0.32%	1.28%	0.31%	0.01%	0.79%
30%	17,195.30	15.41	4,001.17	2.67%	1.91%	7.69%	1.86%	0.08%	4.72%
65%	37,256.48	33.38	8,669.21	5.78%	4.14%	16.7%	4.04%	0.18%	10.2%
	Maximum VaR								
	USD million			% of market RWA			% of CET1		
shock	total	min	max	total	min	max	total	min	max
5%	5,451.43	5.12	1,523.74	0.85%	0.61%	3.23%	0.59%	0.03%	1.43%
30%	32,708.58	30.75	9,142.45	5.07%	3.67%	19.7%	3.54%	0.17%	8.57%
65%	70,868.58	66.62	19,808.65	11.0%	7.96%	41.9%	7.68%	0.36%	18.6%

Table 8: 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.

	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 9: 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). 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.

	Equities	Rates	Gov't	Credit	Securit.	FX	Comm.
Total	1322.29 [86.24]	2397.28 [124.36]	1840.96 [23.94]	1576.39 [6.14]	447.41 [13.45]	1772.89 [71.51]	562.08 [132.09]
Sovereign bonds	653.11	1569.77	1728.60 [21.81]	1020.77	239.20	1022.06	251.28
Corporate bonds	576.92	807.50	843.97	1063.88 [4.99]	51.93	760.82	152.98
Municipal bonds	103.63	229.36	244.31 [1.08]	201.87	23.75	156.51	11.75
Agency MBS	69.47	366.46	376.51 [1.05]	144.03	233.19	98.49	18.22
Non-agency MBS	76.71	259.02	204.99	289.11	341.44 [13.45]	109.01	18.22
CMO	45.43	235.68	227.85	133.15	241.04 [0.00]	66.32	18.22
Index CDS	451.82	795.12	705.78	1104.01 [0.87]	274.19	622.84	78.27
Single-name CDS	569.55	904.79	798.04	1201.04 [0.27]	249.86	747.85	142.91
Tranched credit	155.19	285.79	212.25	412.29 [0.00]	111.16	246.21	7.33
Linear equities	1163.62 [83.36]	792.37	599.21	570.37	55.01	859.73	350.94
Nonlinear equities	920.98 [2.28]	627.87	486.48	531.08	47.69	667.90	175.48
Exotic equities	351.83 [0.59]	245.14	208.24	241.67	3.54	257.79	113.18
Interest rates	916.00 [124.36]	2397.28	1680.27	1179.81	364.59	1569.32	404.04
FX	956.16	1569.32	1055.98	953.84	112.55	1772.89 [71.51]	420.18
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 10: This table reports panel regression results for the P/L normalized by VaR at the subportfolio level. 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	−0.022	−0.018	0.005	−0.012	−0.036	−0.042	−0.029
	(0.023)	(0.026)	(0.019)	(0.020)	(0.124)	(0.026)	(0.023)
MKT	4.390***	6.504**	3.695**	2.454*	23.55	6.991**	−0.356
	(1.510)	(3.116)	(1.465)	(1.445)	(15.30)	(3.477)	(1.307)
DVIX	−0.006	0.031	0.002	0.009	0.149	0.035	0.001
	(0.011)	(0.027)	(0.011)	(0.011)	(0.140)	(0.030)	(0.009)
IR5Y	0.048	−0.532	0.312	0.287	−4.206	−0.881	0.018
	(0.380)	(0.786)	(0.338)	(0.331)	(3.802)	(0.794)	(0.170)
TERM	−0.456	0.574	−0.570*	−0.561*	5.003	1.136	0.032
	(0.368)	(0.743)	(0.343)	(0.306)	(3.397)	(0.735)	(0.157)
DEF	0.040	−0.320	−0.346	−0.205	−0.740	−0.232	0.406**
	(0.475)	(0.437)	(0.333)	(0.329)	(2.127)	(0.476)	(0.168)
SPGSCI	−1.560	0.559	−1.108	−0.435	6.369	1.003	−0.941
	(1.142)	(1.090)	(0.809)	(0.863)	(4.478)	(1.042)	(0.812)
DOL	−3.443	−4.691	−1.562	−1.790	−3.359	−3.923	−4.851***
	(2.638)	(6.965)	(1.855)	(2.110)	(39.45)	(7.995)	(1.701)
Volcker × MKT	−4.001**	−6.918**	−4.187***	−2.770*	−25.43	−6.966*	2.536
	(1.687)	(3.198)	(1.605)	(1.601)	(15.61)	(3.600)	(1.937)
Volcker × DVIX	0.006	−0.030	−0.003	−0.008	−0.139	−0.030	0.008
	(0.012)	(0.027)	(0.011)	(0.011)	(0.141)	(0.031)	(0.012)
Volcker × IR5Y	−0.287	0.425	−0.387	−0.433	4.764	0.864	−0.372
	(0.402)	(0.792)	(0.355)	(0.350)	(3.928)	(0.824)	(0.359)
Volcker × TERM	0.797**	−0.404	0.705**	0.817**	−5.613	−1.030	0.333
	(0.391)	(0.762)	(0.359)	(0.329)	(3.595)	(0.779)	(0.347)
Volcker × DEF	−0.414	−0.186	−0.187	−0.303	−0.435	−0.322	−0.334
	(0.503)	(0.457)	(0.377)	(0.397)	(2.180)	(0.511)	(0.298)
Volcker × SPGSCI	1.820	−0.685	1.056	0.391	−6.727	−1.150	0.630
	(1.179)	(1.096)	(0.846)	(0.898)	(4.465)	(1.060)	(0.943)
Volcker × DOL	2.617	2.772	0.223	0.593	6.248	1.213	−0.501
	(2.778)	(6.981)	(1.988)	(2.210)	(39.59)	(8.022)	(2.930)
R^2	0.002	0.001	0.002	0.001	0.002	0.001	0.004
N	38,216	71,973	52,820	49,328	11,342	57,581	11,680

Table 11: This table reports panel regression results of P/L normalized by VaR on our risk factors interacted with the Volcker indicator variable ("Volcker") and with an indicator variable ("Treated") for SLR/LCR banks (column 1) or CCAR banks (column 2). 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 (column 1) or CCAR (column 2), 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	
Volcker	−0.035	(0.059)	−0.015	(0.045)
MKT	10.264**	(5.061)	6.648**	(2.600)
DVIX	0.084*	(0.047)	0.034	(0.023)
IR5Y	0.689	(1.153)	0.398	(0.520)
TERM	−0.748	(0.899)	−0.781*	(0.474)
DEF	−0.577	(0.650)	−0.446	(0.781)
SPGSCI	1.243	(1.216)	0.699	(0.960)
DOL	1.676	(6.265)	−4.078	(3.968)
Volcker × Treated	−0.003	(0.050)	−0.101***	(0.038)
Volcker × MKT	−11.953**	(5.300)	−8.038***	(2.922)
Treated × MKT	−4.415	(5.127)	1.255	(3.019)
Volcker × DVIX	−0.088*	(0.048)	−0.039	(0.024)
Treated × DVIX	−0.057	(0.045)	0.030	(0.020)
Volcker × IR5Y	−0.012	(1.203)	−0.355	(0.602)
Treated × IR5Y	−0.242	(1.264)	0.494	(0.667)
Volcker × TERM	0.395	(0.944)	0.799	(0.535)
Treated × TERM	−0.132	(0.952)	−0.342	(0.650)
Volcker × DEF	−0.587	(0.795)	−0.549	(0.837)
Treated × DEF	0.249	(0.497)	0.310	(0.451)
Volcker × SPGSCI	−2.061	(1.490)	−0.869	(1.084)
Treated × SPGSCI	−0.448	(1.695)	0.884	(1.001)
Volcker × DOL	1.275	(6.806)	−0.613	(4.421)
Treated × DOL	−7.779	(7.081)	−1.072	(3.131)
Volcker × Treated × MKT	4.677	(5.791)	−1.682	(3.449)
Volcker × Treated × DVIX	0.058	(0.047)	−0.022	(0.022)
Volcker × Treated × IR5Y	−0.630	(1.349)	−0.658	(0.754)
Volcker × Treated × TERM	0.509	(1.079)	−0.011	(0.777)
Volcker × Treated × DEF	−0.652	(0.911)	−2.390***	(0.918)
Volcker × Treated × SPGSCI	1.006	(1.945)	−1.835	(1.292)
Volcker × Treated × DOL	−2.576	(7.809)	−0.329	(4.547)
R^2	0.04		0.04	
N	2913		2913	

Table 12: This table reports panel regression results of P/L normalized by VaR on our risk factors interacted with the Volcker indicator variable ("Volcker") and with an indicator variable for bank size ("Top"), either by by total risk weighted assets (column 1) or by market risk weighted assets (column 2). The Volcker indicator takes the value of one after the introduction of the Volcker rule in April 2014 and zero otherwise. The Top indicator takes the value of one if a bank belongs to the top quartile by total risk weighted assets (column 1) or by market risk weighted assets (column 2), 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.

	Q4/Q3-1 RWA		Q4/Q3-1 mRWA	
Volcker	0.039	(0.033)	−0.002	(0.033)
Volcker × Top	−0.143***	(0.041)	−0.067	(0.048)
MKT	5.982***	(2.199)	5.309**	(2.295)
DVIX	0.038*	(0.021)	0.040*	(0.022)
IR5Y	0.903**	(0.455)	0.927	(0.569)
TERM	−1.241***	(0.457)	−1.116**	(0.480)
DEF	−0.655	(0.496)	−0.370	(0.418)
SPGSCI	0.468	(0.670)	0.883	(0.766)
DOL	0.820	(3.301)	−1.630	(3.711)
Volcker × MKT	−6.900***	(2.526)	−6.929***	(2.566)
Top × MKT	1.719	(3.310)	2.928	(4.268)
Volcker × DVIX	−0.039*	(0.021)	−0.046**	(0.023)
Top × DVIX	0.005	(0.020)	0.001	(0.030)
Volcker × IR5Y	−0.911*	(0.518)	−0.599	(0.627)
Top × IR5Y	−0.742	(0.668)	−0.789	(0.981)
Volcker × TERM	1.036**	(0.504)	0.619	(0.534)
Top × TERM	0.727	(0.568)	0.498	(0.772)
Volcker × DEF	−0.134	(0.579)	−0.516	(0.531)
Top × DEF	0.514	(0.702)	−0.025	(0.849)
Volcker × SPGSCI	−0.895	(0.798)	−1.748*	(0.932)
Top × SPGSCI	0.800	(1.599)	0.026	(1.800)
Volcker × DOL	−1.982	(3.713)	2.855	(4.216)
Top × DOL	−9.595	(5.910)	−4.979	(7.045)
Volcker × Top × MKT	−2.778	(4.002)	−2.684	(4.972)
Volcker × Top × DVIX	−0.009	(0.023)	0.005	(0.032)
Volcker × Top × IR5Y	0.769	(0.881)	0.191	(1.113)
Volcker × Top × TERM	−0.462	(0.751)	0.307	(0.955)
Volcker × Top × DEF	−1.787*	(1.076)	−1.070	(1.200)
Volcker × Top × SPGSCI	−0.732	(1.806)	0.856	(2.033)
Volcker × Top × DOL	2.442	(6.573)	−6.608	(7.674)
R^2	0.049		0.048	
N	2913		2913	

Table 13: This table reports panel regression results of P/L normalized by VaR 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. 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.

	Coeff.	(Std. err.)
Reporting	-0.051	(0.045)
MKT	2.831^{*}	(1.448)
DVIX	0.021^{**}	(0.009)
IR5Y	0.245	(0.293)
TERM	-0.406	(0.287)
DEF	-0.926^{**}	(0.439)
SPGSCI	-0.173	(0.665)
DOL	-0.349	(2.295)
Reporting×MKT	-4.437^{**}	(2.086)
Reporting×DVIX	-0.028^{**}	(0.011)
Reporting×IR5Y	-0.384	(0.380)
Reporting×TERM	0.573	(0.443)
Reporting×DEF	-0.388	(0.689)
Reporting×SPGSCI	0.080	(0.736)
Reporting×DOL	-9.086^{***}	(2.633)
R^2	0.03	
N	2913	

Figures

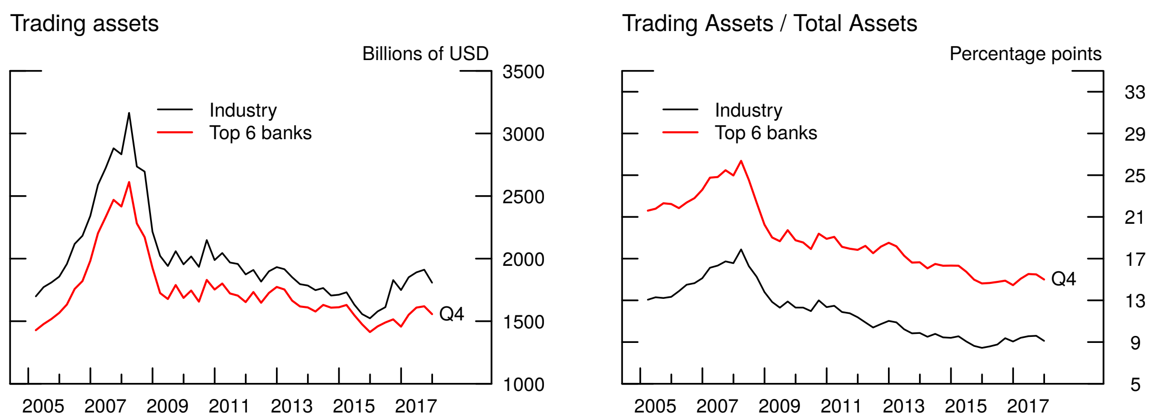

Figure 2: This figure plots the dollar trading assets (left panel) and the ratio of trading assets to total assets for the US banking industry as a whole and separately for the top 6 banks. The data are obtained from form FR-Y9C for bank holding companies and Form 10-K for investment banks.

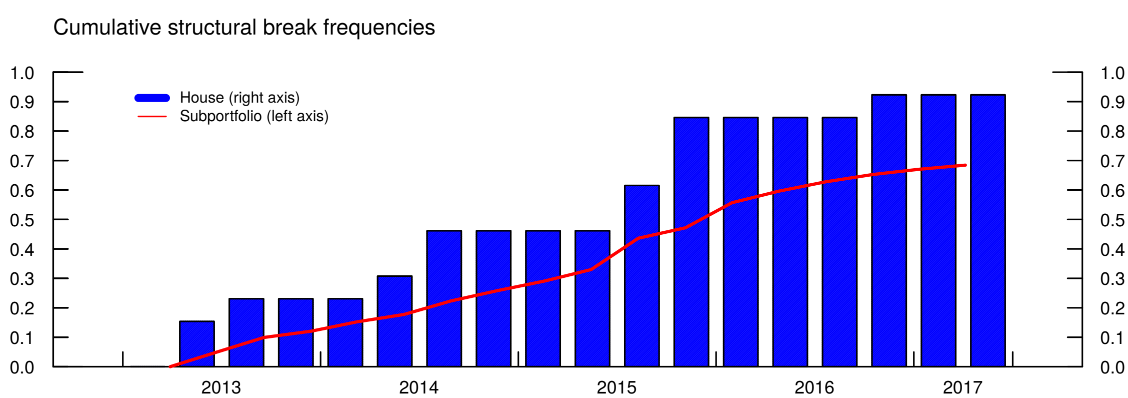

Figure 3: This figure plots the cumulative frequency of structural brakes in the sensitivity of the P/L normalized by VaR to the market return (MKT). We report results at the top-of-the-house level (line) and at the subportfolio level (bars).

Appendix

Table 14: This table reports panel regression results of P/L normalized by market risk capital 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. 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.

	Coeff.	(Std. err.)
Volcker	-0.001^{*}	(0.001)
MKT	0.104^{**}	(0.041)
DVIX	0.001^{*}	(0.0004)
IR5Y	0.007	(0.010)
TERM	−0.012	(0.008)
DEF	−0.008	(0.015)
SPGSCI	0.024	(0.019)
DOL	−0.064	(0.059)
Volcker × MKT	-0.118^{***}	(0.043)
Volcker × DVIX	-0.001^{*}	(0.0004)
Volcker × IR5Y	−0.004	(0.010)
Volcker × TERM	0.010	(0.009)
Volcker × DEF	−0.021	(0.016)
Volcker × SPGSCI	−0.030	(0.019)
Volcker × DOL	0.017	(0.063)
R^2	0.033	
N	2913	