Decomposing Large Banks' Systemic Trading Losses

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Abstract

Simultaneous trading losses by large banks have been key to worsening the crises of 2008 and 2020. But do banks realize simultaneous trading losses because they invest in the same assets, or because different assets are subject to the same macro shocks? This paper decomposes the comovements of bank trading losses into two orthogonal channels: portfolio overlap and common shocks. While portfolio overlap generates strong comovements, I find that the sensitivity to common shocks from non-overlapping assets is higher. This sensitivity operates through two sub-channels: the short-long interest rate correlation and the stock-bond correlation, driven by macroeconomic factors. This reveals a new tradeoff whereby reductions in portfolio overlap can boost the comovement of trading losses by increasing exposures to multi-asset macro shocks. I show that these exposures are not well buffered by Basel capital requirements, and propose three avenues to improve the Basel III standard.

Keywords: portfolio choice, portfolio overlap, diversification, systemic liquidity risk.

JEL Classification: G10, G11, G20.

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1 Introduction

The Great Financial Crisis of 2008 and the Covid-induced market crash of 2020 have served as stark reminders of how trading losses can place sudden and sharp liquidity demands on systemically important banks, reducing both market liquidity and funding liquidity (Basel Committee on Bank Supervision, 2022; Brunnermeier and Pedersen, 2009). The ability of such losses to affect key institutions at the same time has led to extensive regulatory reforms (e.g. the Dodd-Frank Act and the Volcker rule) as well as calls to manage derivatives risks jointly across banks (Cruz-Lopez et al., 2017). Nonetheless, the limited availability of trading position data has curtailed the understanding of why trading losses comove, and whether these comovemets are adequately buffered by macroprudential capital requirements. This paper offers a deeper look at this question.

Traditionally, the tendency of large banks to score simultaneous trading losses has been ascribed to portfolio overlap, whereby different institutions invest in the same assets (Allen and Gale, 2000; Menkveld, 2017; Poledna et al., 2021; Caccioli et al., 2014; Bradoscia et al., 2019). However, portfolio overlap does not fully capture the correlation in bank trading positions. For example, consider bank A, which only holds stock futures, and bank B, which only holds interest rate futures. These two banks do not hold the same assets. Nevertheless, a macro shock that affects both the stock market and interest rates can simultaneously inflict trading losses on both banks. Such macro shocks to the stock market, employment, inflation, and interest rates materialized in both 2008 and 2020, simultaneously affecting multiple financial assets. I label this comovement channel, hitherto unexplored in the literature, the *common shocks channel*, and explore its ability to produce correlated trading losses across systemically important banks. This paper therefore answers two simple, but important questions related to macroprudential risk. First, which of these two comovement channels is stronger — portfolio overlap or common shocks? And second, if common shocks are important, does the Basel III regulation adequately buffer against them?

The paper addresses these questions by decomposing the comovements of bank trading incomes into two comprehensive orthogonal channels: portfolio overlap and common shocks to non-overlapping assets, using proprietary positions data on equity and interest rate derivatives traded at the Montreal Exchange during the Great Financial Crisis. These two channels are comprehensive (in the sense that they are exhaustive of comovement sources) and they are orthogonal in the sense that they operate independently and are uncorrelated. Quantifying them separately allows me to gauge their relative importance and juxtapose them against the relevant Basel III standards for correlated market risks.

I show that, while portfolio overlap plays a major role in generating comovements in bank trading incomes, banks' sensitivity to common shocks from non-overlapping assets is larger. This sensitivity operates through two sub-channels: the short-long interest rate correlation and the stock-bond correlation, which in turn are driven by macroeconomic factors such as inflation, employment, and monetary policy. For example, I find that one standard deviation increase in portfolio overlap boosts the likelihood of core banks realizing simultaneous losses or profits by up to 22.2 percentage points, but a one-standard deviation shock to employment growth, inflation, and a 25-basis point monetary policy tightening increases this probability by up to 6, 16.7, and 28 percentage points, respectively, creating a larger cumulative effect. This result is important because, as I show, Basel III capital requirements treat common shocks inconsistently across asset classes and, in some cases, inadequately within classes, creating capital gaps. My results also show a new tradeoff between portfolio overlap and differentiation, whereby reductions in portfolio overlap (normally seen as reducing macroprudential risk) in reality boost trading loss comovements from common shocks. This sensitivity to common shocks is the highest when there is a combination of upward shocks to inflation, employment and interest rates, as in the recent historical experience. To mitigate the effects of such common shocks, I present three policy options for revising the Basel III standard and advocate for a higher regulatory scrutiny on internal risk models.

I focus on the derivatives market because of its outsized role in risk propagation, rooted in the concept of marking to market. Marking to market is the practice of daily portfolio revaluation according to current market prices, whereby daily losses must be collateralized dollar for dollar with high quality liquid assets known as variation margin (VM). This can create substantial liquidity shocks for banks. Variation margin calls reached record levels during the 2020 downturn, rising globally from about 25 billion in February 2020 to 140 billion on March 9, 2020, an increase of 460%. This increase affected all asset classes, with approximately 85 billion worth of VM calls from derivatives,[1] quickly tying up large sums of liquid assets and prompting some participants to perform fire sales (Basel Committee on Bank Supervision, 2022), which tend to increase risk

[1] Exchange-traded derivatives plus OTC interest rate and foreign exchange swaps.

propagation (Shleifer and Vishny, 2011; Coval and Stafford, 2007). Variation margin calls were likewise responsible for substantial risk propagation in the credit default swaps market in 2008 (Paddrick, Rajan and Young, 2020), and have been studied extensively as a risk propagation device both theoretically and empirically (Biais, Heider, and Hoerova, 2021; Menkveld, 2017; Cifuentes et al., 2005). Aggregate VM calls in my 2008 futures data (discussed in the next section) increased by 452%. Moreover, although futures can be used to hedge investments in other markets, the timing mismatch between VM collection (due end of day) and VM profit payouts (paid next morning) leaves banks exposed to overnight liquidity risk even when such hedging takes place.[2] This institutional feature has key implications for systemic liquidity risk. It implies overnight liquidity risk is retained independent of any potential hedging, which increases the chance of market disruptions when multiple banks face large margin calls as a group. Behaviors aimed at avoiding this problem, such as hoarding liquidity, can instead lead to systemic disruptions (Gai and Kapadia, 2010; Gai et al., 2011). Thus, simultaneous losses caused by portfolio overlap and common shocks to non-overlapping assets both increase systemic liquidity risk through marking to market.

While portfolio overlap has been identified as one of the culprits for such contagion, there is much less agreement on its sources. For example, Menkveld (2017) finds evidence of overlap due to banks concentrating on the same asset, while Wagner (2010, 2011) shows that systemic liquidation costs motivate banks to diversify in the same way, causing overlap due to diversification instead.[3] These two conjectures have diametrically opposing implications. An even more conspicuous gap in the literature is the lack of quantification of the common shocks comovement channel, which, as I show, significantly contributes to loss comovements.

To jointly address these questions, I perform a comprehensive multi-stage decomposition of the factors behind Canadian banks' trading income comovements. It is described in Figure 1. The paper decomposes these comovements into two orthogonal drivers: portfolio overlap, measured by a cosine similarity metric, and common shocks across non-overlapping assets, measured by these assets' return correlations (boxes 2 and 3 in Figure 1). The overlap channel captures comovements solely due to different portfolios containing the same assets. By contrast, the common shocks

[2]In the case of the Montreal Exchange, this rule is codified in the rules of its affiliated central counterparty, the Canadian Derivatives Clearing Corporation (CDCC). See CDCC Operations Manual, Section 2-2 at `www.cdcc.ca/publications_rules_en`.

[3]For example, consider the 3-bank, 3-asset economy from Abad et al. (2022), p. 11. Each bank is fully diversified and holds the portfolio $(1/3, 1/3, 1/3)$, resulting in 100% overlap. A shock to any asset affects all 3 banks at once.

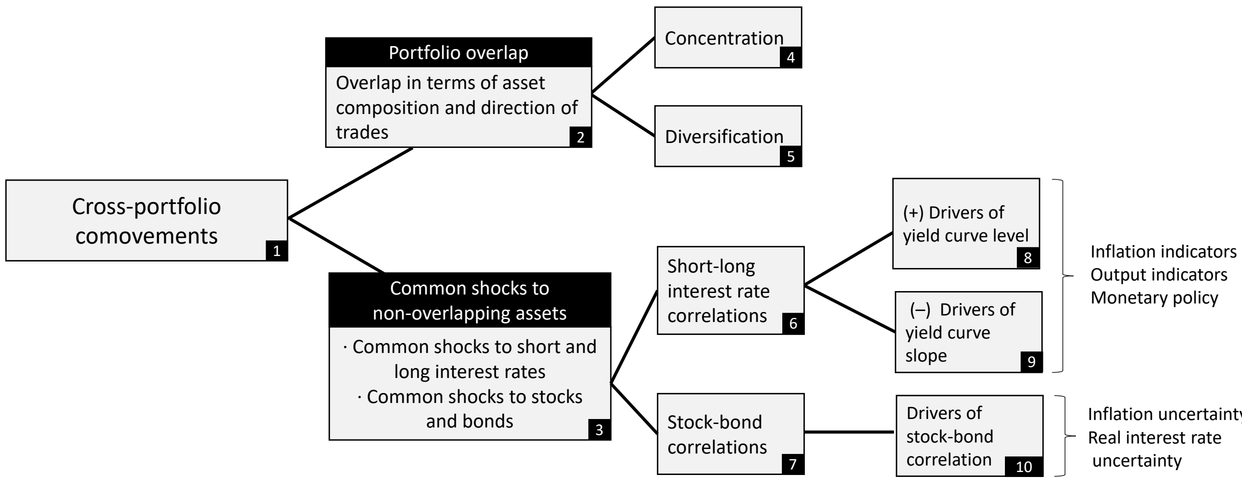

Figure 1: A schematic of the decomposition of portfolio comovements performed in the paper.

channel captures the tendency of unrelated assets to move together (especially during crises). In my data, such unrelated (non-overlapping) assets are futures based on the stock market or on interest rates at the opposite ends of the maturity spectrum. These two channels operate independently: their correlation in my sample is less than 0.01.

I measure the comovement of large banks' trading profits and losses (P&Ls) in two complementary ways: with the probability of joint profits or joint losses, and with the correlation of those P&Ls. These measures treat gains and losses symmetrically, since banks scoring simultaneous gains on a given contract will automatically score simultaneous losses when its price reverses direction. I quantify the influence of each channel separately for core and non-core banks, including the heterogeneous influence of concentrated positions. My results confirm that portfolio overlap was a major comovement driver for both core and non-core banks, which increases the probability of simultaneous losses (gains) by 9 to 10 percentage points for core banks and 7.6 to 8.4 percentage points for non-core banks per one-standard deviation increase in portfolio overlap.

To test competing propositions for portfolio overlap, I decompose overlap into concentration versus diversification (boxes 3 and 4 in Figure 1). I discover that core banks were more diversified as a whole, yet still featured a higher degree of portfolio overlap, consistent with Wagner's (2010, 2011) diversification theory. This high degree of overlap suggests that core banks took the same side of the same trades against the remaining banks, which increases the risk to financial system stability. At the same time, I find that core banks with more concentrated (less diversified) positions experienced a higher increase in the probability of simultaneous gains or losses, consistent with Menkveld's (2017) findings.

On the other hand, the common shocks channel (box 3 in Figure 1) captures the fact that portfolios can comove because of common shocks even without any asset overlap. Since my data contains interest rate and stock market futures, the comovement sources for non-overlapping assets are correlations across interest rates at different maturities and the correlation between interest rates and the stock market (the stock-bond correlation). Hence, I decompose cross-asset correlations into correlations between short and long interest rates and those between interest rates and the stock market (boxes 6 and 7 in Figure 1). I first decompose interest rate correlations into changes in yield curve level, slope and curvature. Both level and slope are highly statistically significant, with level shifts increasing the correlation between short and long interest rates, and slope changes decreasing it, in line with expectations. This motivates me to further look at the variables shaping the yield curve, and link them to portfolio-level comovements.

This exercise, grounded in the yield curve literature (Nelson and Siegel, 1987; Diebold and Li, 2006; Diebold, Rudebusch, and Aruoba, 2009; Evans and Marshall, 1989) is shown in boxes 8, 9 and 10 of Figure 1. It reveals a number of macro factors already known to shape the yield curve (inflation, output-related variables, and monetary policy) as statistically significant contributors to *bank-level* portfolio comovements via interest rate correlations. This new result shows a direct link between the macroeconomy and comovements between individual banks' portfolios.

For example, I find that a one-standard deviation shock to inflation increases the correlation between short and long interest rates and thereby the probability of simultaneous gains or losses for core banks by 6 percentage points. Similarly, a one-standard deviation shock to employment growth increases the chance of simultaneous gains or losses by 16.3 to 16.7 percentage points via the interest rate correlation channel. Finally, a 25-basis point monetary policy shock increases the chance of joint profits or losses by 27 to 28 percentage points via the short-long interest rate correlation. These marginal effects, evaluated at the banks' average portfolio compositions, are economically significant, and, taken together, exceed the sensitivity of comovements to portfolio overlap, even when the latter is interacted with portfolio concentration.[4] To my knowledge, this is the first result comparing the economic importance of common shocks against portfolio overlap.

[4] The latter cumulative effect is 22.2 percentage points based on the coefficients in column (7), Table 5.

My final decomposition is to trace remaining portfolio comovements down to the driving factors behind stock-bond correlations (box 10 in Figure 1). Consistent with Li (2002), Campbell et al. (2017) and Piazzesi and Schneider (2006), I find that, as a driver behind the stock-bond correlation, inflation uncertainty contributes to portfolio-level comovements via non-overlapping stock and interest rate futures. I find that a 0.25 percentage points increase in the standard deviation of inflation results in 8 percentage points higher comovement probability for core banks.

This paper contributes to several literatures. A long strain of banking papers have argued that banks have incentives to undertake correlated investments that increase their comovements. For example, Acharya and Yorulmazer (2005) argue that banks do not internalize the costs of joint failure because of limited liability, thus creating incentives to undertake correlated investments. In Acharya and Yorulmazer (2006 and 2007), banks make correlated investments to increase the likelihood of failing simultaneously to incentivize regulators to bail them out. In Wagner (2010), banks dislike being correlated, but interbank commonality arises as an unwanted side effect of diversification. Motivated by these results, the empirical literature has focused on quantifying portfolio overlap. For example, Poledna et al. (2021) conclude that at least half of the systemic risk in the financial system in Mexico comes from portfolio overlap, while Caccioli et al. (2014) find that portfolio overlap and direct default exposures amplify each other. Bradoscia et al. (2019) show that several UK institutions could experience liquidity shortfalls due to the directionality of their portfolios. Menkveld (2017) finds important correlated risks in the European equity markets as a result of crowding on Nokia stock.

The paper also contributes to the discussion on the adequacy of the Basel regulatory framework. In the spirit of Freixas et al. (2015), it questions capital adequacy against macroprudential risks, but in the context of trading shocks and the newer Basel III standard. Similar to Danielson et al.'s (2001) critique of Basel II, it raises concerns that some of the inadequate modeling of the joint downside risk of different assets has persisted in Basel III. Multiple other papers discuss the evolution of the Basel framework and its effects (e.g. Wagster, 1996; Borio et al., 2001; Mariathasan and Merrouche, 2014; Gehrig and Iannino, 2021). Overall, my paper provides further insight into the sources of banks' common trading exposures during the 2008 crisis and their capital treatment.

2 Market background and data

My data consists of the proprietary end-of-day futures positions of Montral Exchange participants between January 2, 2003 and March 31, 2011. The Montreal Exchange, owned by the TMX Group, is the principal marketplace for exchange-traded futures in Canada. It includes the core Big Six Canadian banks (RBC, TD, Bank of Montreal, CIBC, Scotiabank, and National Bank), smaller domestic institutions, as well as important international banks such as J.P. Morgan, Goldman Sachs, and Merrill Lynch. Proprietary trading in this market is dominated by Canadian banks; foreign participants have relatively small own volumes but mainly serve as a conduit for indirect clients seeking access to this market (Raykov, 2022). Since not all Montreal Exchange participants engage in proprietary trading, the active institutions covered in my sample are listed in Table 1; they are anonymized in the analysis because of data disclosure requirements.[5] The market is centrally cleared through the Canadian Derivatives Clearing Corporation (CDCC), a TMX Group subsidiary, which kindly provided the data.

In 2020, the average notional amount traded daily in Canadian futures was $113.46 billion in approximately 15 broad contract categories (short-term interest rate futures, bond futures, various share futures, index futures, repo and index swap futures, and sector index futures). Total futures trading accounted for an average volume of 321,386 contracts daily, with an average open interest of 2.47 million contracts monthly. These figures reflect both banks' proprietary trading positions and trades undertaken on behalf of investment clients for which Montreal Exchange member banks serve as a conduit.

For the main analysis, I use the end-of-day proprietary positions data on 113 distinct futures contracts traded at the Montreal Exchange between January 2, 2003, and March 31, 2011, belonging to three general types: short-rate, long-rate, and stock market. The short-rate futures are Canadian bankers' acceptance futures (BAX), defined over the 3-month Canadian Dollar Offer Rate (CDOR). The long-rate futures contract is the 10-year Government of Canada bond futures (CGB), while the S&P/TSX 60 index standard future (SXF) is an index future over the 60 most liquid Canadian stocks.

Collectively, these three contracts represent over 90% of the value of futures positions and over

[5] An institution is considered active in the proprietary trading market if its firm account has at least one open position on at least half of the trading days in the sample period.

75% of all derivatives, and are highly representative of Canada's derivatives market (Campbell and Chung, 2003; TMX Montreal Exchange, 2013a, 2013b, 2013c). The summary statistics for open position values by bank type and period are shown in Table 2. The table shows that core banks were more active in holding futures, with an average daily position between 1.5 and 1.8 billion dollars, while the average non-core bank held between 0.58 and 0.63 billion dollars in futures; most of the large banks' counterparties appear to be clients of large US banks (Raykov, 2022). The futures market was not hit as hard as some others (e.g., the market for credit default swaps) during the 2008 crisis. The stock market future SXF scored the largest price move of 10.2%, while maximum price moves for CGB and BAX were 1.99% and 0.35%, respectively. Aggregate daily losses (aggregate VM called) for Canadian futures increased by 452% from an average of 72.1 million (July–August 2008) to 398 million on September 29, 2008. The largest recorded daily VM call facing a single institution in my data is 89 million on proprietary positions and 171.2 million on combined positions including clients. However, under CDCC's current rules, which no longer allow margin netting between client and proprietary positions, clients alone would have generated 401 million CAD worth of VM calls in addition to the 89 million on proprietary positions.

The positions dataset is merged with control variables to form a daily panel, which I use to relate P&L comovements to the underlying portfolio characteristics. Macro variables that can influence the covariance of non-overlapping assets, such as inflation, employment growth, industrial production, the Bank of Canada policy rate, and the 3-month CDOR rate, are sourced from Haver Analytics. Data on the 5- and 10-year swap rates for the yield curve decompositions, as well as the S&P TSX 60 Index, are obtained from Thomson Reuters Datastream. Summary statistics of the variables used in the analysis are shown in Table 2.

3 Empirical Strategy

The main goal of this paper is to trace observed P&L comovements down to the underlying characteristics of the comoving portfolios, such as their overlap, concentration, and holdings of non-overlapping, but correlated assets. I first describe how I measure portfolio characteristics.

3.1 Measures of portfolio characteristics

3.1.1 Portfolio comovements

The systemic risk literature has emphasized the risk posed by the simultaneous nature of gains and losses across important financial institutions.[6] This literature argues that interbank comovements should be measured relative to a benchmark including the most important systemic banks, since if core banks become subject to the same shocks, they can more easily spread financial distress to the remaining financial system. To do so, stock-price based systemic risk measures such as MES (Acharya et al., 2017) and ΔCoVaR (Adrian and Brunnermaier, 2017) benchmark individual banks' worst stock returns against those of a stock market index; however, this approach is inapplicable to derivatives markets, because the latter are inherently zero-sum. Moreover, stock-based measures are unhelpful in separating the liquidity risk from derivatives, which is the focus of this paper. To adapt these authors' ideas to the derivatives market, instead I benchmark each individual bank's futures return to that of an index of core banks, which are systemically important without comprising the full market. I do so by creating a futures return index of the Big Six Canadian banks in Table 1 (henceforth, the core banks) as a value-weighted index of their futures returns:

$$R_{c,t} = \sum_i w_{i,t} R_{i,t}, \quad \text{where} \quad i \in BigSix, \tag{1}$$

$w_{i,t}$ are value weights, and $R_{i,t}$ is each bank i's aggregate portfolio return accross futures contracts. Each portfolio return is calculated as the portfolio's daily dollar P&L divided by the market value of the total portfolio as of the previous day. When bank i belongs to the core, I compute the core's $\text{P\&L}_{c,t}$ and return $R_{c,t}$ by excluding i from the core to prevent a mechanical correlation between the bank and the index. This preserves the ideas in Acharya et al. (2017) and Adrian and Brunnermaier (2017), while adapting them to the specifics of the derivatives market.

Next, I compute the comovements of each bank's profits and losses against those of the (remaining) core. This is easiest to accomplish by looking at how frequently each bank scores joint profits (losses) together with the core, either as a probability or as a correlation. Therefore I measure comovements in two complementary ways: as the probability of simultaneous daily profits or

[6] See, e.g., Acharya et al. (2017); Adrian and Brunnermaier (2017); Poledna et al. (2021); Caccioli (2014); Cifuentes et al. (2005); Menkveld (2017).

losses against the core, $\Pr\Big(\text{sign}(P\&L_{i,t}) = \text{sign}(P\&L_{c,t})\Big)$, and as the cross-sectional correlation $\rho(R_i, R_c)_t$ of the portfolio return of bank i versus the core, computed over a 3-month rolling window. These two measures treat simultaneous losses and simultaneous gains symmetrically, since banks with same-day gains on a given contract will automatically score same-day losses when the contract price reverses direction. The probability measure is proxied by a dummy variable $D_{i,c,t}$ equal to 1 if the P&L's of the bank and the core on day t have the same sign and equal to 0 otherwise, and used in probit regressions. This is my preferred measure because it is less prone to endogeneity (since the sign of realized day t return cannot influence portfolio characteristics chosen on day $t-1$), whereas the correlation measure requires an estimation window involving past time periods. However, correlations provide very similar results, as shown in the Internet Appendix.

Table 2 shows that, overall, core banks comoved considerably more with the remaining core than non-core banks. Core banks featured simultaneous gains or losses with the rest of the core 66% of the time during the normal period and 61.3% of the time during the crisis, with a standard deviation of 0.474 and 0.487, respectively; whereas non-core banks had simultaneous gains and losses against the core 53.6% and 52.6% of the time for each respective period, with a standard deviation of 0.499 in both cases.

3.1.2 Portfolio overlap

Not every two assets that comove are economically identical. Thus, a measure is needed to tell apart portfolios that comove because they are the same, i.e., because of portfolio overlap, from the rest. The most commonly used empirical measure of portfolio overlap is the cosine similarity metric (see, e.g., International Monetary Fund, 2023; Sias, Turtle, and Zykaj, 2016; Girardi et al., 2018; Bech et al., 2015). This metric captures both overlap and the direction of investment (long versus short), while retaining a high degree of intuitive appeal by producing a range of -1 to $+1$ (-1 for two portfolios taking opposite sides on the same trades, and $+1$ for two identical portfolios).[7] To compute cosine similarity for a market with n assets, portfolios are represented as vectors in n-space, with each vector component a_k of a vector $\mathbf{a}$ signifying the number of open contracts in asset k. By convention, long positions are denoted with positive numbers $a_k > 0$, and short positions with negative ones ($a_k < 0$). For two arbitrary position vectors $\mathbf{a}$ and $\mathbf{b} \in \mathbb{R}^n$, their

[7]For a comprehensive discussion of different measures of overlap, see Cha (2007).

cosine similarity measure of overlap is defined as the cosine of the angle θ between them, i.e.,

$$Overlap(\mathbf{a}, \mathbf{b}) = \cos(\theta) = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}. \tag{2}$$

Since opposite positions on the same trade have opposite signs, entities with same-sign cosine similarity are, on average, not counterparties to the same trades. One simple example for $n = 3$ over the asset types (BAX, CGB, SXF) are the portfolios $\mathbf{a} = (100, 50, -50)$, and $\mathbf{b} = (80, 60, -20)$, featuring cosine similarity $Overlap(\mathbf{a}, \mathbf{b}) = 12,000/(\sqrt{15,000}\sqrt{10,400}) = 0.96$. By contrast, the non-overlapping portfolios $\mathbf{c} = (100, 0, 0)$ and $\mathbf{d} = (0, 100, 0)$ have a cosine similarity of 0 because they have no assets in common and $a_k b_k = 0$ for every asset k.

I compute cosine similarity between each bank and the core at the individual contract level, which allows differentiating between contracts with different expiry dates corresponding to different economic bets.[8] In my case, the number of assets is $n = 113$. A benefit of this measure of portfolio overlap is that it focuses on portfolio composition, as prices do not enter the calculation; this allows me to cleanly separate cross-asset correlations as a source of comovement.

Table 2 shows that core banks exhibited significantly higher portfolio overlap with the (rest) of the core than non-core banks. Outside the crisis, core banks had an average overlap of 0.174, which increased to 0.381 during the crisis. Non-core banks overlapped with the core considerably less across both periods (0.103 outside the crisis and 0.284 during the crisis). The crisis featured an increase in both overlap and its variance. The standard deviation of overlap increased from 0.236 to 0.314 for core banks, and from 0.284 to 0.351 for non-core banks.

3.1.3 Banks' exposures to common shocks

Some macroeconomic shocks are so broad-based that they can simultaneously affect multiple assets, as in the example in the introduction. In my futures data, the distinct underlying assets that can be subject to such a multi-asset shock are the 3-month interest rate, the 10-year interest rate, and the stock market. To control for such multi-asset shocks, I calculate the two types of correlations:

[8] An investor may hold opposite positions in two contracts of the same type expiring on different dates in order to reflect a specific belief about the future evolution of market prices. For example, holding simultaneously a short position in a stock market future expiring in 1 month and a long position in the same future type expiring in 3 months indicates a belief that stock prices will fall in the next 1 month and then recover. Since these two contracts correspond to different economic bets, netting them out would be incorrect.

the short-long interest rate correlation $\rho(R_{3m}, R_{10y})$ and the stock-bond correlation $\rho(\bar{R}, Stock)$, where $\bar{R}$ is the average of the 3-month interest rate R_{3m} and the 10-year interest rate R_{10y}.[9] Both correlations are calculated over 3-month rolling windows. To the extent that there is a common shock to long and short interest rates, $\rho(R_{3m}, R_{10y})$ should increase correspondingly; likewise, a shock common to stock and bond markets should change $\rho(\bar{R}, Stock)$. Alternatively, if two assets face no common shocks, their correlation should be 0.

Since different banks are differently exposed to each of these two correlations, in the regressions, I further prorate them by the relevant bank's exposure γ to each correlation, based on its portfolio composition and direction of investment. For instance, if bank i holds no interest rate futures, then $\rho(R_{3m}, R_{10y})$ is irrelevant as a comovement source, and the bank's exposure γ^I to this correlation is 0; but if bank i and the core each hold only one of the two interest rate futures, then $\rho(R_{3m}, R_{10y})$ is their only source of comovement, so there is no need to prorate this correlation. When the individual bank and the core each hold multiple correlated assets, then the exposures γ^I to interest rate correlations and γ^S to the stock-bond correlation are prorated according to the fraction of such non-overlapping, but correlated assets held (the calculation of the exposures γ is detailed in the Internet Appendix.) Each bank i's overall exposure to common shocks is therefore captured by the exposure-weighted correlations across interest rate and stock market assets, $\gamma_i^I \rho(R_{3m}, R_{10y})$ and $\gamma_i^S \rho(\bar{R}, Stock)$. The common shocks channel, as captured by this overall exposure, is independent of portfolio overlap: the correlation between a bank's overlap and its overall exposure defined above is less than 0.01.[10]

3.1.4 Position concentration

To test whether portfolio overlap is due to concentration or diversification, I calculate a commonly used concentration measure, the Herfindahl-Hirsch concentration index (HHI), as the sum of squared asset shares in each bank's portfolio on the contract type level. Table 2 shows that core banks were more diversified overall, with an average HHI of 0.651 in the normal period, versus 0.741 for non-core banks. However, the onset of high volatility in the fall of 2008 spurred both bank types to additionally diversify. The average HHI fell to 0.632 for core banks, and to 0.731 for non-core

[9] The individual correlations between each interest rate and the stock market are very similar.

[10] The average correlation $\rho\Big(Overlap_{i,t}\ ,\ \gamma_i^I \rho(R_{3m}, R_{10y}) + \gamma_i^S \rho(\bar{R}, Stock)\Big) < 0.01$ in my sample. The correlations between overlap and $\gamma_i^I \rho(R_{3m}, R_{10y})$ or overlap and $\gamma_i^S \rho(\bar{R}, Stock)$ are each smaller than 0.04.

banks during the crisis. Table 2 also shows that the crisis period was characterized by an increase in portfolio overlap for both core and non-core banks, suggesting that banks increased both their diversification *and* the degree of overlap. This is in line with Wagner's (2011) predictions, which explain such behavior with systemic portfolio liquidation costs. These findings are even sharper when computing HHI on the individual contract level, and are robust to two alternative measures of concentration: the Tideman-Hall Index (THI) and the Entropy Concentration Index (ECI).[11] The standard deviation of HHI did not differ materially across bank type or period, remaining in the vicinity of 0.2.

3.2 Panel data model and estimation

To perform the decompositions in Figure 1, I perform a series of regressions on variations of the following panel data model, constructed at daily frequency:

$$\begin{aligned} Comove_t(R_i, R_c) = \alpha &+ \beta_1 Overlap_{i,t-1} + \beta_2 (Overlap_{i,t-1} * Crisis_{t-1}) + \\ &+ \beta_3 (Overlap_{i,t-1} * Concentrated_{i,t-1}) + \\ &+ \beta_4 (Overlap_{i,t-1} * Concentrated_{i,t-1} * Crisis_{t-1}) + \\ &+ \beta_5 \gamma^I_{i,t-1} \rho(R_{3m}, R_{10y})_{t-1} + \beta_6 \gamma^S_{i,t-1} \rho(\bar{R}, Stock)_{t-1} + u_i + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where $Comove(R_i, R_c)_t$ is a measure of the return comovement between bank i and the rest of the core, *Overlap* is a cosine similarity measure of bank i versus the core portfolio, *Concentrated* is a HHI-based measure of concentration, *Crisis* is a dummy variable for the 2008 financial crisis, and $\rho(\cdot, \cdot)$ are correlations across economically distinct asset classes, prorated by each bank's exposure γ to the relevant assets. I focus on each of these measures in turn.

In my baseline specification, $Comove(R_i, R_c)_t$ is the probability of simultaneous gains or losses of bank i and the core portfolio. Since the true probability is unobserved, to estimate the equation I resort to a discrete choice model with independent variable $D_{i,c,t}$ equal to 1 if the P&L's of the bank and the core on day t have the same sign, and equal to 0 otherwise. Since the sign of realized time t P&L's cannot influence portfolio characteristics chosen at time $t-1$, this rules out introducing

[11] The Tideman-Hall Concentration Index, or THI (Hall and Tideman, 1967), is considered more sensitive to the number of assets than HHI, and the Entropy Concentration Index or ECI (Jacquemin, 1975) is more sensitive to assets with small portfolio shares. However, the results with all three measures were so similar that the alternatives are not separately reported.

reverse causality (see Section 3.2.4, Endogeneity and Identification). Variants of this specification (some including *Crisis* and *Concentrated* as free terms)[12] are estimated with random effect panel probit regressions. This technique is more appropriate given the high collinearity of some banks' P&Ls.

To ascertain robustness, I re-estimate the panel with fixed-effects OLS and an alternative comovement measure, the pairwise return correlation between bank i and the core, $\rho(R_i, R_c)_t$, measured over a 3-month rolling window. It is regressed over 3-month moving averages of the independent variables, as in Falato et al. (2019). The Internet Appendix validates my main results with this measure, estimated with fixed-effects panel OLS with heteroscedasticity- and autocorrelation-robust Driscoll-Kraay standard errors. The bank-specific term u_i in equation (3) is, therefore, interpreted as a random effect in the random-effects model and as a fixed effect in the fixed-effects model.

To check if concentrated positions had a heterogeneous effect on interbank comovements, in different specifications I interact *Overlap* with two concentration measures based on the concentration index HHI: *Concentrated*, a binary variable equal to 1 for above-median position concentration of bank i, or else with *HiConcentrated*, a dummy equal to 1 for above-75th percentile concentration. The concentration measure is interacted with *Overlap* and a dummy variable labeled *Crisis*, equal to 1 during the period of heightened volatility in this market (September 1, 2008–December 31, 2009), allowing the effects of portfolio overlap and concentration to differ during the crisis period.

The first three lines of equation (3) capture the portfolio overlap channel shown in boxes 2, 4 and 5 of Figure 1. To capture the common shocks channel, which operates through correlations across non-overlapping assets, I include controls for cross-asset correlations. In particular, I include the correlation $\rho(R_{3m}, R_{10y})$ between the interest rates underlying BAX and CGB futures, that is, the 3-month CDOR interest rate R_{3m} and the 10-year swap rate R_{10y}, and the correlation $\rho(\bar{R}, Stock)$ between the average of the latter two interest rates and the stock market, as captured by the S&P TSX 60 stock market index (the underlying asset for SXF futures).[13] These two correlations are

[12]The baseline does not include *Crisis* and *Concentrated* as free terms since the effects of crisis and concentration cannot occur outside of either portfolio overlap or a common shock, both of which are included as controls. Specifications including these two free terms produce results nearly identical to the baseline, so they are not reported separately.

[13]I average the short and long interest rates because their pairwise correlations with the stock market are very similar.

included in the last line of equation (3).

A bank's exposure to cross-asset correlations depends on its portfolio composition. For example, a long BAX-only portfolio will comove positively with a long CGB-only portfolio and *negatively* with a short CGB-only portfolio, because in the latter case, the positive correlation between 3-month and 10-year interest rates will cause losses for one side when the other side has a profit. In addition, as other assets are added to each portfolio, the influence of the BAX-CGB correlation should wane commensurately with BAX's and CGB's reduced portfolio shares. Not controlling for portfolio composition, including directionality, can severely bias the results. The two exposure factors γ^I and γ^S, pre-multiplying the correlations ρ, control for the magnitude and sign of the bank's exposure to each of the two correlations $\rho(R_{3m}, R_{10y})$ and $\rho(\bar{R}, Stock)$, based on the relevant portfolio shares of correlated assets. They prorate the bank's exposure to a given cross-asset correlation commensurate with the bank's holdings of correlated non-overlapping assets, taking into account position direction. The details of the construction are listed in the Internet Appendix.

3.2.1 Yield curve determinants of interest rate correlations

Short and long interest rates, whose correlation $\rho(R_{3m}, R_{10y})$ can impact portfolio-level comovements, are related to each other through the yield curve describing the overall term structure of interest rates. The bond market literature decomposes the yield curve into three factors: a level factor representing the long term, a slope factor representing the short term, and a curvature factor representing the medium term (Nelson and Siegel, 1987; Diebold and Li, 2006). The level factor reflects the long-run inflation expectations; the slope captures the temporary business cycle movements in the economy, and the curvature reflects the stance of monetary policy (Dewachter and Lyrio, 2006). Based on this literature, I perform a yield curve decomposition into level, slope, and curvature factors, and derive the relationship between these factors and the correlation of short and long interest rates.

Given the simple two-maturity data structure, I follow the common practical approach of Diebold and Li (2006) and define the yield curve level as the average $L = \frac{1}{2}(R_{3m} + R_{10y})$ of the 3-month and 10-year rate, and its slope $S = R_{10y} - R_{3m}$ as the 10-year rate minus the 3-month rate. One can additionally define curvature with respect to a medium-maturity rate of 5 years as the double difference $C = (R_{10y} - R_{5y}) - (R_{5y} - R_{3m})$, but in practice, since my assets do not reference any medium maturities, level and slope changes explain practically all of the covariance between short and long rates. The above-defined variables are calculated at daily frequency.

I expect shocks to the yield curve level to move short and long rates together, while shocks to the slope to reduce their correlation (as the short and the long rate would move in opposite directions). Based on the definitions of level and slope, I next relate the correlation between short and long rates to these two factors. One can prove that this relationship is:

$$Cov(R_{3m}, R_{10y}) = Var(L) - \frac{1}{4}Var(S). \tag{4}$$

The proof is relegated to the Internet Appendix. Equation (4) states that the covariance between 3-month and 10-year interest rates responds positively to shifts in the yield curve level and negatively to changes in yield curve slope, in line with the intuition that level shifts cause all rates to move in the same direction, whereas slope changes move short and long rates in opposite directions. Recalling the definition of pairwise correlation, $\rho(R_{3m}, R_{10y}) = \frac{Cov(R_{3m}, R_{10y})}{\sigma_{R_{3m}}\sigma_{R_{10y}}}$, I arrive at the decomposition

$$\rho(R_{3m}, R_{10y})_t = \frac{1}{\sigma_{r_{3m,t}}\sigma_{r_{10y,t}}}\left(Var(L_t) - \frac{1}{4}Var(S_t)\right), \tag{5}$$

where the correlation between short and long rates depends on the variance of the yield curve's level and slope. In specifications (1)–(4) in Table 4, I therefore replace $\rho(R_{3m}, R_{10y})$ in regression equation (3) with the independent variables *Var(Level)* and *Var(Slope)*, defined as

$$\begin{aligned} Var(Level)_t &= \frac{1}{\sigma_{r_{3m,t}}\sigma_{r_{10y,t}}}Var(L_t) \\ Var(Slope)_t &= \frac{-1}{\sigma_{r_{3m,t}}\sigma_{r_{10y,t}}}\frac{1}{4}Var(S_t), \end{aligned} \tag{6}$$

reflecting the (normalized) variances of the level and slope factor as drivers of interest rate correlations. The prior is that $Var(Level)$ enters the regression with a positive coefficient and $Var(Slope)$ with a negative one.

3.2.2 Macroeconomic determinants of interest rate correlations

As a final step in the decomposition of interest rate correlations, I relate the yield curve factors to their respective macroeconomic drivers (boxes 8 and 9 in Figure 1). This allows me to trace portfolio-level comovents down to the underlying macroeconomic conditions that can alter the correlation between interest rates.

The bond market literature has extensively analyzed how the yield curve's level, slope, and curvature respond to changes in macroeconomic conditions. For example, there is broad consensus that shocks from inflation-related indicators influence the level of the term structure, while shocks from indicators of real economic activity influence the slope of the term structure (Lu and Wu, 2009). Positive monetary policy rate shocks tend to affect short rates more than long rates (Evans and Marshall, 1998), thereby changing both the level and slope of the yield curve (Diebold, Rudebusch and Aruoba, 2009). Figure 2 in the Internet Appendix illustrates some of these movements. For example, the yield curve level drops from about 4 in mid-2008 to 1.7 in January 2009, consistent with monetary policy easing and reduced inflation expectations during the crisis. At the same time, from late 2008 to mid-2010, the yield curve steepens from about 1 to 3.25, consistent with both negative shocks to real activity (Lu and Wu, 2009) and with monetary policy action, which reduced short rates disproportionately. Based on this literature, which is further discussed in the Results section, I decompose the variances of the yield curve's level and slope into their underlying macroeconomic drivers by including shocks to inflation (as the change in CPI inflation), shocks to real activity (as the percent change in full time employment), and monetary policy shocks (as the change in the Bank of Canada policy rate) in equation (3) in place of $Var(Level)$ and $Var(Slope)$. This allows me to decompose the short-long interest rate correlation into its ultimate macroeconomic determinants and quantify their influence on cross-portfolio comovement.

3.2.3 Macroeconomic determinants of stock-bond correlations

As a next step, I decompose the stock-bond correlation $\rho(\bar{R}, Stock)$ into macroeconomic determinants (Figure 1, box 10). Different studies attribute this correlation to different factors; the literature on this topic is sparse.[14] My results are most consistent with Campbell et al. (2017), who attribute stock-bond correlation to the relationship between expected inflation and the real interest rate, and Li (2002), who distills this insight into a model predicting inflation uncertainty as the main driver behind the stock-bond correlation, and real interest rate uncertainty as a secondary driver with harder to capture effects. Consistent with this line of thought, I include the

[14] See Campbell, Pflueger and Viceira (2020), Campbell et al. (2017), and Piazzesi and Schneider (2006).

standard deviation of the real interest rate and that of inflation as potential drivers of the stock-bond correlations. Both of these uncertainties increased during the crisis. For instance, the standard deviation of monthly inflation increased from 0.002 to 0.003, and that of the real interest rate, from 0.092 to 0.170, consistent with the swift monetary policy action. The final form of my regression specification, including all decompositions in Figure 1, is therefore,

$$\begin{aligned} Comove(R_i, R_c)_t = {} & \alpha + \beta_1 Overlap_{i,t-1} + \beta_2 (Overlap_{i,t-1} * Crisis_{t-1}) \\ & + \beta_3 (Overlap_{i,t-1} * Concentrated_{i,t-1}) \\ & + \beta_4 (Overlap_{i,t-1} * Concentrated_{i,t-1} * Crisis_{t-1}) \\ & + \beta_5 \gamma^I_{i,t-1} \Delta Inflation_{t-1} + \beta_6 \gamma^I_{i,t-1} \% \Delta Empl_{t-1} + \beta_7 \gamma^I_{i,t-1} \Delta Policyrate_{t-1} \\ & + \beta_8 \gamma^S_{i,t-1} SD(Realint)_{t-1} + \beta_9 \gamma^S_{i,t-1} SD(Inflation)_{t-1} + u_i + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where $\Delta Inflation$ is the monthly change in inflation, $\% \Delta Empl$ is the monthly full-time employment growth rate, $\Delta Policyrate$ is the monthly change in Bank of Canada policy rate, and $SD(Realint)$ and $SD(Inflation)$ indicate the standard deviations of the real interest rate and inflation, respectively. Inflation, employment and the policy rate are included as changes since their shocks increase the variances of the yield curve's level and slope (see Lu and Wu, 2009), as reflected in equation (4).[15] Equation (7) is estimated separately for core and non-core banks; when the coefficient of a higher-level variable is insignificant, it is not decomposed further into granular components.

3.2.4 Endogeneity and identification

The above estimation is based on the premise that time $t-1$ portfolio characteristics determine the portfolio comovement at time t. Since portfolio choice always precedes the return realization, realized time t returns cannot influence portfolio characteristics chosen at time $t-1$. However, one could still argue that observed correlations in past returns could influence two banks to choose their current portfolios in a certain way, creating endogeneity. The institutional setup of centrally cleared markets precludes this possibility, since trading parties remain anonymous to each other and are known only to the central counterparty.[16] Thus, this threat to exogeneity is not applicable

[15] In a series of unreported robustness tests, I also include inflation, employment, and the policy rates as levels, contrary to the literature. The estimated effects are still statistically significant but the marginal effects are smaller.

[16] A central counterparty (CCP) interposes itself between contract buyers and sellers, thereby fully anonymizing the trading counterparties. In a centrally cleared market, transactors deal exclusively with the CCP even under extreme

to my setting. Another threat to exogeneity could arise if large banks, by perhaps unwittingly taking on similar positions, were able to move market prices and change cross-asset correlations, creating an unforeseen interaction between the overlap and non-overlap channels. To do that, they would need to have sufficient market share to move prices in the entire market, and not just its proprietary segment. Raykov (2022) shows this is not the case. Proprietary positions of Canadian banks (both core and non-core) accounted for less than 20% of the open interest in this market during the sample period. Thus, it is highly unlikely that similar positions of large banks can swing the market. Endogeneity should, therefore, not be a major concern in this setting.

4 Results

I begin by estimating equation (3) and consecutively expand this specification by decomposing each channel in further stages, as shown in Figure 1, until reaching specification (7). The results of this estimation are shown in Tables 3 and 4.

4.1 Baseline specification

Portfolio overlap and portfolio concentration effects. The baseline results in columns (1)–(4) of Table 4 confirm that portfolio overlap is a statistically and economically significant driver behind the comovement of both core and non-core banks against the core, but the effect is larger for core banks. The estimated probit coefficient is 0.907 for core banks versus 0.676 for non-core banks, both highly significant at 1%. In terms of marginal effects, one-standard deviation[17] increase in portfolio overlap (0.282) increases the probability of contemporaneous gains or losses together with (the rest of) the core by 9.2 percentage points for core banks, and by 7.6 percentage points for non-core banks (in columns 1 and 2), when evaluated at the sample point of means. The coefficients in columns (3) and (4), which control for above 75-percentile position concentration, are of similar magnitude (respectively 0.972 and 0.730), corresponding to 9.8 and 8.2 percentage points. The effect of portfolio overlap is highly significant at 1% across all four columns.

In addition, columns (1)-(4) show that portfolio overlap due to concentration on the same asset type (as captured by interactions with the dummy variables *Concentrated* and *HiConcentrated*)

outcomes such as participant default.

[17] Here and going forward, the standard deviation refers to the full sample period unless noted otherwise.

further increased the probability of simultaneous losses for concentrated core banks. The estimated probit coefficient for banks with above-median portfolio concentration (in column 2) is 0.504, corresponding to an additional 5.1 percentage point higher probability per standard deviation of portfolio overlap. The coefficient for core banks with an above 75-th percentile concentration (in column 4) is 1.165, corresponding to a marginal effect of an additional 11.8 percentage points per a one-standard deviation of portfolio overlap. Taken together, core banks with concentrated positions increased their probability of joint gains/losses by 14.1 to 21.6 percentage points per one standard deviation (0.282) increase in portfolio overlap, depending on the specification. These results are highly significant at 1%. By contrast, portfolio overlap due to concentration did not appear to play a statistically significant role for non-core banks.

The above result confirms portfolio overlap plays a major role in interbank commonality, consistent with Poledna et al. (2021), who attribute half of banks' total systemic risk to portfolio overlap. This is also consistent with Falato et al. (2019), who find large US banks are sensitive to the same set of risk factors, suggesting sizable overlap also in other investments outside futures. At the same time, I find this effect is stronger for core banks and especially for concentrated core banks, reinforcing Menkveld's (2017) argument about crowding on the same asset as a source of correlated returns. On the other hand, Table 2 shows that core banks were more diversified overall (with HHI of 0.63 to 0.65 versus 0.54 to 0.58 for non-core banks) yet overlapped more than non-core banks, thereby lending credibility to Wagner's (2010 and 2011) predictions that large banks face incentives to diversify in the same way. These findings add important nuances to the debate on diversification versus concentration as sources of interbank commonality.

Interactions with the *Crisis* dummy. As shown in Table 2, panel D, volatility during the 2008 crisis significantly decorrelated returns across all three asset types. This sharp change in correlations may not be immediately reflected by the rolling 3-month cross-asset correlations used as controls. Provisioning for this, I have interacted portfolio overlap and concentration with a crisis dummy equal to 1 during the high-volatility period (September 2008 to December 2009) to absorb the part of this correlation change not already captured. Consistent with my prior, the crisis dummy's interactions with portfolio overlap and concentration enter the model with negative coefficients. The probit coefficients of -0.534 and -0.384 in columns (1) and (2) of Table 3 are significant at 1% for the interaction $Overlap * Crisis$ for both bank types across all specifications.

The triple interaction $Overlap * Crisis * Concentrated$ is negative and significant (at 1%) for core banks only, consistent with existing results that concentration did not play a role for non-core banks. The results in Table 3 remain practically unchanged when *Concentrated* and *Crisis* are added as free terms in the regression, so I do not report them separately.

Short-long interest rate correlations. In line with my main hypothesis, I find that core banks each holding non-overlapping futures over short and long interest rates face a higher chance of comovement when the short-long interest rate correlation increases. This effect is estimated at 0.232 (significant at 5%) in column (1), and 0.235 in column (3) of Table 3, also significant at 5%. These coefficients correspond to an average marginal effect of a 4.6 percentage point increase in probability for a one-standard deviation (0.551) increase in the correlation between 3-month and 10-year rates. These effects are economically significant. In particular, Table 2 shows the BAX-CGB pairwise correlation in my data fell during the 2008 crisis by 8 percentage points, corresponding to a reduction of core banks' simultaneous gain or loss probability by 0.7 percentage points. By contrast, there is no significant effect for non-core banks. This could be explained by the fact that core banks are more diversified, and hence each bank is more likely to hold both 3-month and 10-year interest rate futures, each interacting with the remaining non-overlapping interest rate future held by the core.

Correlation between interest rates and the stock market. I also expect that banks holding non-overlapping interest rate and stock market futures will be affected by changes to the stock-bond correlation. In line with this, I observe positive and significant coefficients of 0.152 and 0.135 in columns (1) and (2) of Table 3 (significant at 1% for core banks and at 5% for non-core banks). A one-standard deviation increase (0.535) in the correlation between the stock market and interest rates increases the probability of a bank having a simultaneous gain or loss with the core by 2.9 percentage points. In specification (3), this effect goes up to 3.1 percentage points. Thus, the stock-bond correlation affects core and non-core banks' commonality. This result is also economically significant.

4.2 Extended decomposition

Next I decompose the interest rate correlation and the stock-bond correlation into their underlying drivers, covering boxes 8 to 10 in Figure 1. The macro drivers behind these two correlations are of interest because they are largely exogenous to banks' portfolio choice, yet can alter their comovements.

I first decompose the short-long rates correlation $\rho(R_{3m}, R_{10y})$ into variances of the yield curve level and slope, as shown in equation (6). The results for core banks are shown in column (1) of Table 4. Both $Var(Level)$ and $Var(Slope)$ enter the regression with highly significant coefficients at the 1% level and signs consistent with the prediction (positive for $Var(Level)$ and negative for $Var(Slope)$). Since the interest rate correlation was insignificant for non-core banks in columns (1) to (4) of Table 3, I expect that its components $Var(Level)$ and $Var(Slope)$ will be insignificant for non-core banks. This is indeed the case in columns (2) and (4) in Table 4. The remaining effects (of concentration and overlap) remain practically unaffected by this decomposition.

Next, I proceed to disaggregate the short-long rate correlation into macro factors affecting the level and slope of the yield curve. The extensive literature on the subject has identified three main drivers that influence the shape of the yield curve: inflation-related indicators, output-related indicators, and monetary policy. I discuss each in turn.

Inflation. The bond market literature finds that shocks from inflation-related indicators produce large positive impacts on interest rates that are relatively uniform across maturities (Lu and Wu, 2009). Therefore, I expect that inflation changes shift the yield curve level, increasing the correlation of short and long rates and, through that, the covariance of banks' P&Ls. My findings confirm that. Changes in inflation enter the regression with a positive coefficient of 45.77, significant at 1%, corresponding to a marginal effect of 6 percentage points per a one-standard deviation (0.36 percentage points) inflation shock. This result is highly economically significant.

Employment. It has long been known that the shape of the yield curve changes across the business cycle (Ang, Piazzesi and Wei, 2006). The yield curve literature has identified a number of output-related indicators (such as employment, durable goods orders, industrial production), which impact the short end of the yield curve, influencing its slope. In particular, positive shocks to these variables flatten the yield curve by boosting its short end, while negative shocks steepen it (Lu and Wu, 2009). Since positive changes to output indicators boost both the 3-month and 10-year rate, albeit in different amounts, this also shifts the yield curve level L. Therefore, I expect output-related indicators to increase both $Var(Level)$ and $Var(Slope)$. In my data, full-time employment exhibits the strongest effect on these variables, so I concentrate on it going forward.

In the level-slope decompositions in equations (4) to (6), the variance of the level enters with a coefficient of 1, while the variance of the slope enters with a negative coefficient of 1/4. Thus I expect the level effect to dominate, as the two variances in Table 2 are similar (1.79 vs. 1.48). The results in model (5) of Table 4 confirm this. Employment growth enters the regression with a positive coefficient of 59.33, significant at 1%, corresponding to a 16.3 percentage point higher probability of simultaneous gains or losses per one standard deviation (0.76 percentage points) shock in employment growth.

Monetary policy. The yield curve literature finds that monetary policy shocks affect mostly short-term rates, and have diminishing effects on the long term rates at future horizons (Evans and Marshall, 1998). The uniformity of this effect across maturities depends on whether the monetary action is expected. The response of long rates is weaker for anticipated monetary policy changes (Berument and Froyen, 2009), while unexpected rate increases translate more uniformly across maturities (Diebold, Rudebusch and Aruoba, 2009; Morales, 2010). Therefore, monetary policy tightening can affect both the level and slope of the yield curve (Diebold, Rudebusch, and Aruoba, 2009). Since $Var(Level)$ enters the decomposition in equation (6) with a positive coefficient of 1, compared to the negative coefficient of $Var(Slope)$ of 1/4, and the two variances are very close (1.79 vs. 1.48 on average), I expect the level effect to dominate, so that monetary policy shocks increase the covariance between short and long interest rates. My findings are consistent with this. I find a positive coefficient of 3.144 in column (5), and 3.046 in column (7), both significant at 10%. Thus, a 25-basis point monetary policy shock increases the probability of simultaneous losses by 28.1 percentage points in column (5) and 27.3 points in column (7) for core banks.

Drivers of the stock-bond correlation. My final decomposition traces the remaining portfolio comovements down to the driving factors behind the stock-bond correlation (box 10 in Figure 1). The literature on this topic is still evolving, with different studies attributing the stock-bond correlation to different factors.[18] My results are most consistent with Campbell et al. (2017), Piazzesi and Schneider (2006), and Li (2002), who attribute the stock-bond correlation to the relationship between permanent and transitory inflation components and the real economy. The most concrete testable implications appear in Li (2002), whose model derives inflation uncertainty as the dominant driver of stock-bond correlations, with interest rate uncertainty playing a subtle

[18] For different recent treatments, see Campbell, Pflueger, and Viceira (2020); Campbell et al., (2017); Piazzesi and Scheider (2006); and Li (2002).

secondary role. My results are in line with this proposition. Measuring inflation uncertainty as the spread of the distribution of CPI inflation, I find coefficients of 87.27 in model (5) and 88.52 in model (7) of Table 4, both significant at 1%. These correspond to a marginal effect of approximately 8 percentage points per a 0.25 percentage point increase in the standard deviation of inflation. This effect is significant at 1% for core banks, and is insignificant for non-core banks. Consistent with the caveats expressed in Li (2002), I did not find consistent effects of real interest rate uncertainty (measured as the standard deviation of the average real 3-months and 10-year interest rates) on this correlation; coefficients have the correct sign only for non-core banks.[19] These findings are consistent with the considerations in Campbell et al. (2017) and Piazzesi and Schneider (2006).

4.3 Discussion

These results provide a contrast to the perception of portfolio overlap as the main driver behind large banks' simultaneous trading losses. Specifically, the results show that the cumulative sensitivity of trading loss comovements to common macro shocks is higher than to portfolio overlap. For instance, a combination of one-standard deviation shocks to inflation, employment growth, and a 25-basis point monetary policy tightening increases the chance of simultaneous losses or profits by big banks by up to 50.4 percentage points,[20] while one standard deviation of portfolio overlap does so by at most 22.2 percentage points. Hence, sensitivity to macro shocks is the highest when there is a combination of upward shocks to inflation, employment, and interest rates, as in the recent experience of developed economies. This outlines a new, unexplored tradeoff in the portfolio choice of large banks: while on the one hand, reducing portfolio overlap brings down their trading loss comovements, on the other hand, it also increases their comovements from common shocks. The estimated terms of this tradeoff do not appear to favor containing macroprudential risk.

I also observe two negative effects of portfolio diversification of large banks. Firstly, their diversification turns out to be a source of portfolio overlap, as they exhibit a tendency to diversify in the same way, confirming the predictions of Wagner (2010 and 2011). And secondly, large banks' diversification results in holding multiple assets, which facilitates cross-links with other distinct assets held by remaining banks through the common shocks channel. This diversification appears

[19]This could be due to Li's (2002) findings on interest rate uncertainty working mostly when the latter is measured with a highly specific GARCH process. Even in these specifications, the estimated effect is small.

[20]Based on the coefficients in column (5) of Table 5.

to be the main reason why large Canadian banks exhibit comovements due to both interest rate correlations and stock-bond correlations, in contrast to the less-diversified non-core banks.

5 Implications for Basel III capital requirements

These results point out specific avenues for improving Basel III capital requirements, which buffer comovements from some multi-asset shocks but not others.

The consolidated Basel III framework includes minimum capital requirements for market risk grounded in the sensitivity-based method (SBM). According to the SBM, portfolio sensitivities with respect to a number of risk factors are estimated within risk classes and risk buckets, and then aggregated according to pre-specified risk weights.[21] Examples of risk factors include interest rates at concrete maturities, specific exchange rates, concrete stock or commodity market indices, etc. Risk buckets represent groups of risk factors of the same type, and risk classes comprise the broadest categories, like general interest rate risk, equity risk, FX risk, commodity risk, and others.[22] The SBM assigns concrete risk weights to each risk factor and bucket, and prescribes specific correlations between risk factors within and across buckets to be used in the capital requirements calculation. For example, the capital requirement K_b within a risk bucket b is a function of the portfolio's estimated weighted sensitivities ws_κ towards each the risk factor κ and a prescribed correlation ρ_{kl} between each pair of risk factors k and l within the bucket:

$$K_b = \sqrt{\max\{0, \sum_k ws_k^2 + \sum_k \sum_{k \neq l} \rho_{kl} \; ws_k \; ws_l\}}. \tag{8}$$

An identical formula is used to aggregate risks across buckets within each risk class. The total capital requirement for the regulatory portfolio is then obtained as the direct sum of capital accross risk classes[23] (Basel Committee on Banking Supervision (2019), section MAR 21.7).

[21] In addition to SBM requirements, Basel III also provisions for default risk capital (DRC) and a residual risk add-on (RRAO).

[22] The Basel classification provisions for seven distinct risk classes: General interest rate risk, credit spread risk (non-securitization), credit spread risk (securitization, non-correlation trading portfolio), credit spread risk (securitization, correlation trading portfolio), FX risk, equity risk, and commodity risk. See section MAR21 in Basel Committee on Banking Supervision (2019).

[23] This is the capital requirement for delta risk, i.e. the risk of portfolio losses that are linear in a price movement, such as for stocks, bonds, or futures. For instruments that are non-linear in the price of the underlying asset, such as options, Basel III also calculates capital requirements for so-called vega risk and curvature risk. These two risks are not applicable to my data.

This last step implies that cross-asset correlations are applied within and across risk buckets, but not across risk classes when summing up capital requirements. This results in an inconsistent capital treatment of different multi-asset shocks. For instance, a multi-asset shock across the interest rate spectrum (a shift in the yield curve caused by monetary policy or inflation) would receive proper capital treatment, because different interest rates belong to the same bucket and their mutual correlations are reflected in special tables (Basel Committee on Banking Supervision (2019), section MAR 21.46). However, the joint downward shock to equities and interest rates during 2008 would not receive the same treatment, because these are two different risk classes, whose capital requirements are summed up separately. For instance, the sharp spike in the stock-bond correlation from 0.003 to 0.281 during 2008 does not generate a higher capital requirement for holding both stock- and interest rate-based futures, but it would do so if correlations across risk classes were reflected as in formula (8). This leaves potential for capital gaps that could be important in future systemic crises.[24]

A second related issue is that the cross-asset correlations prescribed by the Basel III framework appear low compared to those in our sample. For example, the Basel III standardized approach assumes a correlation between 3-month and 10-year interest rates equal to 0.40,[25] whereas the one observed in our sample is 0.58. Moreover, the correlation of the futures returns based on these two rates is 0.78 — almost twice higher than the Basel III assumption. Even though Basel III considers a high-correlation scenario, which multiplies the prescribed correlation by 1.25, this is still low relative to observed values. Given that joint liquidity shocks not buffered by capital are more likely to be addressed by borrowing or by fire sales, a more adequate reflection of cross-asset correlations could improve financial stability.

One saving grace could be that large banks primarily use the internal models approach (IMA), which allows for more sophistication than the standardized Basel approach above. However, it is important to recognize that nothing in the IMA requires sophistication on this specific dimension. Hence, if policymakers want to close capital gaps caused by the tendency of unrelated assets to

[24] To illustrate with an example, consider a stock portfolio and a bond portfolio with equal risk-weighted sensitivities $s_1 = s_2 = s$ and a correlation $\rho > 0$, and apply equation (8). It is easy to show that the joint capital requirement is $K_b = s\sqrt{2+\rho}$ if correlations are taken into account. Now compare this to the requirement K_b^0 where one assumes $\rho = 0$. The ratio $K_b/K_b^0 = \sqrt{(2+\rho)/2} = \sqrt{1+0.5\rho}$. Putting $\rho = 0.28$ as in the data yields $K_b/K_b^0 = \sqrt{1.14} = 1.0677$. So, leaving out the stock-bond correlation in this stylized example generates a 6.8% capital gap. This analysis could be extended in future research using more comprehensive asset class data.

[25] See item MAR 21.46 in Basel Committee on Banking Supervision (2019).

comove in crises, they face a choice between alternatives with different pros and cons. First, they could introduce more accurate risk aggregation across risk classes using formulas such as (8). This would introduce correlations between risk classes and likely require a periodic review of their values. The downside of this solution is that it complicates an already complex regulation, introduces time-varying parameters in it, and requires political consensus among Basel stakeholders. A second solution might be to aim for simplicity, keeping the current approach and hoping that the effect of ignored cross-class correlations is small. The results in this paper, however, do not support this view; even simple back-of-the envelope calculations (such as those in footnote 25) suggest the existence of capital gaps. A third solution might be to target improvements in internal risk models used by large banks without changing the standard approach used by the smaller banks. This could be done by implementing a higher review standard for internal models when it comes to correlations across risk classes. The latter solution, in addition to being somewhat customizable, would exceed the standardized Basel approach for those banks where this matters without making regulation more complex or time-dependent.

6 Conclusion

Liquidity shocks to large banks from their trading activities played an important role in the downturns of 2008 and 2020. The concern that simultaneous trading losses could affect key, systemically important banks during periods of scarce market liquidity has contributed to regulatory reforms (such as the Dodd-Frank Act and the Volcker rule) and resulted in calls to margin derivatives jointly across banks (Cruz-Lopez et al., 2017). Two questions, however, remain understudied: why large banks' trading losses comove so much in the first place, and whether new regulation treats such co-movements adequately. This paper addresses these questions with a unique dataset of proprietary derivatives trading positions from the Montreal Exchange between 2003 and 2011.

The existing literature attributes the comovement of trading losses mostly to portfolio overlap, which creates common exposures across institutions. By contrast, this paper shows that overlap is the smaller of two principal drivers affecting the comovement of large banks' trading losses. I highlight the existence of a second comovement channel, dubbed the common shocks channel, which captures the tendency of unrelated assets to comove in crises, and show that this tendency is not adequately buffered by Basel III capital requirements.

I find that the cumulative sensitivity of simultaneous trading losses to common shocks is higher than the sensitivity to portfolio overlap, underscoring the importance of closing capital gaps related to common shocks. This finding is explained by the high diversification of the core Canadian banks, which were holding assets sensitive to different interest rates across the maturity spectrum as well as the stock market. I show this created significant exposures to common macro shocks via the short-long interest rate correlation and the stock-bond correlation. Thus, I document two negative effects of diversification on the comovements of large banks. Firstly, their diversification turns out to be a source of portfolio overlap, as they exhibit a tendency to diversify in the same way. And secondly, large banks' diversification results in their holding multiple assets that cross-link with other distinct assets in the remaining banks' portfolios, causing comovements through common macro shocks not adequately buffered by the Basel III framework.

I propose three policy options for improving the Basel III standard, and advocate for higher regulatory scrutiny on how internal risk models capture such common shocks. My findings suggest that macroprudential authorities should implement a consistent and adequate treatment of common shocks across multiple asset classes, as they are responsible for a significant portion of comovements. These results suggest a new tradeoff between the two sources of simultaneous trading losses, which could affect interbank contagion in future systemic crises.

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7 Tables

Table 1: Alphabetical List of Financial Institutions

Name	Country of Headquarters
Bank of Montreal*	Canada
Bank of Nova Scotia*	Canada
CIBC*	Canada
Desjardins	Canada
J.P. Morgan	USA
Laurentian Bank	Canada
Merrill Lynch	USA
MF Global	USA
National Bank*	Canada
Newedge Canada Inc.	Canada
Royal Bank of Canada*	Canada
Toronto Dominion (TD)*	Canada

This table presents the financial institutions with active firm accounts in the Canadian futures market during the sample period (January 2, 2003, to March 31, 2011) and their country of headquarters. Core banks (members of the Big Six) are flagged with an asterisk (*). An account is considered active if it has a non-zero open position on at least half of the trading days during the sample period. Any subsidiaries are subsumed under the parent institution and their positions consolidated with those of the parent if participating through more than one entity.

Table 2: Summary Statistics

	Non-crisis					Crisis (1 Sept. 2008–31 Dec. 2009)				
	Mean	Std. Dev.	Min.	Max.	N	Mean	Std. Dev.	Min.	Max.	N
Panel A: Core Banks										
Open positions value (mill.)	1567.3	1202.2	2.3	10309.6	9705	1774.5	1483.6	0.4	6094.2	1673
$D_{i,c,t}$	0.660	0.474	0	1	9705	0.613	0.487	0	1	1673
Overlap	0.174	0.236	-0.648	0.776	9705	0.381	0.314	-0.683	0.910	1673
HHI	0.651	0.206	0.331	1	9705	0.632	0.209	0.334	1	1673
Concentrated	0.441	0.497	0	1	9705	0.388	0.487	0	1	1673
HiConcentrated	0.174	0.379	0	1	9705	0.173	0.379	0	1	1673
γ^I	0.019	0.185	-0.912	0.884	9705	0.126	0.296	-0.848	0.806	1673
γ^S	-0.098	0.446	-0.987	0.978	9705	-0.149	0.318	-0.948	0.825	1673
Panel B: Non-core Banks										
Open positions value (mill.)	597.3	1041.3	0.1	6413.9	8039	634.1	805.2	0.1	4375.3	1450
$D_{i,c,t}$	0.536	0.499	0	1	8039	0.526	0.499	0	1	1450
Overlap	0.103	0.284	-0.733	0.807	8039	0.284	0.351	-0.759	0.916	1450
HHI	0.741	0.215	0.334	1	8039	0.731	0.207	0.354	1	1450
Concentrated	0.583	0.493	0	1	8039	0.539	0.499	0	1	1450
HiConcentrated	0.341	0.474	0	1	8039	0.317	0.466	0	1	1450
γ^I	0.027	0.291	-0.881	0.778	8039	0.119	0.349	-0.869	0.848	1450
γ^S	-0.072	0.423	-0.983	0.977	8039	-0.088	0.266	-0.993	0.990	1450
Panel C: Aggregate variables										
Return BAX (percent)	0.002	0.059	-0.389	0.250	1731	0.005	0.071	-0.349	0.381	334
Return CGB (percent)	0.014	0.320	-1.246	1.090	1731	0.016	0.477	-1.991	1.671	334
Return SXF (percent)	0.054	0.894	-4.485	4.514	1731	-0.014	2.544	-10.203	9.534	334
Var(Level)	1.794	2.253	0.053	11.945	1671	4.829	5.985	0.208	21.046	334
Var(Slope)	1.477	2.105	0.030	11.310	1671	4.600	5.920	0.023	20.591	334
Δ Inflation (monthly)	-7.28E-06	0.004	-0.0120065	0.010	261	7.28E-12	0.005	-0.008	0.007	16
SD(Inflation) (monthly)	0.002	0.001	0.000	0.007	261	0.003	0.001	0.001	0.005	16
$\%\Delta$ Employment (monthly)	1.33E-03	0.008	-0.0978913	0.041	262	-0.001	0.004	-0.009	0.006	16
Δ Policyrate	0.001	0.032	-0.500	0.25	1803	-0.008	0.064	-0.750	0	341
SD(Realint)	0.092	0.042	0.030	0.243	1737	0.170	0.160	0.034	0.583	349
Panel D: Correlations										
$\rho(R_{BAX}, R_{CGB})$	0.783	-	-	-	1738	0.702	-	-	-	334
$\rho(R_{BAX}, R_{SXF})$	-0.140	-	-	-	1738	-0.334	-	-	-	334
$\rho(R_{CGB}, R_{SXF})$	-0.171	-	-	-	1738	-0.338	-	-	-	334
$\rho(R_{3m}, R_{10y})$	0.580	-	-	-	1738	0.316	-	-	-	334
$\rho(\bar{R}, Stock)$	0.003	-	-	-	1738	0.281	-	-	-	334

Summary statistics for in-sample banks by bank type and time period. Bank-specific variables, contract related variables, and interest rate variables are at a daily frequency. Inflation, employment, and their standard deviations are reported at monthly frequency and their summary statistics are computed at that frequency. Correlation variables ($\rho(\cdot)$) are calculated from daily-frequency data for each full period (non-crisis / crisis). The sample period is from January 2, 2003, to March 31, 2011. The in-sample banks are listed in Table 1.

Table 3: Effect of Portfolio Characteristics on Return Comovements

	(1)	(2)	(3)	(4)
Dependent Variable: $D_{i,c,t}$	Core	Non-Core	Core	Non-Core
Overlap$_{t-1}$	0.907***	0.676***	0.972***	0.730***
	(0.0687)	(0.0790)	(0.0605)	(0.0657)
Overlap$_{t-1}$*Concentrated$_{t-1}$	0.504***	0.00847		
	(0.109)	(0.0978)		
Overlap$_{t-1}$*Crisis	-0.534***	-0.384***	-0.627***	-0.475***
	(0.100)	(0.123)	(0.0875)	(0.102)
Overlap$_{t-1}$*Concentrated$_{t-1}$*Crisis	-0.621***	-0.0865		
	(0.174)	(0.178)		
Overlap$_{t-1}$*HiConcentrated$_{t-1}$			1.165***	-0.149
			(0.187)	(0.107)
Overlap$_{t-1}$*HiConcentrated$_{t-1}$*Crisis			-1.272***	0.198
			(0.256)	(0.214)
$\gamma^I_{t-1}\rho(R_{3m}, R_{10y})_{t-1}$	0.232**	0.0771	0.235**	0.0862
	(0.0922)	(0.0667)	(0.0923)	(0.0665)
$\gamma^S_{t-1}\rho(\bar{R}, Stock)_{t-1}$	0.152***	0.135**	0.166***	0.135**
	(0.0520)	(0.0584)	(0.0521)	(0.0584)
Constant	0.280*	0.00235	0.270*	-0.000386
	(0.157)	(0.0593)	(0.151)	(0.0592)
Bank-level RE	Yes	Yes	Yes	Yes
Observations	11,378	9,489	11,378	9,489
Number of banks	6	6	6	6

This table shows the effect of portfolio characteristics on the probability of each bank scoring simultaneous gains or losses together with the core group of banks. *Overlap* is bank i's cosine similarity to the core, defined in Section 3.1. *Concentrated* is a dummy equal to 1 if the portfolio HHI is above its median value. *HiConcentrated* is a dummy equal to 1 if the bank's portfolio HHI exceeds its 75th percentile. HHI is a Herfindahl concentration index calculated on the contract type level. *Crisis* is a dummy equal to 1 from September 1, 2008 to December 31, 2009. γ^I and γ^S are bank exposures to the short-long interest rate correlation and the stock-bond correlation, respectively. The estimation is random effect panel probit. Standard errors are shown in parentheses. The sample period is from January 2, 2003, to March 31, 2011. The in-sample banks are listed in Table 1.

Table 4: Effect of Portfolio Characteristics on Return Comovements: Further Decompositions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: $D_{i,c,t}$	Core	Non-Core	Core	Non-Core	Core	Non-Core	Core	Non-Core
Overlap_{t-1}	0.906***	0.680***	0.971***	0.730***	0.914***	0.689***	0.986***	0.747***
	(0.069)	(0.079)	(0.061)	(0.066)	(0.069)	(0.079)	(0.061)	(0.066)
Overlap_{t-1}*$\text{Concentrated}_{t-1}$	0.508***	0.0016			0.539***	0.029		
	(0.109)	(0.098)			(0.109)	(0.098)		
Overlap_{t-1}*Crisis	-0.511***	-0.464***	-0.606***	-0.540***	-0.558***	-0.347***	-0.672***	-0.447***
	(0.101)	(0.127)	(0.089)	(0.105)	(0.104)	(0.123)	(0.091)	(0.102)
Overlap_{t-1}*$\text{Concentrated}_{t-1}$*Crisis	-0.598***	-0.063			-0.672***	-0.112		
	(0.175)	(0.179)			(0.175)	(0.178)		
$\gamma^I \text{Var(Level)}_{t-1}$	0.294***	0.0112	0.299***	0.0193				
	(0.102)	(0.071)	(0.102)	(0.071)				
$\gamma^I \text{Var(Slope)}_{t-1}$	-0.310***	0.0183	-0.315***	0.0101				
	(0.107)	(0.076)	(0.108)	(0.076)				
$\gamma^S \rho(\bar{R}, Stock)_{t-1}$	0.149***	0.142**	0.163***	0.143**				
	(0.052)	(0.059)	(0.052)	(0.059)				
Overlap_{t-1}*$\text{HiConcentrated}_{t-1}$			1.170***	-0.145			1.208***	-0.123
			(0.187)	(0.107)			(0.187)	(0.107)
Overlap_{t-1}*$\text{HiConcentrated}_{t-1}$*Crisis			-1.213***	0.18			-1.272***	0.183
			(0.259)	(0.215)			(0.257)	(0.214)
$\gamma^I\ \Delta\text{Inflation}_{t-1}$					45.77***		46.70***	
					(14.780)		(14.820)	
$\gamma^I\ \%\Delta\text{Employment}_{t-1}$					59.33***		60.74***	
					(17.040)		(17.060)	
$\gamma^I \Delta\text{Policyrate}_{t-1}$					3.144*		3.046*	
					(1.757)		(1.756)	
$\gamma^S \text{SD(Realint)}_{t-1}$					-1.431***	1.255***	-1.444***	1.228***
					(0.386)	(0.431)	(0.387)	(0.432)
$\gamma^S \text{SD(Inflation)}_{t-1}$					87.27***	-17.53	88.52***	-16.16
					(16.390)	(17.950)	(16.420)	(17.990)
Constant	0.280*	0.00244	0.270*	-0.000212	0.281*	0.00818	0.271*	0.00584
	(0.157)	(0.060)	(0.151)	(0.059)	(0.157)	(0.060)	(0.151)	(0.060)
Observations	11,378	9,489	11,378	9,489	11,378	9,489	11,378	9,489
Bank-level RE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of banks	6	6	6	6	6	6	6	6

This table shows the effect of additional portfolio characteristics on the probability of a bank scoring simultaneous gains or losses together with the core group of banks. *Overlap* is bank i's cosine similarity to the core, defined in Section 3.1. *Concentrated* is a dummy equal to 1 if the portfolio HHI is above its median value. *HiConcentrated* is a dummy equal to 1 if the bank's portfolio HHI exceeds its 75th percentile. *Crisis* is a dummy equal to 1 from September 1, 2008 to December 31, 2009. For a definition of variables, refer to Section 3.1. The estimation is random effect panel probit. Standard errors are shown in parentheses. The sample period is from January 2, 2003, to March 31, 2011. The in-sample banks are listed in Table 1.

8 Internet Appendix

8.1 Additional figures

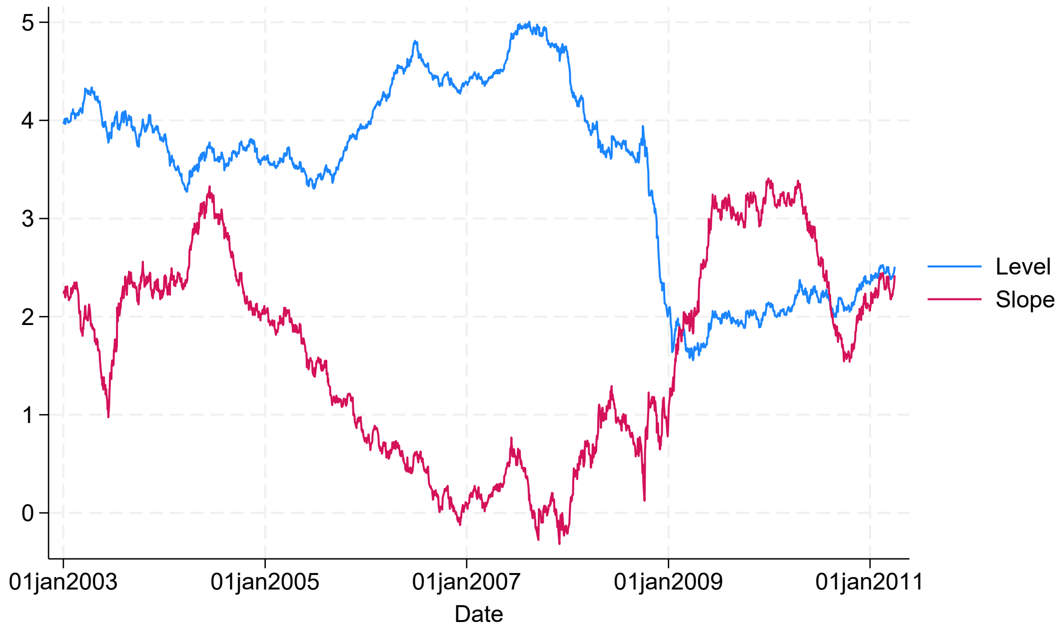

Figure 2: This figure shows the time evolution of the level and slope of the yield curve as defined in Section 3.2.1.

8.2 Proof of the covariance decomposition of interest rates

Let R_{3m} and R_{10y} be two random variables reflecting the 3-month and 10-year interest rate, respectively. Let the yield curve level be $L = \frac{1}{2}(R_{3m} + R_{10y})$ and slope be $S = R_{10y} - R_{3m}$. I will prove that

$$Cov(R_{3m}, R_{10y}) = Var(L) - \frac{1}{4}Var(S). \tag{9}$$

To show that this decomposition is true, perform the substitutions

$$
\begin{aligned}
Cov(R_{3m}, R_{10y}) =& Var(L) - \frac{1}{4}Var(S) \\
Cov(R_{3m}, R_{10y}) =& Var\left(\frac{1}{2}(R_{3m} + R_{10y})\right) - \frac{1}{4}Var(R_{10y} - R_{3m}) \\
Cov(R_{3m}, R_{10y}) =& \frac{1}{4}\Big[Var(R_{3m}) + Var(R_{10y}) + 2Cov(R_{3m}, R_{10y})\Big] \\
& - \frac{1}{4}\Big[Var(R_{3m}) + Var(R_{10y}) - 2Cov(R_{3m}, R_{10y})\Big] \\
Cov(R_{3m}, R_{10y}) =& \frac{1}{4}\Big[Var(R_{3m}) + Var(R_{10y}) + 2Cov(R_{3m}, R_{10y}) \\
& - Var(R_{3m}) - Var(R_{10y}) + 2Cov(R_{3m}, R_{10y})\Big] \\
Cov(R_{3m}, R_{10y}) =& \frac{1}{4}\Big[4Cov(R_{3m}, R_{10y})\Big] \\
Cov(R_{3m}, R_{10y}) =& Cov(R_{3m}, R_{10y})
\end{aligned}
$$

which is an identity, thereby proving the point.

8.3 Construction of the exposure controls γ^I and γ^S

Let α^k be the portfolio share of asset k in the portfolio (a_1, a_2, a_3), so that $\alpha^k = \frac{a_k}{|a_1|+|a_2|+|a_3|}$.

Bank i' exposures γ^I and γ^S to $\rho(R_{3m}, R_{10y})$ and $\rho(\bar{R}, Stock)$ depend on (i) how much of such correlated, but non-overlapping assets are held in i's portfolio versus that of the core and (ii) the direction of i's investment compared to that of the core. For example, if bank i holds no asset that can be subject to one of these two correlations, its respective exposure γ to the relevant correlation is 0. By contrast, if i takes a long position in BAX and the core, a long position in CGB, then the positive BAX-CGB correlation will translate into correlated P&L's for bank i and the core. However, if i takes a direction of investment opposite to the core (e.g., short on BAX), then the positive BAX-CGB correlation will translate into negative return correlations (one side has a loss while the other has a profit).

Therefore, I construct the cross-asset exposure metrics γ^I and γ^S as follows. The positive correlation between short and long interest rates can manifest itself in two ways as a portfolio comovement between bank i and the core. First, i may be holding BAX and the core CGB interest rate futures. Or conversely, i might be holding CGB and the core BAX futures. Therefore, I account for both possibilities by constructing the interest rate exposure γ^I as the sum of exposures across both cases:

$$\gamma^I = \alpha_i^{BAX} \cdot \alpha_c^{CGB} + \alpha_i^{CGB} \cdot \alpha_c^{BAX}, \tag{10}$$

where each α is signed positively for long positions and negatively for short positions. For instance, if i is holding a short position in BAX and the core a long position in CGB, the product $\alpha_i^{BAX} \cdot \alpha_c^{CGB}$ will be negative, consistent with the fact that the positive BAX-CGB correlation will cause a negative portfolio comovement because once side will have losses while the other has profits.

Similarly, the stock-bond correlation can affect bank i and the core if one of them holds interest-rate based assets and the other one, stock-based assets. Since the pairwise correlations of the two interest rate futures BAX and CGB versus SXF in Table 2 are very close, I aggregate the two interest rate futures into a single category and define the stock-bond correlation exposure factor as

$$\gamma^S = \alpha_i^{BAX+CGB} \cdot \alpha_c^{SXF} + \alpha_i^{SXF} \cdot \alpha_c^{BAX+CGB}, \tag{11}$$

where again each α is signed positively for long positions and negatively for short positions.

It is easy to verify that the γ metrics constructed this way satisfy three desirable properties:

Property 1. When cross-asset correlations are the only comovement source (i.e., portfolio overlap is not present but there is still a comovement), then the relevant exposure $\gamma = 1$ *for same-direction positions and* $\gamma = -1$ *for opposite-direction positions.*

Property 2. When correlated non-overlapping assets are not present across two portfolios, the relevant exposure to such assets γ *should equal 0.*

Property 3. When both cross-asset correlations and portfolio overlap are present, the relevant exposure to cross-asset correlations γ *takes intermediate values between* 0 *and* ± 1*, depending on the direction and size of both investments.*

I show this for γ^I since the reasoning for γ^S is analogous.

Property 1. Consider the BAX-only portfolio $(a_1, 0, 0)$ and the CGB-only portfolio $(0, b_2, 0)$, which have no overlapping assets. For this pair of portfolios, given the definition of γ^I,

$$\gamma^I = \begin{cases} 1 \cdot 1 + 0 \cdot 0 = 1 & \text{if } a_1 > 0, b_2 > 0 \\ -1 \cdot (-1) + 0 \cdot 0 = 1 & \text{if } a_1 < 0, b_2 < 0 \\ -1 \cdot 1 + 0 \cdot 0 = -1 & \text{if } a_1 < 0, b_2 > 0 \\ 1 \cdot (-1) + 0 \cdot 0 = -1 & \text{if } a_1 > 0, b_2 < 0. \end{cases} \tag{12}$$

Property 2. Let two arbitrary portfolios without correlated interest rate assets be denoted $\mathbf{a} = (a_1, 0, a_3)$ and $\mathbf{b} = (b_1, 0, b_3)$. Then,

$$\gamma^I = \frac{a_1}{|a_1| + |a_3|} 0 + 0 \frac{b_1}{|b_1| + |b_3|} = 0. \tag{13}$$

The proof is analogous if instead $\mathbf{a} = (0, a_2, a_3)$ and $\mathbf{b} = (0, b_2, b_3)$.

Property 3. Consider the portfolios (a_1, a_2, a_3) and (b_1, b_2, b_3), which feature comovements due to both overlap and the cross-asset correlation between BAX and CGB. According to the definition of γ^I,

$$\gamma^I = \frac{a_1}{|a_1| + |a_2| + |a_3|} \frac{b_2}{|b_1| + |b_2| + |b_3|} + \frac{a_2}{|a_1| + |a_2| + |a_3|} \frac{b_1}{|b_1| + |b_2| + |b_3|} \tag{14}$$

Using the inequalities $a_1 b_2 \leq |a_1||b_2|$ and $a_2 b_1 \leq |a_2||b_1|$, some easy but tedious algebra shows that

$$-1 \leq \frac{a_1 b_2 + a_2 b_1}{(|a_1| + |a_2| + |a_3|)(|b_1| + |b_2| + |b_3|)} \leq 1, \tag{15}$$

with the inequality being strict when $|a_i||b_j| \neq 0$ for at least one of the ordered pairs $(i, j) \in \{(1,1), (1,3), (2,2), (2,3), (3,1), (3,2), (3,3)\}$.

8.4 Robustness checks

8.4.1 Alternative comovement measure and OLS estimates

In this set of regressions, I measure cross-portfolio comovements with an alternative measure of comovement by setting $Comove_{i,t}$ equal to $\rho(R_i, R_c)_t$, the correlation of bank i's return R_i and the core return R_c, calculated using a 3-month rolling window. I estimate the panel regressions with the OLS fixed-effects estimator with Driscoll-Kraay heteroscedasticity- and autocorrelation-robust standard errors (Driscoll and Kraay, 1998), which are also robust against serial dependence. This measure is inherently noisier (due to factoring in past information before time $t-1$) as well as more prone to endogeneity than my baseline measure (due to the overlap of its estimation window with the moving average window for independent variables). However, the results, listed in Table 5, are qualitatively and quantitatively similar to those in Table 3, confirming my findings. For this reason, I do not pursue this specification further.

Table 5: Effect of Portfolio Characteristics on Return Comovements (OLS)

	(1)	(2)	(3)	(4)
Dependent Variable: $\rho(R_i, R_c)_t$	Core	Non-Core	Core	Non-Core
Overlap_{t-1}	1.106***	0.769***	1.154***	0.789***
	(0.202)	(0.136)	(0.190)	(0.113)
Overlap_{t-1}*$\text{Concentrated}_{t-1}$	0.419*	0.0842		
	(0.221)	(0.133)		
Overlap_{t-1} * Crisis	-0.486**	-0.327	-0.656***	-0.353**
	(0.192)	(0.231)	(0.169)	(0.153)
Overlap_{t-1}*$\text{Concentrated}_{t-1}$ * Crisis	-0.838**	-0.0652		
	(0.332)	(0.260)		
Overlap_{t-1}*$\text{HiConcentrated}_{t-1}$			0.659*	0.108
			(0.353)	(0.151)
Overlap_{t-1}*$\text{HiConcentrated}_{t-1}$*Crisis			-0.671	0.0155
			(0.416)	(0.240)
$\gamma^I_{t-1}\rho(R_{3m}, R_{10y})_{t-1}$	0.373*	-0.0176	0.383*	-0.0159
	(0.213)	(0.122)	(0.217)	(0.122)
$\gamma^S_{t-1}\rho(\bar{R}, Stock)_{t-1}$	0.0237	-0.162*	0.00461	-0.162*
	(0.106)	(0.0941)	(0.108)	(0.0946)
Constant	0.109**	0.0158	0.106*	0.0170
	(0.0535)	(0.0197)	(0.0548)	(0.0200)
Bank-level FE	Yes	Yes	Yes	Yes
Observations	11,384	9,432	11,384	9,432
R^2	0.14	0.12	0.14	0.12
Number of banks	6	6	6	6

This table shows the effect of portfolio characteristics on return correlation against the core portfolio. *Overlap* is bank i's cosine similarity to the core, defined in Section 3.1. *Concentrated* is a dummy equal to 1 if the portfolio HHI is above its median value. *HiConcentrated* is a dummy equal to 1 if the bank's portfolio HHI exceeds its 75th percentile. HHI is a Herfindahl concentration index calculated on the contract type level. *Crisis* is a dummy equal to 1 from September 1, 2008 to December 31, 2009. γ^I and γ^S are bank exposures to the short-long interest rate correlation and the stock-bond correlation, respectively. The estimation is ordinary least squares with bank-level fixed effects and Driscoll-Kraay standard errors. Standard errors are shown in parentheses. The sample period is from January 2, 2003, to March 31, 2011. The in-sample banks are listed in Table 1.