What Binds Matters: Bank Constraints and Asset Prices*

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Abstract

I show that the implications of intermediary constraints for asset prices depend on which specific constraints bind, a distinction that is obscured by aggregate relationships between intermediary constraints and asset prices. Using an LLM-based framework, I construct novel text-based constraint (TBC) measures from conference calls of primary-dealer holding companies that identify which constraints limit banks' activities and how severely they bind, capturing dimensions difficult to isolate from balance-sheet data alone. I find distinct relationships between specific constraints and arbitrage spreads. Among these relationships, tighter liquidity constraints are associated with wider covered interest parity deviations, while tighter leverage constraints are associated with wider Treasury spot–futures spreads, consistent with differences in the intermediation activities underlying each strategy. These findings refine the intermediary asset pricing view of financial markets by showing that the transmission of intermediary frictions to asset prices depends critically on which constraints bind and the intermediation activities they restrict.

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1 Introduction

Financial intermediaries' risk-bearing capacity is central to asset pricing. Canonical models show that intermediaries' constraints shape equilibrium risk premia and asset prices (He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Gabaix and Maggiori (2015)). Empirical studies support this relationship, typically using balance-sheet measures such as leverage and capitalization ratios to proxy for risk-bearing capacity (Adrian and Shin (2010), Adrian et al. (2014), He et al. (2017)). These measures provide important information about intermediaries' overall financial conditions but do not reveal which underlying constraints are binding. Different constraints have different implications for banks' balance-sheet activities, which can ultimately impact asset prices. For example, leverage constraints limit total exposures, thus disproportionately penalizing safer assets, while risk constraints impose greater costs on riskier assets.

In this paper, I show that different intermediary constraints are associated with distinct patterns in asset prices across markets and in banks' financing of nonbank intermediaries. I argue that these patterns reflect differences in the intermediation activities underlying arbitrage strategies: different constraints restrict different activities, and therefore matter for different arbitrage prices. My findings suggest that understanding intermediary asset pricing requires identifying not only how constrained intermediaries are, but also which constraints bind. I study these effects using large banks, which are central to intermediation across financial markets. These banks often serve as holding companies for primary dealers that intermediate Treasury markets (Bräuning and Stein (2026)), play an important role in pricing in other markets, including CIP (Moskowitz et al. (2026)), and increasingly finance nonbank investors.*Beyond their direct intermediation activities, banks can also influence asset prices through their financing of nonbank investors.

Following the global financial crisis (GFC), these banks have faced multiple regulatory constraints that limit their intermediation activities. As Citigroup management noted in 2014 when discussing potential binding constraints, "we need to keep our eye on all of those, and it doesn't do you any good to just manage one." Identifying which constraints are binding is challenging because traditional balance-sheet measures reflect the combined effects of multiple constraints and do not necessarily reveal which ones drive banks' decisions.

To address this challenge, I develop an LLM-based measurement framework using quarterly

*According to the *Financial Times*, hedge fund borrowing from banks has tripled since 2020, and "revenues from equity and fixed income prime broking – two of the main ways that banks lend to hedge funds – are forecast to hit $47.9bn [in 2026]."

conference call transcripts from primary-dealer holding companies. In these calls, banks discuss factors affecting their activities, providing information about binding constraints that is difficult to infer from balance-sheet data alone. My framework extracts passages in which banks discuss constraints on their activities, classifies the types of constraints they face, and assesses the extent to which these constraints bind or ease. I group the resulting descriptions into distinct topics, organized into four broader themes: risk-weighted capital, leverage, liquidity and funding, and stress-test constraints. These novel text-based constraint (TBC) measures allow me to examine how different constraints shape banks' balance-sheet decisions, arbitrage spreads across markets, and financing of nonbank intermediaries.

My first set of results validates these TBC measures by examining whether they capture economically meaningful variation in intermediary constraints, both in the aggregate and, more importantly, across specific constraint types. I first aggregate the bank-level measures across banks and constraint types to compare them with existing measures of intermediary risk-bearing capacity. The aggregate measure correlates in the expected direction with established indicators of financial and market stress, as well as proxies for intermediary risk-bearing capacity such as those studied in Adrian et al. (2014) and He et al. (2017). Importantly, my measure is not spanned by existing measures, suggesting it contains additional information about intermediary constraints beyond existing balance-sheet and market-based measures.

While the TBC measures capture meaningful information about intermediary conditions not captured by existing measures, the main contribution of these measures is to distinguish which specific constraints bind. To validate this, I examine whether the individual constraint measures predict the balance-sheet adjustments implied by their underlying mechanisms. Using bank-level regulatory filings, I find that tighter leverage constraints predict lower subsequent holdings of high-quality liquid assets and higher risk-weighted density of assets, consistent with banks shifting their balance sheets toward riskier assets when leverage becomes more costly. Tighter liquidity constraints predict higher subsequent holdings of liquid assets and less reliance on short-term wholesale funding, consistent with banks improving their liquidity positions. Tighter risk-weighted capital constraints predict lower subsequent risk-weighted density, while tighter stress-test constraints predict lower subsequent shareholder payouts. These patterns provide evidence that the TBC measures do in fact capture which specific constraints bind.

Having established that the TBC measures capture economically distinct constraints, my second set of results examines how these constraints are reflected in asset prices. I use the arbitrage

activity in equity, fixed income, and foreign exchange markets studied in Siriwardane et al. (2025), which provide a particularly useful setting for studying intermediary frictions since these trades are largely intermediated by financial institutions (Haddad and Muir (2026)). I find that tighter risk-weighted capital and liquidity constraints are associated with wider arbitrage spreads on average, but each constraint is associated with a different set of strategies. Risk-weighted capital constraints are primarily associated with secured arbitrage strategies, particularly the Treasury–swap spread and the CDS–bond basis; leverage constraints are associated with Treasury spot–futures spreads; liquidity constraints are strongly associated with Treasury–swap spreads, as well as CIP and TIPS–Treasury spreads. These differences are consistent with the balance-sheet segmentation observed by Siriwardane et al. (2025), where different strategies depend on different balance-sheet capacities. The difference in this paper is that I look at different balance-sheet capacities within the same intermediary sector. These findings suggest that bank constraints affect asset prices by limiting different intermediation activities, rather than through a single, common reduction in intermediary risk-bearing capacity.

Finally, my third set of results provides evidence that differences in how banks intermediate across markets can help explain these market-specific pricing effects. I focus on two markets in particular: CIP and Treasury spot-futures, two markets that have been previously studied in the literature and provide clean predictions on which bank constraints should matter for prices. It is well established that banks trade in foreign exchange markets and play a key role in persistent CIP deviations (Du et al. (2018), Moskowitz et al. (2026)). Banks lend dollars and receives foreign currency; as a result banks need liquid assets (cash) to participate. Therefore, we would expect that tighter liquidity constraints from banks would widen the CIP spreads, which is exactly what I find.

The Treasury cash–futures basis trade provides a useful example of how bank constraints are important even if they are not directly trading the underlying arbitrage opportunity. Hedge funds are the important arbitrageurs in this market rather than banks (Barth and Kahn (2025), Siriwardane et al. (2025)); however, they rely heavily on banks for repo financing. These loans are backed by Treasuries and are nearly riskless, so we would expect leverage constraints to matter here. When leverage constraints bind, this penalizes less risky assets, such as treasury-backed loans. Therefore, tighter bank leverage constraints can reduce repo financing to hedge funds, limiting their ability to exploit the cash–futures basis and allowing arbitrage spreads to widen. To investigate this channel, I examine how bank constraints affect the financing and risk-taking capacity of nonbank intermediaries, specifically hedge funds, and how that affects spreads.

I first show that tighter bank leverage constraints are indeed significantly associated with wider Treasury basis spreads. Linking constraints to prices, I show that leverage constraints are associated with reduced risk-taking by relative-value hedge funds, which are particularly active in basis trades. Specifically, tighter bank leverage constraints are associated with lower gross exposures and less repo borrowing among these funds. A one-standard-deviation tightening is associated with about $18 billion less hedge-fund repo borrowing at quarter-end. Importantly, lower repo borrowing is also associated with wider Treasury basis spreads. A 10% reduction in borrowing is associated with a widening of about 3.5 basis points. This is about a quarter of the quarterly standard deviation. Putting these results together, tighter bank leverage constraints are associated with reduced hedge fund exposures and repo borrowing, and lower repo borrowing is in turn associated with wider Treasury basis spreads, providing suggestive evidence that bank constraints can transmit to prices even when banks are not the marginal trader. More broadly, the differences in how CIP and Treasury spot-futures arbitrages are intermediated provides useful case studies for better understanding why different constraints matter for different markets.

This paper contributes to several strands of the existing literature. First, it builds on the intermediary asset pricing literature, which emphasizes the role of intermediaries' financial conditions in determining risk premia and asset prices (He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Adrian et al. (2014), He et al. (2017), Haddad and Muir (2021), Baron and Muir (2022), Haddad and Muir (2026)). These studies typically measure intermediary risk-bearing capacity using balance-sheet measures, such as leverage or capitalization. These measures provide valuable information about intermediaries' financial conditions, but they do not distinguish or reveal the underlying constraints limiting intermediation. This paper extends this literature by emphasizing the multidimensional nature of intermediary constraints and their distinct implications for intermediation. While Siriwardane et al. (2025) emphasize segmentation across intermediaries and markets, I highlight how heterogeneity in balance sheet constraints within the same intermediary sector can also generate distinct effects across markets.

Second, this paper contributes to the literature on limits to arbitrage. Theoretical work shows how limited capital and funding constraints can sustain price discrepancies (Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2008)). Du et al. (2018) document persistent deviations from covered interest parity, linking these deviations to bank balance-sheet costs imposed by post-GFC regulation. However, limits to arbitrage do not necessarily need to reflect a single underlying constraint, since different arbitrages rely on different underlying resources.

This paper highlights the multidimensional and heterogeneous nature of limits to arbitrage.

Third, this paper relates to the literature that ties bank regulation to financial intermediation. Existing studies show that regulatory constraints can shape banks' portfolio allocations, lending decisions, and market-making activities. Choi et al. (2020) show that leverage requirements can encourage substitution toward riskier assets. Cimon and Garriott (2019) study how regulatory constraints affect dealer market-making. These effects can also extend to nonbank intermediaries. Boyarchenko et al. (2018) show that banking regulation can constrain arbitrage through both banks' direct trading and their financing of nonbank arbitrageurs, while Li et al. (2024) document the effects of prime-broker credit supply on hedge-fund borrowing and performance. Relatedly, Kruttli et al. (2025) highlight the role of hedge funds' internal risk constraints during market stress. I contribute to this literature by highlighting that the type of binding constraint is important to which activities are affected.

Finally, this work contributes to the literature using text data to measure otherwise difficult-to-observe economic conditions. Hassan et al. (2019) and Hassan et al. (2025) use earnings-call transcripts to measure firm-level exposure to economic and political risks. Bybee et al. (2023) and Bybee et al. (2024) develop methods to extract economically interpretable information from text and link it to economic outcomes and asset prices. I build on this literature using primary-dealer conference calls to measure which constraints on financial intermediation are binding and how severely they bind.

The rest of the paper proceeds as follows. Section 2 describes the data used in the analysis. Section 3 describes the construction of the TBC measure, which is then validated in Section 4. Section 5 shows that different constraint types predict different balance-sheet outcomes. Section 6 shows which constraints are associated with which arbitrage spreads. Section 7 shows which constraints are associated with bank financing patterns to nonbank intermediaries, which in turn are associated with lower risk-taking by those intermediaries. Finally, Section 8 concludes.

2 Data

The analysis combines conference call transcripts, regulatory bank filings, dealer surveys, hedge fund data, and arbitrage spreads. Table 1 summarizes the sources and sample periods.

Bank Conference-Call Transcripts. Following He et al. (2017), I focus on institutions designated as primary dealers by the Federal Reserve Bank of New York, which are institutions that

Table 1: Data Sources

Source	Unit	Sample	What it measures
Conference-call transcripts (Capital IQ)	Bank × quarter	2006Q3–2025Q4	Which constraint binds for each bank, and whether it is tightening or loosening
FR Y-9C	Bank × quarter	2010Q1–2025Q4	How each bank adjusts its own balance sheet, including the financing it provides to nonbanks
SCOOS	Aggregate, quarterly	2011Q3–2025Q4	The terms on which dealers finance hedge funds, and dealers' stated reasons for changing them
Form PF (OFR)	Aggregate, quarterly	2013Q1–2025Q4	Risk-taking activity of hedge funds
Arbitrage spreads	Strategy, quarterly	2010Q1–2025Q4	Prices of trades that reflect intermediary balance-sheet costs
HKM, AEM, market conditions	Aggregate, quarterly	Varies	Benchmarks for existing measures of intermediary conditions and for market stress

SCOOS is the Federal Reserve's Senior Credit Officer Opinion Survey on Dealer Financing Terms. Form PF data are the aggregate hedge-fund statistics published by the Office of Financial Research (OFR). Arbitrage spreads are from Siriwardane et al. (2025). HKM is the intermediary capital ratio of He et al. (2017), and AEM is the broker-dealer leverage factor of Adrian et al. (2014).

serve as trading counterparties to the FRBNY. Primary dealers are a natural sample for studying intermediary constraints since they include many large, systemically important banks and play a central role in securities trading, market-making, and financing to other institutions.

I use the historical primary-dealer universe and link dealers to their publicly traded holding companies. The holding companies' conference calls are from Capital IQ. These calls are a natural setting to study banks' constraints since management regularly discusses factors shaping their balance-sheet decisions, such as regulatory requirements, funding conditions, and capital allocation priorities. The resulting sample contains 2,498 conference calls from 24 firms over 78 quarters, spanning 2006Q3 to 2025Q4. I use these transcripts to construct my constraint measure, which I discuss in further detail in Section 3.

Bank Balance Sheets. To measure bank activity, I use quarterly FR Y-9C filings for U.S. bank holding companies and the U.S. intermediate holding companies of foreign banks. I gather data for 14 banks, including six U.S. bank holding companies (JPMorgan, Bank of America, Citigroup, Wells Fargo, Goldman Sachs, and Morgan Stanley) and eight foreign banks that file the FR Y-9C through their U.S. holding companies (Barclays, BMO, Credit Suisse, Deutsche Bank, HSBC, Mizuho, Royal Bank of Canada, and UBS).

The FR Y-9C data show how each bank adjusts its own balance sheet. Table A1 lists the FR Y-9C items behind each variable used in the analysis.

Hedge-Fund Financing and Risk-Taking. To measure the terms on which banks finance hedge funds, I use the Federal Reserve's Senior Credit Officer Opinion Survey on Dealer Financing Terms (SCOOS), a quarterly survey of senior credit officers at major securities dealers. I use the responses of all surveyed dealers to two questions about hedge-fund financing, which are available from 2011Q3:

- *Price terms.* How have the price terms (for example, financing rates) offered to hedge funds, across all securities financing and OTC derivatives transactions, changed over the past three months?

- *Reasons.* Dealers that tightened or eased terms rank the most important reasons for the change. One of the listed reasons for tightening is "diminished availability of balance sheet or capital at your institution."

To measure how hedge funds respond, I use the aggregate Form PF statistics on qualifying hedge funds (hedge funds with at least $500 million in net assets) published in the Office of Financial Research's Hedge Fund Monitor, as of each quarter end from 2013Q1 to 2025Q4. I use two sets of series. The first is gross notional exposure and net asset value, from which I compute gross notional exposure relative to net assets, a measure of leverage. The second is the average ratio of cash to net assets among the ten largest hedge funds by gross assets. Both series are used as proxies for hedge fund risk-taking.

Arbitrage Spreads. To measure price outcomes, I use the arbitrage spreads of Siriwardane et al. (2025), constructed from Bloomberg data with the authors' public code. Arbitrage spreads are a natural setting to study the price effects of intermediary constraints, since in a frictionless market they would be zero, and deviations reflect the balance-sheet cost of executing the trades

(Du et al. (2018)). Each spread is the difference, in basis points, between the riskless rate implied by an arbitrage trade and a benchmark riskless rate (the overnight indexed swap rate or, at longer maturities, the Treasury yield). I use the absolute value of each spread, so that a larger value always means a larger deviation from no-arbitrage. The data contain 31 daily spreads grouped into seven strategies:

- *Covered interest parity (CIP)*: the Australian dollar, Canadian dollar, Swiss franc, euro, British pound, Japanese yen, and New Zealand dollar against the U.S. dollar (7 spreads).
- *Treasury–swap*: maturities of 1, 2, 3, 5, 10, 20, and 30 years (7).
- *Treasury spot–futures*: 2-, 5-, 10-, 20-, and 30-year contracts (5).
- *TIPS–Treasury*: maturities of 2, 5, 10, and 20 years (4).
- *Equity box*: tenors of 6, 12, and 18 months (3).
- *Equity spot–futures*: the S&P 500, Nasdaq-100, and Dow Jones Industrial Average (3).
- *CDS–bond basis*: investment grade and high yield (2).

For each strategy, I take the equal-weighted mean of the spreads available on each day and average this daily series over the calendar quarter. When I average across strategies, I first divide each strategy's quarterly change in spread by its standard deviation over this sample, so that every strategy receives the same weight.

Existing Measures and Market Conditions. I compare the TBC measures I construct in Section 3 with the two most widely used measures of intermediary conditions. These benchmarks show how much of the information in the text is already captured by measures of how well capitalized intermediaries are.

- *HKM.* The intermediary capital ratio of He et al. (2017), the aggregate market equity of primary-dealer holding companies divided by their market equity plus book debt. I use the monthly series from the authors' website and take its value in the last month of each quarter. The series ends in 2025Q1.
- *AEM.* The broker-dealer leverage of Adrian et al. (2014), which I construct from the Financial Accounts of the United States (table L.130) as broker-dealers' total financial assets divided

by total financial assets minus total liabilities. The AEM leverage factor is the quarterly log change in this ratio; I do not seasonally adjust it.

To separate bank constraints from general market stress, I use five measures of market conditions, each averaged over the calendar quarter: the VIX; the Chicago Fed National Financial Conditions Index (NFCI); the spread between Moody's BAA corporate bond yield and the 10-year Treasury yield; the excess bond premium of Gilchrist and Zakrajšek (2012), as updated by the Federal Reserve Board; and the effective federal funds rate. All except the excess bond premium are from FRED. These measures enter as controls. For the six U.S. banks, I use CRSP daily stock data to measure each bank's quarter-end market equity, quarterly log return, and annualized daily return volatility, which enter the bank-level controls in Section 4.4.

3 Identifying and Measuring Firm Constraints

This section describes the construction of the TBC measure from quarterly conference-call transcripts of primary dealers. Conference calls provide a natural setting to study intermediary constraints, as dealers regularly discuss the factors shaping their balance-sheet decisions. I use a large-language model framework to extract measures of financial constraints from conference call transcripts. The procedure has three stages. First, a *screening stage* filters the universe of transcript paragraphs to keep any paragraph potentially related to financial constraints. Second, a *classification stage* examines the remaining paragraphs, removes false positives by retaining only references to a firm's own constraints, and then assigns each passage to a constraint type and scores its binding severity. Finally, an *aggregation stage* collapses these classifications into a panel of firm-quarter-theme measures.

Section 3.1 motivates the need for a new intermediary constraint measure. Sections 3.2, 3.3, and 3.4 detail the three stages of this procedure and the resulting time series plots. Section 3.5 provides descriptive results of how these measures vary across banks and time. Full details and summary statistics of the transcripts used are given in Appendix C.1– C.3. The full LLM prompts are given in the Online Appendix. Example outputs are given in Appendix C.4.

3.1 Motivating the New Constraint Measure

A central challenge in intermediary asset pricing is that constraints are not directly observed. Existing empirical work relies on proxies constructed from intermediary balance sheets, such as leverage ratios (Adrian et al. (2014)) and capital ratios (He et al. (2017)). These measures have been useful for studying the role of intermediaries in asset prices, but have two main limitations that my new measure seeks to address, particularly in the post-crisis regulatory environment.

The first limitation is that balance-sheet quantities may be less informative about intermediary constraints in the post-crisis regulatory regime. Measures such as leverage and capital ratios were particularly useful when fluctuations in intermediary balance sheets reflected changes in intermediaries' capacity to bear risk. Since the crisis, however, regulation has constrained intermediaries' risk-bearing capacity and altered their role in financial markets. Intermediaries nonetheless remain important for asset prices. For example, persistent deviations from covered interest parity following the crisis suggest that limits to intermediary risk-taking can prevent large and systematic price deviations from being arbitraged away (Du et al. (2018)). Therefore, intermediary constraints con-

tinue to shape asset prices, even as traditional balance-sheet measures have become less informative about the constraints intermediaries face.

A second limitation is that balance-sheet measures do not identify the source of intermediary constraints. Identifying the source has also become increasingly important in the post-crisis regulatory environment, where dealers simultaneously face multiple constraints on their balance-sheet capacity, such as risk-based capital requirements, leverage requirements, liquidity requirements, and internal risk limits. Dealers themselves emphasize the need to manage these constraints jointly. When asked in October 2014 which regulatory measure was binding for the bank, Citigroup management pointed to multiple potential constraints and concluded that "we need to keep our eye on all of those, and it doesn't do you any good to just manage one." Deutsche Bank management similarly observed in February 2019 that banks today "have to manage a wide range of metrics, so it's multiple constraints," while JPMorgan management referred to a "multi-variance of binding constraints" in October 2013.[†] This multiplicity limits what can be learned about intermediary constraints from balance-sheet proxies: the same observed balance-sheet position can be consistent with different underlying constraints.

The TBC measure is designed to capture this variation directly by identifying the constraints dealers themselves describe as shaping their decisions. Rather than inferring constraints or risk-bearing capacity from dealers' balance-sheet outcomes, the measure is constructed from conference-call text; it does not rely on the asset-price and balance-sheet data underlying existing measures, therefore avoiding a mechanical link to asset-price outcomes.

3.2 Stage 1: Screening Transcript Components

Stage 1 screens the transcript corpus for sentences that could plausibly relate to a dealer's financial or balance-sheet constraints (full LLM prompt given in Online Appendix Section OA1.1). This stage is deliberately left broad and prioritizes removing clearly unrelated sentences rather than precise classification of constraint-related text. Classification of the sentences remaining from this step occurs in the next stage. Sentences that are removed during this stage are never examined again. Splitting the prepared remarks and Q&A sections yields 306,243 paragraphs comprising 1,319,688 sentences, all of which are analyzed during this stage.

I use Claude Haiku 4.5 through Anthropic's Message Batches API. Each request consists of a system prompt and a single user message. I do not explicitly specify temperature, `top_p`, or `top_k`,

[†]The quotes are taken from Capital IQ transcripts, which are discussed in detail in Appendix C.1.

and therefore use the API defaults for these sampling parameters.

For each observation, the model receives a paragraph along with the firm, quarter, transcript section, and speaker role. The paragraph is further split into numbered sentences and the model is provided with both the full paragraph and the numbered sentences. Screening decisions are made at the sentence level conditional on the paragraph-level context. For responses in the Q&A section, I additionally provide the preceding analyst question as context. The question is included solely as context for interpreting the response and is not itself subject to sentence-level screening. The model identifies the specific sentences that may be relevant to financial constraints, retaining the full paragraph as context for the next stage.

In the prompt, I don't define relevance by applying a fixed keyword list. Instead, I provide illustrative examples of topics that can limit capacity to intermediate, such as regulatory capital, internal risk limits, etc. I emphasize that these are meant as examples for the LLM model, rather than an exhaustive list. I also explicitly instruct the model to err on the side of caution if the relevance of a sentence is unclear.

As mentioned earlier, this stage is purposely left broad. However, one explicit exclusion addresses the use of the word "capital." While the term can occasionally refer to balance-sheet constraints, it also frequently refers to unrelated concepts such as human capital, capital expenditures, or capital-markets business. These references are excluded unless the surrounding context also indicates a plausible balance-sheet or financial constraint.

The screening stage retains 68,025 sentences across 43,041 unique passages. These retained passages form the candidate set for the Stage 2 classification procedure.

3.3 Stage 2: Classifying Constraint Statements

Stage 2 classifies the candidate passages retained by the Stage 1 screening process (full LLM prompt given in Online Appendix Section OA1.2). As discussed in the previous section, Stage 1 is designed to broadly retrieve potentially relevant passages. Stage 2 then determines whether these passages describe constraints on the speaking firm's own balance-sheet capacity rather than those that discuss capacity constraints faced by the broader market, industry, or other firms. Broader discussions of exogenous developments, such as changes in market conditions or regulatory changes, are excluded unless they explicitly connect to the firm's own capacity (for example, if regulatory uncertainty makes a bank selectively deploy capital). The passage is classified as an own-firm observation only if it indicates that the firm's ability to fund activities, deploy capital, expand its balance sheet, or

bear risk is affected.

For passages that meet these criteria, the model then classifies the underlying constraint limiting the bank's activities and provides a short description, allowing for open-ended classification rather than imposing fixed categories ex-ante. When a passage describes more than one economically distinct constraint, the model designates the constraint most central to the passage as the primary constraint and records up to two additional constraints as secondary constraints.

The model then rates how binding the primary constraint is using an ordinal scale ranging from -3 to $+3$. Positive values indicate increasingly binding constraints, whereas negative values capture increasingly slack constraints. A value of 0 is assigned when the passage does not provide sufficient information to determine how binding the constraint is. Reported financial ratios do not determine binding severity in isolation; they affect the binding-severity classification when accompanied by a requirement, target, or some other type of comparison that makes the ratio interpretable.

Finally, the model reports a confidence score between zero and one, provides a brief justification for the own-firm and constraint classification, and extracts a short verbatim quotation providing the strongest support for its classification. I require these additional outputs to encourage the model to base its classification on explicit textual evidence rather than relying on a superficial reading of the passage. Together, the confidence score, justification, and supporting quotation also make the basis for the resulting classification more transparent to the reader, partially mitigating the "black box" nature of LLM-based classification. Following the classification stage, 30,160 passages from 2,332 transcripts remain and are used to construct the final measure. Table A5 gives the full step-by-step breakdown, while Appendix C.4 gives example outputs from each step of the procedure.

3.4 Stage 3: Topic Consolidation and Aggregate Constraint Measure

Stage 3 consolidates the passage-level classifications from Stage 2 into a common set of economically meaningful constraint topics, which I then organize into four broader themes. I use the resulting themes to construct a firm-quarter-theme panel and derive quarterly theme-level and aggregate constraint measures.

This stage has four steps (the full LLM prompt for steps one through three is given in Online Appendix Section OA1.3). First, the model reconciles the full set of open-ended constraint descriptions from Stage 2 into a common set of constraint topics. Descriptions of the same or similar underlying constraint may differ across firms or over time due to differences in terminology or institutional language. The purpose of this step is to reconcile these types of variations while preserving

economically meaningful distinctions between different constraint mechanisms. This procedure results in 14 common constraint topics that are used across all firms and quarters. I then group 12 of these 14 topics into four themes, which are summarized in Table 2; the remaining two topics are not assigned to a theme.

Second, once these topics have been defined, I map each passage and accompanying outputs from Stage 2 to the appropriate topic based on its constraint description. Each primary constraint description is assigned to exactly one topic. The binding-severity scores from Stage 2 are then carried forward with each topic assignment to be used in constructing the firm-quarter-topic panel.

Third, having assigned each Stage 2 passage to one of the 14 consolidated topics, I aggregate the passage-level classifications to the firm-quarter-topic level. Specifically, for each firm and quarter, I group passages according to their assigned topic and average their binding-severity scores within each group. This yields a panel containing one binding-severity measure for each firm-quarter-topic combination. Firm-quarter-topic combinations with no supporting passage are assigned a missing value, rather than being assigned 0.

Finally, I use the firm-quarter-topic panel to construct a quarterly time series for each of the 14 topics by averaging the binding severity across firms with an observed value for that quarter and topic. Specifically, for topic k in quarter t, I define the topic-level text-based constraint (TBC) measure as

$$TBC_{kt} = \frac{1}{N_{kt}} \sum_{i \in \mathcal{I}_{kt}} TBC_{ikt}, \tag{1}$$

where TBC_{ikt} is the binding severity for firm i, topic k, and quarter t; $\mathcal{I}_{kt}$ is the set of firms with an observed binding severity for topic k in quarter t; and $N_{kt} = |\mathcal{I}_{kt}|$ is the number of firms in this set.

I then construct a quarterly constraint measure for each of the four themes by taking the equal-weighted average of the topic-level series belonging to that theme. I define

$$TBC_{gt} = \frac{1}{K_g} \sum_{k \in \mathcal{K}_g} TBC_{kt}, \tag{2}$$

where $\mathcal{K}_g$ is the set of topics belonging to theme g, and $K_g = |\mathcal{K}_g|$ is the number of topics in that theme.

In addition, mostly for validation purposes, I construct the aggregate constraint measure by taking the equal-weighted average of these four theme-level series in each quarter:

$$TBC_t^{\text{Aggregate}} = \frac{1}{4} \sum_{g=1}^{4} TBC_{gt}. \tag{3}$$

Thus, the aggregate measure is constructed from the theme-level series, which are themselves constructed from the topic-level series, rather than directly from the underlying passages or firm-level observations. This two-stage aggregation assigns equal weight to each of the four constraint themes (and to the topics within each theme). This prevents topics with more passages from mechanically driving the more aggregated measures. Higher values of the topic-level, theme-level, and aggregate series correspond to more binding constraints.

Figure 1 plots the TBC measure for each of the four themes listed in Table 2. Figure A4 gives the time series of the full 14 LLM-generated topics. The gray shading around the blue time series lines gives the interquartile range of binding severity across banks; larger gray bands indicate larger bank-level heterogeneity of that reported constraint. The time series plots show that the constraint measures have substantial bank-level heterogeneity over time, and that the constraint themes have quite different time-series patterns, suggesting heterogeneity between the themes as well. Figure 2 quantifies this: the mean pairwise correlation between the six theme pairs is -0.02, with the largest being between leverage and risk-weighted capital themes at 0.36. This suggests that the themes exhibit little systematic co-movement and capture distinct dimensions of intermediary constraints. Figure A5 plots the heatmap of the 14 LLM-generated topics and reveals a similar pattern.

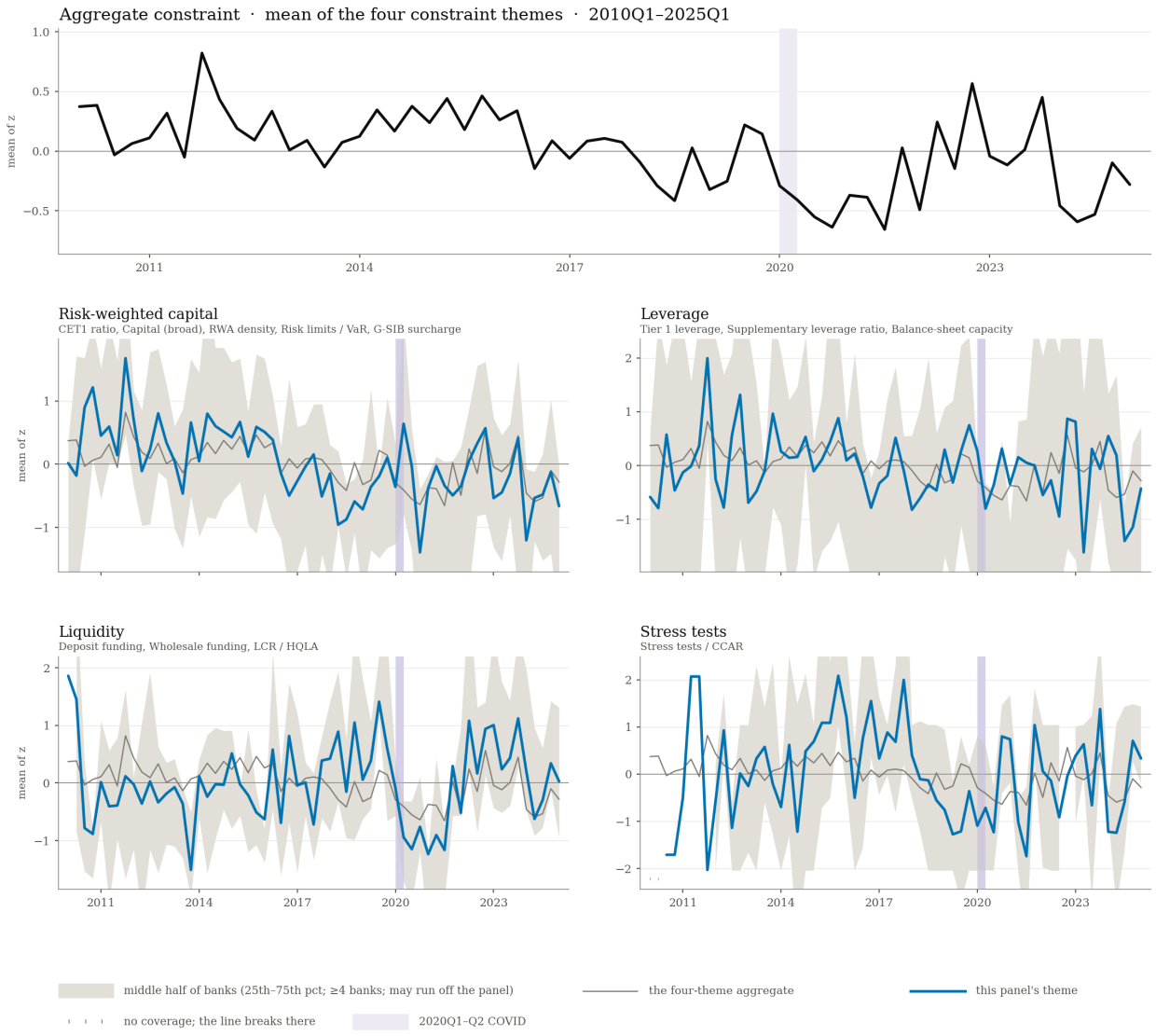
In the next section, I validate these measures and examine whether they capture economically meaningful variation in firm constraints.

Table 2: Constraint Themes

Group	**Included topics**	**What it constrains**
RW	`cet1`, `capital_broad`, `rwa_density`, `risk_limits_var`, `gsib_surcharge`	How much risk a bank can take relative to its capital
LEV	`tier1_leverage`, `slr`, `balance_sheet_capacity`	Overall exposure, regardless of how risky the assets are
LIQ	`lcr_hqla`, `deposit_funding`, `wholesale_funding`	Ability to meet obligations with available liquid funds
STR	`stress_test_ccar`	Ability to maintain sufficient capital during economic stress

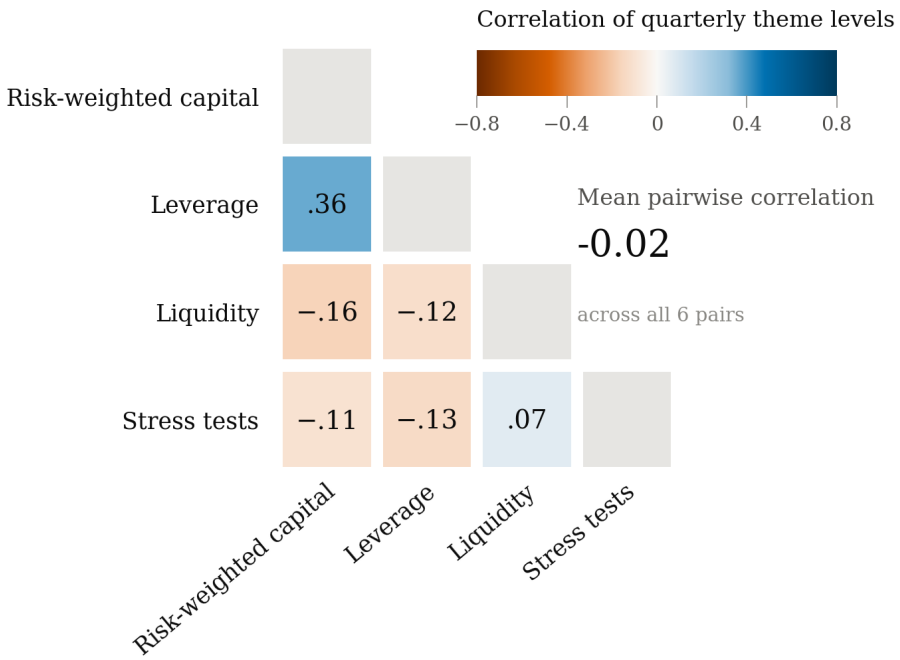
This table assigns the 14 constraint topics from Stage 3 to four themes. The topics `tlac_mrel` and `basel_rule_uncertainty` are not assigned to a theme.

Figure 1: Dealer Text-Based Constraint (TBC) Measures



The top panel plots the aggregate constraint measure, the equal-weighted average of the four constraint themes. The panels below plot each theme (blue) against the aggregate (gray). Each theme is an equal-weighted average of the topics from Table 2. The shaded band is the interquartile range across banks when at least four banks discuss the theme in that quarter. Breaks in a line mark quarters with no coverage. Higher values mean more binding constraints. Purple shading marks 2020Q1–Q2. Sample: 2010Q1–2025Q4.

Figure 2: Constraint Theme Measures — Pairwise Correlations



Pearson correlations between the quarterly levels of the four constraint themes, using quarters in which both themes are observed. Each theme is an equal-weighted average of the topics from Table 2. Higher values mean more binding constraints. Sample: 2010Q1–2025Q4.

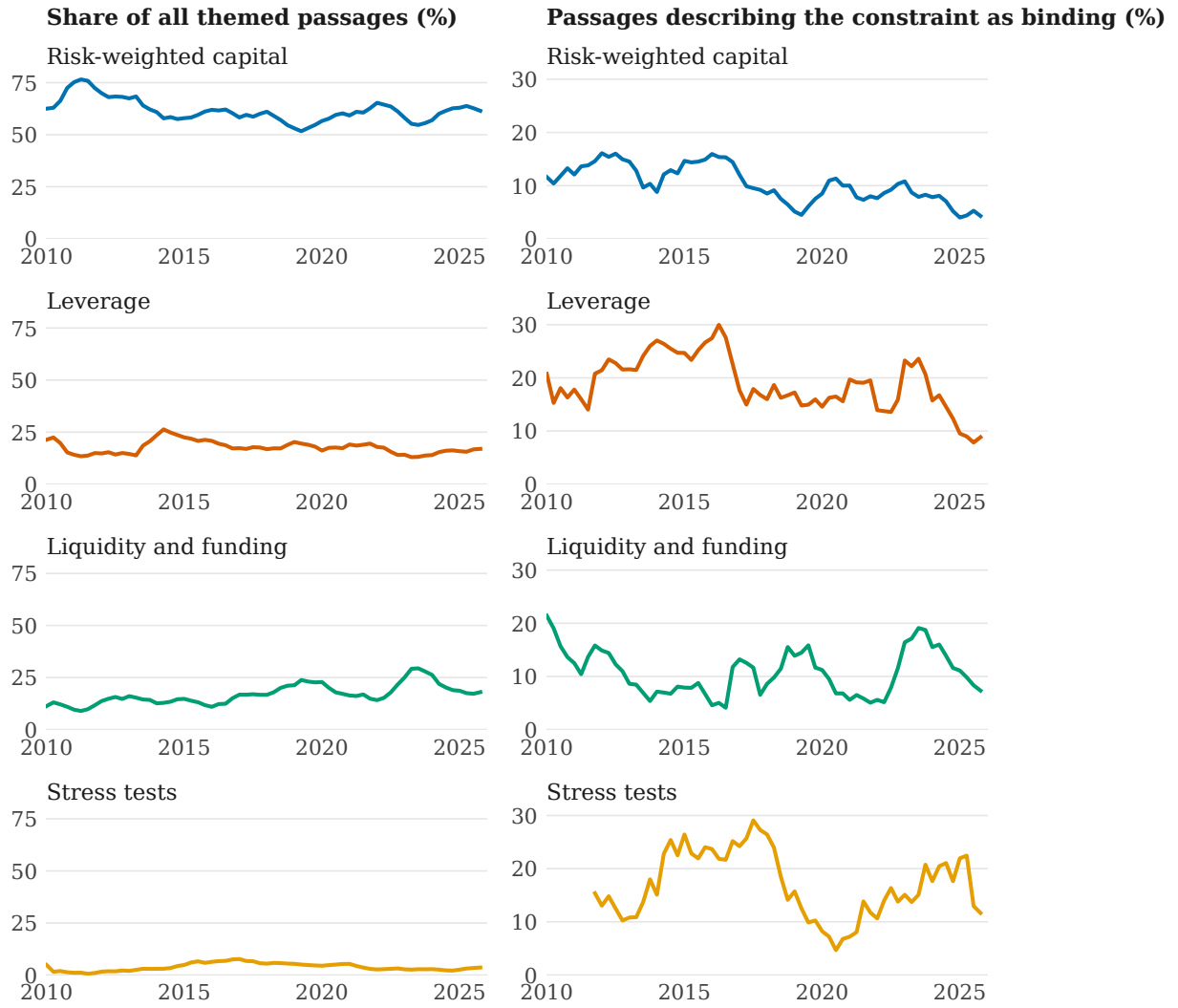
3.5 Descriptive Analysis of TBC Measures

A natural question that arises is how much variation there is in the constraints that banks face, both across banks and over time. In this section I provide descriptive evidence to show that there is substantial heterogeneity in how these constraints are discussed and how binding they are over time.

Figure 3 shows how the constraint discussions change over time. The left column shows the constraint's share of all constraint passages over time, and the right column shows what percentage of the respective discussions are marked as binding. The relative shares of constraint passages remain relatively stable over time: most constraint discussions are related to risk-weighted capital, comfortably hovering over 50%; stress test constraints are overall not discussed often; leverage and liquidity constraints generally make up around 20-25% of discussions. Nevertheless, there is quite a bit of heterogeneity in how binding these discussions are across all four themes. This shows that even if the types of constraints banks face remain relatively stable, the constraints that matter over time can vary.

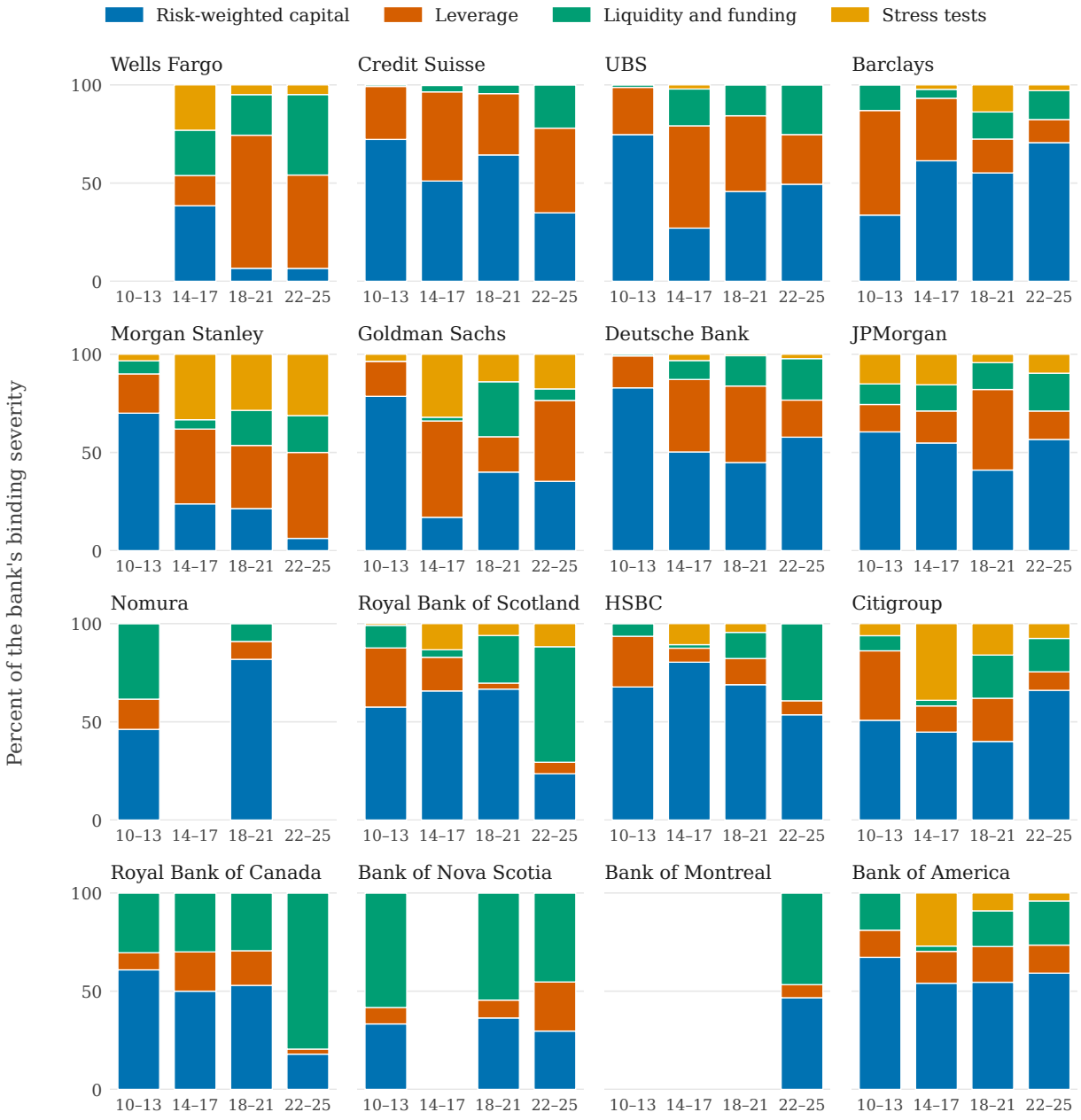
Figure 4 shows heterogeneity of constraints at the bank level and over time by plotting the composition of a bank's binding constraints. For various banks, I plot the share of the bank's binding constraint passages attributed to each constraint type. Banks discuss different constraints; for example, Morgan Stanley has a substantial portion attributed to stress test constraints, whereas Credit Suisse and Barclays have more binding passages related to risk-weighted capital. Within a bank this changes over time too; Goldman Sachs primarily discussed risk-weighted capital as their binding constraints in 2010-2013, but then talked about leverage in 2014-2017, while liquidity had a more prominent role in 2018-2021. The main takeaway of these is to show the importance of distinguishing which constraints bind, as they can differ substantially across banks and over time. Further descriptive statistics and results can be found in Appendix B. In the next section, I validate these measures.

Figure 3: Constraint Themes over Time



Each row is one theme. Columns plot, over the trailing four quarters, the theme's share of all themed passages and the percentage of the theme's passages that are binding. The vertical scale is common within a column. Points with fewer than 10 passages in the trailing four quarters are omitted. Sample: 2010Q1–2025Q4.

Figure 4: Which Constraints Bind, by Bank and Period



Each bar is a theme's share of the bank's total binding constraint passages. Sample: 2010Q1–2025Q4.

4 Validating the Constraint Measure

An important question is whether the TBC measures capture economically meaningful variation in intermediaries' balance-sheet constraints. In this section, I test the validity of the TBC measures in four complementary ways. First, in Section 4.1, I compare the measures against standard proxies for funding and financial conditions and intermediary health. Then, in Section 4.2, I compare the measures with bank-level outcomes from the Federal Reserve's stress tests. In Section 4.3, I test whether more constrained firms subsequently adjust their holdings. Finally, in Section 4.4, I show that the TBC measures contain information beyond existing proxies.

4.1 Relation to Existing Constraint Proxies

Table 3 compares the aggregate constraint measure against a broad set of existing proxies capturing different dimensions of intermediary constraints. The proxies capture different aspects of financial-market stress. TED/CP-bill spread, financial–nonfinancial commercial paper spread, and Treasury settlement fails reflect conditions in Treasury and short-term funding markets. The National Financial Conditions Index (NFCI) and Adjusted NFCI (ANFCI) summarize broader financial conditions. The Excess Bond Premium (EBP) and VIX capture market-wide risk and investor sentiment. The balance-sheet measures from He et al. (2017) (HKM) and Adrian et al. (2014) (AEM) capture broad intermediary conditions. Tier-1 ratio and RWA density capture regulatory capital adequacy and balance-sheet risk intensity.

Overall, the aggregate constraint measure is related to existing proxies in expected ways. In the full sample, correlations are the highest with funding-market and financial-conditions proxies, ranging from about 0.50 to 0.79. The correlation signs with respect to the balance-sheet measures are also consistent: the constraint measure is negatively correlated with the HKM capital ratio and Tier-1 ratio and positively correlated with dealer leverage and RWA density. Spearman rank correlations, also reported in Table 3, are generally smaller in magnitude, but the directions of these relationships mostly hold.

These relationships are not solely driven by the GFC. Although correlations decline after the crisis, as expected, all but the VIX retain the same signs. In particular, post-crisis correlations are 0.35 with the EBP, 0.41 with dealer leverage, -0.39 with the Tier-1 ratio, and 0.45 with RWA density. The main exception is the VIX, whose correlation is essentially zero. Taken together, the moderate correlations post-crisis suggest that the constraint measure overlaps with existing proxies,

Table 3: Correlation of Aggregate Text-Based Constraint Measure with Existing Proxies

	Pearson		**Spearman**	
Incumbent	**Full**	**Post**	**Full**	**Post**
Funding markets				
TED / CP-bill	0.79	0.28	0.46	0.29
CP fin–nonfin	0.72	0.21	0.38	0.21
UST fails (spike)	0.69	0.19	0.30	0.24
Financial conditions				
ANFCI	0.78	0.28	0.45	0.21
NFCI	0.76	0.25	0.43	0.19
EBP	0.72	0.35	0.45	0.26
VIX	0.50	−0.05	0.24	0.00
Intermediary capital				
HKM capital ratio	−0.49	−0.17	−0.37	−0.21
HKM risk factor	−0.21	−0.04	−0.13	−0.04
Dealer leverage				
AEM leverage	0.54	0.41	0.52	0.41
Regulatory ratios				
Tier-1 ratio	−0.59	−0.39	−0.51	−0.39
RWA density	0.50	0.45	0.50	0.40

Pearson and Spearman rank correlations between the aggregate constraint measure and existing measures of funding conditions, financial conditions, intermediary capital, dealer leverage, and bank regulatory ratios, computed over the same quarters. "Full" uses 2006Q3–2025Q4 and "Post" uses 2010Q1–2025Q4.

while still capturing variation that is not fully reflected by any single existing proxy.

4.2 Federal Reserve Stress Tests

If the measure captures constraints, dealers reporting more binding constraints should be less able to absorb adverse shocks. I test this implication using the Federal Reserve's annual supervisory stress tests. These tests assess how large banks perform under the same hypothetical severe recession scenario, focusing on their losses, revenues, and regulatory capital over the stress horizon. The Federal Reserve has conducted these annual supervisory stress tests under the Dodd-Frank framework since 2013. The results of these tests are reported in the Federal Reserve's annual *Supervisory Stress Test Results*.

I measure CET1 drawdown as the difference between a bank's starting Common Equity Tier 1 (CET1) ratio and its lowest projected CET1 ratio under the Fed's severely adverse scenario. I focus on drawdown rather than the minimum projected ratio to measure the decline in capital relative to each bank's starting position.

Six U.S. banks — Bank of America, Citigroup, Goldman Sachs, JPMorgan, Morgan Stanley, and Wells Fargo — are covered throughout the 2013–2025 sample. The U.S. subsidiaries of Barclays, Credit Suisse, Deutsche Bank, UBS, and HSBC enter the stress tests beginning in 2017–2018. Other dealers, such as Nomura, Mizuho, and Daiwa, are not covered by the U.S. stress tests. This yields 117 bank-year observations. For each test, I average my TBC measures over the four quarters preceding the release of the stress-test results.

Table 4 reports correlations between the constraint measure and CET1 drawdown. The pooled specification uses the full bank-year panel. The within-bank specification removes bank-specific averages, testing whether a dealer experiences a larger projected drawdown when its constraints are more binding than usual. The within-year specification removes year-specific averages, capturing whether dealers with relatively more binding constraints that year experience larger projected drawdowns.

The aggregate constraint measure is positively and significantly correlated with CET1 drawdown across all three specifications: the correlation is 0.21 in both the pooled and within-bank specifications and 0.22 in the within-year specification. The stress-test/CCAR topic provides a more targeted validation and is similarly positive and significant across all three specifications. Dealers with more binding constraints have larger projected capital drawdowns, both over time and relative to other dealers. This is consistent with interpreting the measure as a proxy for limits on dealers'

Table 4: Constraint Correlation with CET1 Drawdown

	Bank-year panel		
Measure	Pooled	Within-bank	Within-year
Aggregate constraint	$+0.21^{**}$	$+0.21^{**}$	$+0.22^{**}$
Individual topic			
Stress-test / CCAR	$+0.24^{**}$	$+0.28^{***}$	$+0.18^{*}$
HKM capital ratio (level)	-0.02	-0.05	$0.00^{\dagger}$

Correlations between the constraint measures and banks' CET1 drawdowns in the Federal Reserve's annual supervisory stress tests, 2013–2025. The drawdown is the difference between a bank's starting CET1 ratio and its minimum projected ratio. Each constraint measure is averaged over the four quarters before the results are released. "Pooled" is the raw correlation; "Within-bank" and "Within-year" remove bank and year means. The sample has 117 bank-years. †The HKM capital ratio is a single aggregate series, so it has no within-year variation. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

capacity to absorb adverse shocks.

4.3 Subsequent Holdings Adjustment

As a further validation exercise, I test whether firms that disclose tighter constraints subsequently adjust their balance sheets. I use quarterly FR Y-9C filings for bank holding companies and U.S. intermediate holding companies of foreign banks. Nonbank broker-dealers, such as Jefferies and Cantor Fitzgerald, do not file FR Y-9C reports and are therefore excluded. This restricts the sample of dealers relative to the sample used to construct the constraint measure. I use 12 of the 14 FR Y-9C banks described in Section 2: the six U.S. bank holding companies and the U.S. holding companies of Barclays, Credit Suisse, Deutsche Bank, HSBC, Mizuho, and UBS. BMO and RBC are not included in this exercise. Using these firms, I estimate:

$$\sum_{j=1}^{h} y_{i,t+j} = \alpha_i + \delta_t + \beta x_{i,t} + \varepsilon_{i,t}^{(h)}. \tag{4}$$

where $x_{i,t}$ is the standardized bank-level aggregate constraint measure $TBC_{it}^{\text{Aggregate}}$, which applies the same topic-to-theme-to-aggregate averaging to bank i's own topic measures TBC_{ikt}, and $y_{i,t+j}$ is the one-quarter change in balance-sheet size or capitalization, so the left-hand side is the cumulative

change over h quarters. I consider horizons of one, two, and four quarters ahead.

Table 5 shows that tighter constraints predict subsequent balance-sheet shrinkage. In the full 12-firm sample, a one-standard-deviation tightening in constraints predicts 0.75, 1.15, and 2.10 percentage points lower cumulative asset growth over the subsequent one, two, and four quarters, respectively, when accounting for firm and quarter fixed effects. These are statistically significant at each horizon and increase in magnitude with the horizon. The same relationship appears in the U.S.-only sample, although estimates are smaller and less statistically significant.

Also in Table 5, I test whether tighter constraints predict subsequent deleveraging. I measure capitalization as equity/assets rather than conventional book leverage (assets/equity). For some international firms in the sample, book equity approaches zero, making assets/equity unstable; using equity/assets avoids this near-zero denominator problem.

Tighter constraints also predict higher subsequent capitalization. In the full 12-firm sample, a one-standard-deviation tightening in constraints predicts higher capital ratios over the next one, two, and four quarters (0.104, 0.148, 0.266 percentage points, respectively, when accounting for firm and quarter fixed effects). The results are statistically significant and also hold for the six U.S.-firm sample.

An important question is whether the text predicts subsequent adjustment or simply describes adjustments that have already occurred. I test this with a direction placebo in Table A7, finding that constraint language precedes the balance-sheet adjustment it predicts. Overall, firms identified by the TBC measure as more constrained subsequently exhibit lower balance-sheet growth and higher capitalization. These results provide firm-level validation that the TBC measure captures economically meaningful limits on intermediaries' balance-sheet capacity.

4.4 Information Beyond Existing Measures

If the TBC measures merely restated how well capitalized banks are, they would add nothing to HKM and AEM. I test this here by asking whether existing measures span the TBC measures. Later sections test whether the text also explains each outcome beyond existing measures.

Table 6 reports the R^2 from regressing each cross-bank average TBC measure on HKM and AEM, and on a broad set of 13 incumbents that adds the VIX, the NFCI, the BAA spread, the excess bond premium, the federal funds rate, and banks' own average Tier 1 ratio, leverage ratio, and risk density from the FR Y-9C. Quarter-to-quarter changes in the binding severity of the themes are essentially orthogonal to HKM and AEM: the R^2 is 0.06 for risk-weighted capital, 0.03 for leverage,

Table 5: Intermediary Constraints and Subsequent Balance-Sheet Adjustment

Set	h	firms	β_{2wFE}	p_{2wFE}	β_{firmFE} (p)
Balance-sheet size — asset growth ($100 \cdot \Delta \log$ assets)					
Full reporting sample	1	12	-0.750^{**}	0.018	-0.393 (0.113)
Full reporting sample	2	12	-1.151^{***}	0.005	-0.993^{***} (0.004)
Full reporting sample	4	12	-2.100^{***}	0.001	-2.119^{***} (0.000)
U.S. BHCs	1	6	-0.418	0.213	-0.072 (0.727)
U.S. BHCs	2	6	-0.814^{**}	0.035	-0.501^{*} (0.075)
U.S. BHCs	4	6	-1.080^{*}	0.087	-0.739^{*} (0.061)
Capitalization — Δ equity/assets (percentage points)					
Full reporting sample	1	12	$+0.104^{***}$	0.001	$+0.096^{***}$ (0.001)
Full reporting sample	2	12	$+0.148^{***}$	0.003	$+0.170^{***}$ (0.000)
Full reporting sample	4	12	$+0.266^{***}$	0.001	$+0.350^{***}$ (0.000)
U.S. BHCs	1	6	$+0.038^{**}$	0.031	$+0.050^{***}$ (0.003)
U.S. BHCs	2	6	$+0.062^{**}$	0.021	$+0.103^{***}$ (0.000)
U.S. BHCs	4	6	$+0.106^{***}$	0.005	$+0.225^{***}$ (0.000)

Each row regresses a bank's cumulative change in the outcome over the next h quarters on its aggregate constraint measure. The full reporting sample has 12 U.S. and foreign banks that file the FR Y-9C; "U.S. BHCs" are the six U.S. bank holding companies. β_{2wFE} includes firm and quarter fixed effects, and β_{firmFE} includes firm fixed effects only. p-values are from permutations within quarter (two-way FE) or within firm (firm FE). I use capitalization rather than leverage because book equity is close to zero for some foreign banks. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

0.01 for liquidity, 0.07 for stress tests, and 0.10 for the aggregate, and none is significant at the 5% level. Even the full set of 13 incumbents explains at most 32% of any change series, not much more than the 22% that 13 unrelated regressors would explain on average in 60 quarters, and no R^2 is significant at the 5% level. The one dimension that existing measures partly capture is risk-weighted capital in levels: HKM and AEM explain 42% of its binding severity, consistent with HKM and AEM measuring how well capitalized banks are. Leverage, liquidity, and stress-test constraints are not spanned in levels or in changes.

Table 6: How Much of the Constraint Measures Do Existing Measures Explain?

	Levels		Changes	
Incumbents:	HKM, AEM	All	HKM, AEM	All
Risk-weighted capital	0.42***	0.46*	0.06	0.14
	[0.004]	[0.057]	[0.251]	[0.703]
Leverage	0.04	0.18	0.03	0.21
	[0.649]	[0.627]	[0.575]	[0.287]
Liquidity	0.07	0.29	0.01	0.30*
	[0.631]	[0.397]	[0.924]	[0.077]
Stress test	0.04	0.22	0.07	0.18
	[0.779]	[0.607]	[0.193]	[0.467]
Aggregate	0.23	0.47**	0.10*	0.32*
	[0.103]	[0.047]	[0.090]	[0.059]
Observations	60	60	60	60

R^2 from regressing the cross-bank average of each constraint theme, in levels and in quarterly changes, on existing measures. "HKM, AEM" is the level and change of the HKM capital ratio, plus the level of AEM leverage and the AEM leverage factor. "All" adds changes in the VIX, NFCI, and BAA spread; the level and change of the excess bond premium; the change in the federal funds rate; and changes in the cross-bank average Tier 1 ratio, leverage ratio, and risk density from the FR Y-9C (13 regressors in total). The aggregate is the equal-weighted average of the four themes. Brackets report p-values for whether the R^2 is larger than for an independent series, from a moving-block bootstrap of the TBC measure (eight-quarter blocks, 1,999 draws). Sample: 2010Q2–2025Q1. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5 Constraints and Balance-Sheet Adjustments

If the TBC measure captures which regulatory constraints banks face, it should predict how banks subsequently adjust their activities. Different constraints put pressure on different aspects of banks' balance sheets; for example, risk-weighted capital constraints limit the riskiness of the balance sheet, while leverage constraints limit the overall size relative to capital. Therefore, a bank's balance-sheet adjustments should follow different patterns depending on which constraint it faces. If the measure simply reflects a general reduction in risk-taking during periods of stress, balance-sheet responses should be similar regardless of the constraint reported by the bank. This section therefore assesses the validity of the TBC measure by testing whether banks' balance-sheet adjustments are consistent with the incentives associated with the constraints they report facing.

5.1 Predictions

I use the FR Y-9C panel described in Section 2 to test whether banks adjust their balance sheets in the directions implied by their regulatory constraints. I report results for all 14 banks in the sample; results for the six U.S. banks are in Appendix E.3. Table 7 lists the outcomes, each measured as the change from quarter t to $t+4$. I study asset risk composition, liquidity holdings, wholesale funding, and shareholder distributions, each of which should respond differently to different regulatory constraints.

Table 7: FR Y-9C Outcomes

Outcome	**What it measures**
ΔRW^{fix}	Risk-weighted asset density, computed with fixed risk weights
ΔHQLA share	LCR-weighted liquid assets / (cash + securities + trading securities + reverse repo + loans)
ΔSTW share	Short-term wholesale funding / total assets
Total payout / equity	Buybacks + dividends over quarters $t+1$ to $t+4$, relative to equity
$\Delta FinMix$	$\Delta \log(\text{NBFI loans}) - \Delta \log(\text{secured financing})$

All outcomes are constructed from FR Y-9C filings. Changes are measured from quarter t to $t+4$, and payouts are cumulated over quarters $t+1$ to $t+4$.

For each outcome, I estimate

$$\Delta Y_{i,t\to t+4} = \alpha_i + \gamma_t + \sum_{k\in\{RW,LEV,LIQ,STR\}} \beta_k TBC_{it}^k + \varepsilon_{it}, \tag{5}$$

where TBC_{it}^k is the binding severity of constraint theme k for bank i in quarter t. Banks face multiple regulatory requirements simultaneously. Therefore, all four constraint themes are included in the model together so that each coefficient captures the relationship between a constraint and subsequent balance-sheet adjustment conditional on other constraints. Bank fixed effects are captured by α_i and absorb persistent, latent differences across banks, such as balance-sheet composition or business models. Quarter fixed effects are captured by γ_t and absorb common shocks across all banks, such as underlying market conditions, the business cycle, and regulatory changes. With these fixed effects, identification comes from differences across banks within a quarter: I test whether banks facing relatively tighter constraints adjust their balance sheets along the predicted margin. To account for potential persistence over time in bank-level discussions of constraints, I calculate permutation-based p-values by randomly reassigning entire histories of constraint measures across banks.

I first discuss how the economic incentives associated with each regulatory constraint lead to predictions about banks' balance-sheet adjustments. Table 8 then summarizes the resulting predictions and their expected coefficient signs. These predictions are specified before estimation to limit concerns about selective reporting; rather than testing individual coefficients, I test whether the estimated relationships collectively follow the predicted directions.

Risk-Weighted Capital Constraints. Risk-weighted capital constraints limit how much risk a bank can take relative to the amount of capital it holds; assets with higher risk weights use up more of a bank's risk capacity than those with lower weights. When this requirement becomes binding, banks should shift the composition of their balance sheets toward assets that carry lower regulatory risk weights. I therefore expect tighter risk-weighted capital constraints to predict lower risk density.

Leverage Constraints. Leverage requirements limit the total size of a bank's exposure relative to its capital, regardless of how risky these exposures are. This operates differently from risk-weighted capital constraints because even assets with low risk weights use up leverage capacity. Moving from a high-risk-weight asset to a lower-risk-weight asset therefore has no effect on the leverage ratio. As a result, banks facing a binding leverage constraint may shift their exposures toward riskier assets that offer higher returns relative to overall exposure.

This generates two predictions. First, tighter leverage constraints are expected to increase risk density, since low-risk-weight assets consume leverage capacity while generating relatively low returns. Second, tighter leverage constraints should reduce the share of high-quality liquid assets (HQLA), which are assets that banks can quickly and easily convert to cash, for similar reasons.

Liquidity Constraints. Liquidity requirements affect how banks hold their assets and fund their activities. Banks can meet their liquidity requirements by holding more liquid assets or relying on more stable sources of funding. Tighter liquidity constraints should therefore increase the HQLA share, since holding HQLA helps banks meet their liquidity requirements. Tighter liquidity constraints should also reduce the short-term wholesale funding share. Short-term wholesale funding can be withdrawn or become due quickly, making it a less stable source of funding during times of high stress. Banks therefore have an incentive to rely less on short-term funding and more on stable funding sources to reduce their liquidity needs.

Stress-Test Constraints. Stress tests require banks to demonstrate they can maintain sufficient capital to withstand severe economic and financial shocks. While conventional capital requirements focus on current capital ratios, stress tests account for potential losses under adverse conditions; banks may face stress-test pressures even if they currently hold sufficient capital to meet regulatory minimums. Banks can retain a larger share of their earnings and preserve capital by limiting distributions to shareholders, such as dividend payments and share repurchases, strengthening their ability to absorb losses under stressed conditions.

Table 8: Balance-Sheet Outcome Predictions

Group	**Outcome**	**Sign**	**Economic chain**
LEV	ΔRW^{fix}	+	Broad exposure becomes scarce → low-weight assets still use capacity → risk density can rise.
LEV	ΔHQLA share	−	Safe assets still consume leverage exposure → liquid-asset share can fall.
LIQ	ΔHQLA share	+	Liquidity requirements favor larger liquid buffers → HQLA share rises.
LIQ	ΔSTW share	−	Short-term wholesale funding creates rollover risk → funding reliance falls.
STR	Total payout / equity	−	Stress-test capital plans constrain distributions → payout falls.
RW	ΔRW^{fix}	−	Risk-weighted capital becomes scarce → high-weight assets become relatively expensive → risk density falls.

Predicted sign of the effect of each constraint theme on the balance-sheet outcome it most directly affects. RW, LEV, LIQ, and STR are the risk-weighted capital, leverage, liquidity, and stress-test constraint themes. All predictions were set before estimation.

5.2 Results

Table 9 reports the estimated relationships between different constraints and subsequent balance-sheet adjustments for the full sample of 14 banks. The estimated coefficients align with the predicted directions, suggesting that banks adjust their balance sheets differently depending on which regulatory constraint is tight. Leverage constraints predict lower HQLA holdings and higher risk density; liquidity constraints predict higher HQLA holdings and less reliance on short-term wholesale funding; stress-test constraints predict lower shareholder distributions.

While all of the results point in their predicted directions, there is variation in their statistical precision. Therefore, to test whether the coefficients jointly support the predictions, I use a signed joint test. The results are statistically significant, with a p-value of 0.006. Therefore, although most coefficients are individually insignificant under permutation inference, the overall pattern supports the prediction that different constraints are associated with different subsequent balance-sheet adjustments.

To further establish that these predictions are specific to each respective constraint, I recompute the joint signed statistic under all 24 possible alignments of the four constraint measures to the four outcomes tested. If the measures primarily capture general regulatory pressure, alternative assignments could potentially generate similarly strong predictions. Instead, the actual assignment ranks first out of the 24 potential alignments, providing additional evidence that the TBC measures distinguish among different sources of regulatory pressure, rather than merely capturing overall regulatory tightness. Results are robust to leaving out individual firms, outcomes, and predicted relationships, as shown in Appendix E.

Table 9: Different Constraints, Different Balance-Sheet Adjustments

All 14 ($n = 633$)		
Prediction cell [sign]	b (t)	p_{perm}
LEV → ΔHQLA share [−]	−0.64 (−3.09)	0.085
LIQ → ΔHQLA share [+]	+0.25 (1.02)	0.501
LIQ → ΔST wholesale share [−]	−0.33 (−1.75)	0.313
STR → Payout/equity [−]	−0.35 (−2.58)	0.251
LEV → ΔRW^{fix} density [+]	+0.39 (2.11)	0.296
RW → ΔRW^{fix} density [−]	−0.26 (−1.62)	0.354
Joint signed test, p_{perm}	0.006	
Rank of true mapping among 24 relabelings	1	

Estimates of equation (5) for all 14 banks, with bank and quarter fixed effects. Coefficients report the estimated percentage-point change in the outcome over the following four quarters associated with a one-standard-deviation tightening in the indicated constraint. t-statistics are in parentheses. The permutation-based p-value is based on 999 permutations that reassign each bank's full history of constraint measures to another bank. The joint signed test sums the t-statistics across the predicted constraint-outcome cells. Rank is the position of the true assignment of constraints to predictions among all 24 possible assignments of the four themes, where 1 is the strongest alignment. Sample: 2010Q1–2025Q4.

6 Constraints and Price Outcomes

Bank constraints can affect arbitrage spreads through two channels. Banks can either directly trade in some markets, holding one leg of the trade on their own balance sheets (as in CIP trades; see Moskowitz et al. (2026)), or banks can finance the hedge funds or other institutions that hold risky assets. Either way, a bank's constraint should matter for a spread only if it binds on a resource the trade uses. Arbitrage trades differ in the resources they use. Siriwardane et al. (2025) show that arbitrage spreads are only weakly correlated with each other and suggest that intermediation is segmented along two dimensions: funding, because some trades are financed with secured and others with unsecured funding; and balance sheets, since different intermediaries specialize in different trades. Different constraints could therefore move different spreads.

This section first shows the familiar intermediary asset pricing result that average arbitrage spreads widen when banks report tighter constraints. It then decomposes this relationship along the four constraint themes. Risk-weighted capital and liquidity constraints are associated with spread movements, while leverage and stress-test constraints largely do not. The strategies associated with each constraint line up with the funding and balance-sheet needs of the trade. Risk-weighted capital constraints co-move with the secured trades that require holding a bond, such as the Treasury–swap spread and the CDS–bond basis. Liquidity constraints co-move with the trades that rely most on bank funding, CIP and TIPS–Treasury, as well as the Treasury–swap spread.

6.1 Aggregate Constraints and Arbitrage Spreads

The previous sections validated that the TBC measure captures limits on banks' capacity to deploy balance sheets. If so, tighter constraints should coincide with larger deviations from arbitrage relationships (Du et al. (2018)). I relate changes in the aggregate measure to changes in the seven arbitrage spread strategies described in Section 2. To make spreads comparable across markets, I standardize changes in each spread by its own standard deviation, and I average the standardized changes across the seven strategies.

Figure 5 and Table 10 provide evidence that the aggregate relationship is statistically significant and robust. A one-standard-deviation increase in the aggregate measure is associated with a 1.0 standard deviation widening of the average spread over the full sample and 0.27 standard deviations after 2010 ($p = 0.024$). The relationship remains significant controlling for the VIX, realized spread volatility, NFCI, and the full control set. Figure 5 plots the post-2010 relationship quarter by

quarter. Changes in the aggregate measure have a correlation of 0.47 with changes in the average spread ($p = 0.001$). The correlation is strongest for CIP (0.48, $p = 0.009$), equity spot–futures (0.40, $p = 0.061$), and the Treasury–swap spread (0.25, $p = 0.048$). Over the full sample, all seven correlations are positive (0.22 to 0.55) and significant at the 5% level (Figure 5).

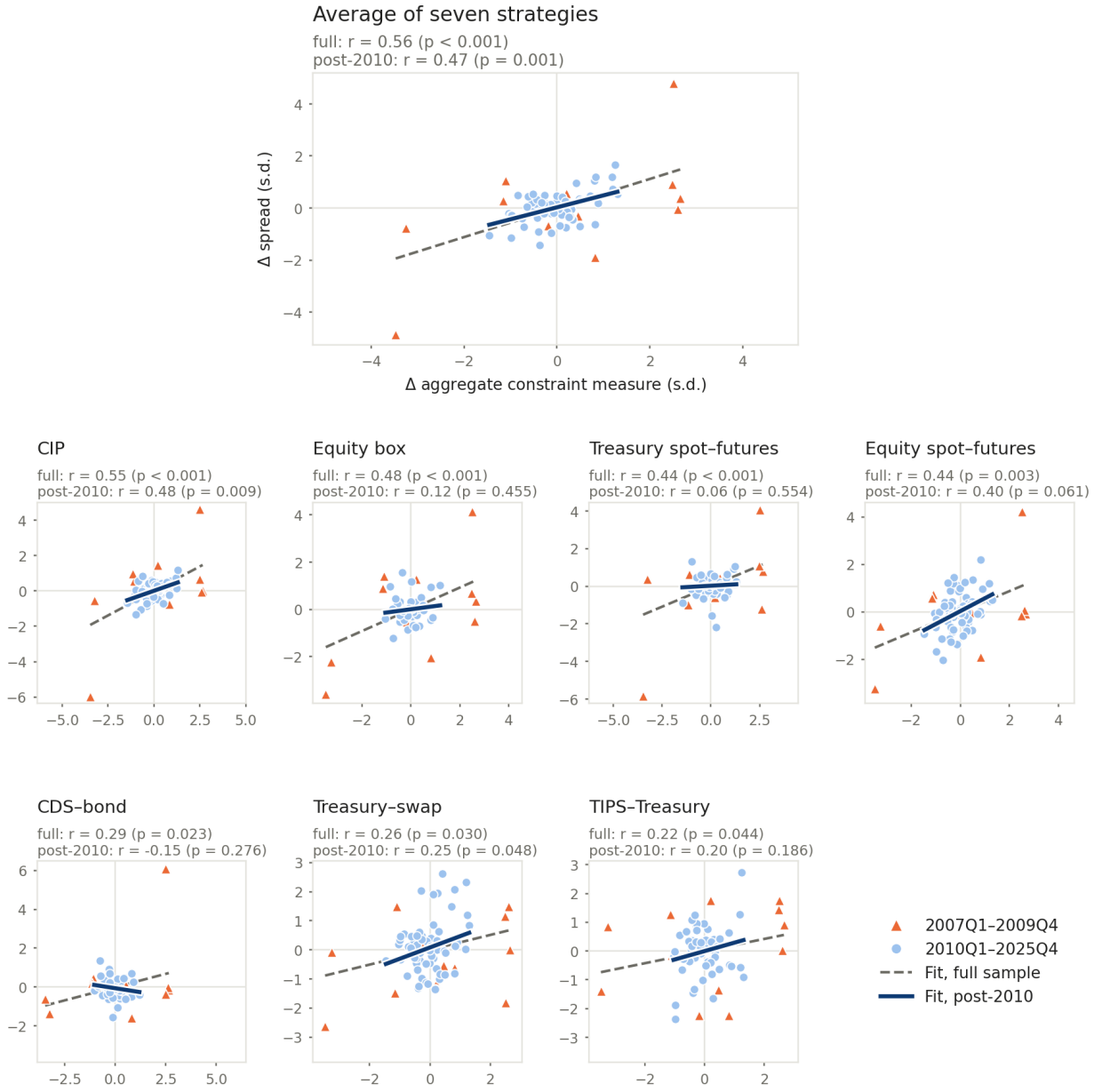
Table 11 compares the aggregate TBC measure with HKM and AEM measures. The TBC measure remains associated with average arbitrage spreads and statistically significant even when controlling for both measures (0.30, $p = 0.028$), while HKM and AEM are individually insignificant. This provides evidence that the TBC measure carries information about spreads beyond what can be extracted from capitalization and leverage ratios. This, by itself, does not show which constraint is associated with which spreads, which the rest of the section investigates.

Table 10: Intermediary Constraints and Arbitrage Spreads

Specification	β (p)	R^2	partial R^2	N
Full sample, 2007Q1–2025Q4				
Univariate	$+1.007^{***}$ (0.002)	0.609	0.605	76
+ VIX	$+0.805^{***}$ (<.001)	0.698	0.500	76
+ realised vol	$+0.460^{**}$ (0.033)	0.761	0.195	76
+ VIX + vol	$+0.478^{**}$ (0.031)	0.763	0.204	76
+ NFCI	$+0.449^{**}$ (0.024)	0.777	0.203	76
Full controls	$+0.329^{**}$ (0.050)	0.797	0.107	76
Post-2010, 2010Q1–2025Q4				
Univariate	$+0.273^{**}$ (0.024)	0.557	0.104	64
+ VIX	$+0.295^{**}$ (0.011)	0.573	0.121	64
+ realised vol	$+0.255^{**}$ (0.025)	0.577	0.095	64
+ VIX + vol	$+0.271^{**}$ (0.010)	0.579	0.100	64
+ NFCI	$+0.213^{**}$ (0.024)	0.627	0.075	64
Full controls	$+0.189^{*}$ (0.086)	0.630	0.054	64

Quarterly regressions of the average arbitrage spread on the aggregate constraint measure, both standardized within the estimation sample. All specifications include a linear time trend. Controls are the VIX, realized spread volatility, and the Chicago Fed NFCI, as indicated. Standard errors are Newey–West with four lags. p-values in parentheses and significance stars come from a stationary bootstrap of the constraint series (mean block length six quarters, 5,000 draws). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 5: Changes in Constraints and Changes in Arbitrage Spreads



Each point is a quarter. The horizontal axis is the quarterly change in the aggregate constraint measure and the vertical axis is the quarterly change in the indicated spread, both standardized. Each strategy's spread is the daily equal-weighted mean of its spreads, averaged to quarterly frequency, and the top panel averages the seven strategies' standardized changes. Triangles are 2007Q1–2009Q4 and circles are 2010Q1–2025Q4. The dashed line is the full-sample OLS fit and the solid line is the post-2010 fit. Panel headings give both correlations with phase-randomized p-values (3,000 surrogates of the constraint series). Panels are ordered by full-sample correlation.

Table 11: Aggregate Constraint Measures, HKM, and AEM

Controls	Specification	Text (aggregate)	HKM	AEM	n
None	Text only	0.32 (3.40) [0.012]			61
None	HKM only		−0.22 (−1.95) [0.177]		61
None	AEM only			0.54 (1.74) [0.299]	61
None	Text + HKM + AEM	0.30 (2.93) [0.028]	−0.07 (−0.68) [0.634]	0.46 (1.63) [0.310]	61
Full	Text only	0.21 (2.73) [0.061]			61
Full	HKM only		−0.53 (−2.83) [0.074]		61
Full	AEM only			0.78 (4.14) [0.037]	61
Full	Text + HKM + AEM	0.14 (1.86) [0.171]	−0.34 (−1.75) [0.253]	0.56 (2.73) [0.143]	61

Regressions of the detrended composite arbitrage spread on the aggregate TBC measure, the HKM capital ratio, and AEM leverage, each signed so that higher values mean more constrained. Full controls are the VIX, realized spread volatility, and the NFCI. t-statistics are in parentheses and phase-randomization p-values are in brackets. Sample: 2010Q1–2025Q1.

6.2 Which Constraints Co-move with Arbitrage Spreads

To identify which constraints co-move with spreads, I regress changes in spreads on changes in the four constraint themes:

$$\Delta s_t = \alpha + \sum_{k \in \{RW, LEV, LIQ, STR\}} \beta_k \Delta TBC_t^k + \gamma' \Delta X_t + \varepsilon_t, \tag{6}$$

where Δs_t is the change in the quarterly average spread, ΔTBC_t^k is the change in the measure of constraint k, and ΔX_t contains changes in the VIX, the NFCI, and the BAA spread. Inference uses a moving-block bootstrap of the constraint measures.

Table 12 reports the results for the average spread against the constraint themes. Two themes in particular are associated with wider spreads: risk-weighted capital and liquidity. A one-standard-deviation increase in the risk-weighted capital constraint is associated with a 0.23 standard deviation widening of the average spread ($p = 0.002$), and a 0.20 standard deviation widening ($p < 0.001$) for a one-standard-deviation increase in the liquidity constraint. Both are robust to controlling for financial conditions and for the HKM and AEM measures. Leverage and stress-test constraints are not associated with the average spread in any specification. The four themes explain about 30% of the variation in changes in the average spread.

Siriwardane et al. (2025) classify arbitrage trades into two groups based on how they are funded.

Unsecured strategies—CIP, equity spot–futures, and the equity box—are "high-margin strategies [that] require more unsecured funding." Secured strategies—Treasury–swap, Treasury spot–futures, TIPS–Treasury, and CDS–bond trades—are the remaining ones.

Columns (5)–(6) of Table 12 report the estimates of the different constraint themes on these two strategy groups. Risk-weighted capital is significantly associated with wider spreads for secured strategies (0.19, $p = 0.009$); liquidity is associated with wider spreads for both sets of strategies, but has more than double the magnitude (0.26 vs. 0.11) and stronger statistical significance ($p = 0.003$ vs. $p = 0.058$) for unsecured strategies over secured strategies. These findings are economically intuitive, as secured and unsecured arbitrage activities are exposed to different balance-sheet constraints. Unsecured strategies rely more on the availability of funding and expose banks to liquidity risk. Tables A12-A14 show that results are robust to market controls and to controls for sentiment, and that spread outcomes do not predict constraints.

6.3 Individual Strategy Results

Table 13 reports the themes' loadings on the individual arbitrage strategies. Risk-weighted capital loads significantly on Treasury–swap spreads (secured), and marginally on CDS–bond spreads (secured) and equity spot–futures (unsecured); leverage is significant on the Treasury spot–futures basis (secured); liquidity is significant on Treasury–swap (secured) and CIP (unsecured), and marginal on TIPS–Treasury (secured); the stress-test theme is marginal on CIP and equity spot–futures. The results suggest that different balance-sheet constraints affect arbitrage spreads through different economic channels.

For example, risk-weighted capital constraints are marginally associated with CDS–bond spreads, where financing corporate bonds can be costly because of their potentially high risk weights, depending on the issued bond. In contrast, leverage constraints are associated with the Treasury spot–futures basis, where banks provide financing against relatively safe Treasury securities. These loans involve little credit risk but still use bank balance-sheet capacity, which can therefore be costly when leverage constraints tighten. Liquidity constraints are associated with CIP, Treasury–swap, and TIPS–Treasury spreads, consistent with the importance of funding availability for these strategies. More generally, the results suggest that different constraints matter for different arbitrage strategies, although individual trades may be affected by more than one balance-sheet constraint.

Table 12: Constraint Themes and the Average Arbitrage Spread

	Average of seven strategies				Stacked strategies	
					Unsecured	Secured
	(1)	(2)	(3)	(4)	(5)	(6)
Risk-weighted capital	0.23***	0.18***	0.13**	0.21***	0.14	0.19***
	[0.002]	[0.006]	[0.013]	[0.007]	[0.199]	[0.009]
Leverage	0.05	0.06	0.04	0.06	0.09	0.01
	[0.356]	[0.189]	[0.397]	[0.246]	[0.253]	[0.792]
Liquidity	0.20***	0.18***	0.18***	0.21***	0.26***	0.11*
	[<0.001]	[0.004]	[<0.001]	[<0.001]	[0.003]	[0.058]
Stress test	0.08	0.09	0.04	0.07	0.12	0.04
	[0.189]	[0.101]	[0.391]	[0.211]	[0.176]	[0.444]
Δ VIX, NFCI, BAA	No	Yes	Yes	No	Yes	Yes
Δ HKM, AEM	No	No	Yes	No	No	No
Excludes 2020	No	No	No	Yes	No	No
Unique R^2	0.32	0.23	0.14	0.31		
Observations	63	63	60	60	394	

Estimates of equation (6). In columns (1)–(4), the outcome is the quarterly change in the average of the seven strategies' standardized spreads. Columns (5) and (6) come from one stacked regression of the seven strategies' standardized spread changes with strategy fixed effects, in which each theme has separate coefficients for the unsecured trades (CIP, equity spot–futures, equity box) and the secured trades (Treasury–swap, Treasury spot–futures, TIPS–Treasury, CDS–bond) of Siriwardane et al. (2025). The four themes enter jointly as changes in binding severity, standardized over 2010Q2–2025Q4. Unique R^2 is the increase in R^2 from adding the themes to a regression on the controls alone. Brackets report p-values from a moving-block bootstrap of the TBC measures (eight-quarter blocks, 1,999 draws); the stacked regression applies the same resampled path to every strategy. Sample: 2010Q2 onward. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13: Constraint Themes and Individual Arbitrage Spreads

	Unsecured			Secured			
	CIP	Equity spot–fut.	Equity box	Treasury–swap	Treasury spot–fut.	TIPS–Treasury	CDS–bond
Risk-weighted capital	0.80	4.98*	−0.15	1.37***	1.35	0.68	4.30*
	[0.448]	[0.077]	[0.885]	[0.007]	[0.440]	[0.597]	[0.072]
Leverage	1.18	1.22	−0.42	−0.06	2.44**	−0.31	−2.11
	[0.132]	[0.548]	[0.609]	[0.873]	[0.041]	[0.737]	[0.229]
Liquidity	1.96**	4.40	0.15	1.29***	0.85	1.81*	−0.14
	[0.049]	[0.109]	[0.881]	[0.002]	[0.631]	[0.073]	[0.930]
Stress test	1.65*	4.22*	−1.03	−0.29	1.15	0.56	1.23
	[0.064]	[0.083]	[0.192]	[0.479]	[0.429]	[0.581]	[0.496]
Unique R^2	0.16	0.16	0.03	0.18	0.08	0.08	0.05
Observations	63	63	47	63	63	53	42

Estimates of equation (6) for each strategy. The outcome is the quarterly change in the strategy's spread in basis points, so coefficients are basis points per standard deviation of the theme. Strategies are split into the unsecured and secured trades of Siriwardane et al. (2025). All regressions control for changes in the VIX, NFCI, and BAA spread. The four themes enter jointly as changes in binding severity, standardized over 2010Q2–2025Q4. Unique R^2 is the increase in R^2 from adding the themes to a regression on the controls alone. Brackets report p-values from a moving-block bootstrap of the TBC measures (eight-quarter blocks, 1,999 draws). Sample: 2010Q2 onward. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

7 Bank Constraints and Nonbank Intermediation

Canonical intermediary asset pricing models emphasize intermediaries' capacity to directly hold risky assets. Since the crisis, however, banks have increasingly shifted from directly holding risky assets toward financing the risk-taking of hedge funds and trading firms. It is therefore reasonable to expect that banks' constraints should affect the terms on which they finance hedge funds, which in turn could affect the funds' capacity to bear risk. This section examines whether bank constraints affect hedge funds through this channel, and which ones.

7.1 Bank Constraints and Financing Composition

I first examine whether different regulatory constraints affect the composition of financing that banks provide to nonbank financial institutions. Banks provide financing to nonbanks through secured financing, such as repos and margin loans, which are backed by collateral, and unsecured financing, which consists of loans made without pledged collateral. The two types carry different risk weights: secured financing carries low risk weights, unsecured financing high ones. Following the logic of Section 5, a leverage constraint should therefore make secured financing relatively costly. Secured financing consumes balance-sheet capacity that could otherwise support higher-risk-weight lending, raising its opportunity cost when leverage constraints are binding. On the other hand, a risk-weighted capital constraint should do the opposite, since unsecured lending increases risk-weighted assets.

To test these predictions, I measure the financing mix as

$$\Delta FinMix_{i,t} = \underbrace{\Delta \log(\text{NBFI loans})}_{\text{Unsecured financing}} - \underbrace{\Delta \log(\text{Fed funds sold} + \text{Reverse repo} + \text{Margin loans})}_{\text{Secured financing}}, \quad (7)$$

where unsecured financing consists of loans to nondepository financial institutions, and secured financing consists of federal funds sold, reverse repos, and margin loans. A positive value indicates that unsecured financing grows faster, or contracts less, relative to secured financing. This captures changes in the composition of bank financing independently of total financing changes. All components are measured using FR Y-9C regulatory filings detailed in Section 2.

I estimate

$$\Delta FinMix_{i,t\to t+h} = \alpha_i + \gamma_t + \sum_{k\in\{RW,LEV,LIQ,STR\}} \beta_k TBC_{it}^k + \varepsilon_{it}, \quad (8)$$

using the same bank and quarter fixed effects and firm-path permutation inference as in Section 5. Table 14 reports the signed predictions. We would expect $\beta_{LEV} - \beta_{RW} > 0$. When banks face tighter

leverage constraints, this should shift the financing mix towards unsecured financing. Tighter risk-weighted capital constraints, on the other hand, should shift towards secured financing.

Table 14: Predictions for the Financing Mix

Group	**Outcome**	**Sign**	**Economic chain**
LEV	$\Delta FinMix$	$+$	Leverage exposure becomes scarce $\rightarrow$ low-risk-weight secured financing still uses balance-sheet capacity $\rightarrow$ secured financing falls relative to unsecured loans.
RW	$\Delta FinMix$	$-$	Risk-weighted capital becomes scarce $\rightarrow$ unsecured NBFI loans carry higher risk weights $\rightarrow$ unsecured lending falls relative to secured financing.

The table reports the predicted signs for the effect of leverage (LEV) and risk-weighted capital (RW) constraints on $\Delta FinMix$. I define $FinMix$ as the growth rate of banks' unsecured loans to nonbank financial institutions relative to their secured financing. Both predictions were set before estimation.

Table 15 reports the results. The estimated difference $\beta_{LEV} - \beta_{RW}$ is positive at both horizons, consistent with the ex-ante predictions. For the two-quarter horizon, the estimated difference is 5.75 log points ($p_{perm} = 0.020$); at the four-quarter horizon, the difference remains positive (6.80), although slightly less significant ($p_{perm} = 0.082$). Nonetheless, the direction of the estimated difference is stable. The economic magnitude is substantial. A one-standard-deviation tightening of the leverage constraint is associated with an approximately $2.8 billion reduction in secured financing per bank two quarters ahead, and $4.2 billion four quarters ahead.

These results show that regulatory constraints predict the composition of financing banks provide to nonbank institutions. Tighter leverage constraints predict a shift in financing away from balance-sheet-intensive secured instruments, such as reverse repos and margin loans, whereas tighter risk-weighted capital constraints predict a shift toward these instruments relative to unsecured lending.

These results may appear inconsistent with the pricing results in Section 6, where leverage constraints are not associated with wider spreads on secured arbitrage trades on average, despite predicting lower secured financing. Two distinctions may help reconcile this difference. First, the financing analysis compares banks within the same quarter, whereas the pricing results reflect aggregate variation over time; one bank reducing secured financing relative to others need not reduce the total financing available in the market. Second, banks affect arbitrage spreads both by financing other investors and by holding positions directly, and secured trades that require

Table 15: Constraints and the Composition of Financing to Nonbanks

	$h = 2$	$h = 4$
LEV $\rightarrow \Delta FinMix$ [+]	+3.38 (2.35)	+4.44 (2.15)
RW $\rightarrow \Delta FinMix$ [−]	−2.37 (−1.48)	−2.35 (−1.13)
LEV − RW contrast [+]	+5.75 (2.57)	+6.80 (2.41)
One-sided p_{perm}	0.020	0.082
LEV $\rightarrow \Delta$ log secured financing, \$bn per SD	−2.8	−4.2
n	635	606

Estimates of equation (8), with bank and quarter fixed effects, over $h = 2$ and $h = 4$ quarters. The outcome, $\Delta FinMix$, is the change in log loans to nondepository financial institutions (unsecured financing) minus the change in log federal funds sold, reverse repos, and margin loans (secured financing), in log points $\times 100$. LEV and RW are the leverage and risk-weighted capital constraint themes; t-statistics are in parentheses. The LEV − RW contrast is predicted to be positive, and its one-sided p_{perm} comes from permutations that reassign each bank's full history of constraint measures to another bank. The second-to-last row expresses the LEV effect on secured financing in billions of dollars per standard deviation.

holding the underlying bond consume risk-weighted capital directly. These results, however, capture financing to a broad set of nonbank institutions without identifying the specific borrowers that are affected. To examine whether these effects extend to hedge funds in particular, I next turn to banks' reported financing terms for hedge funds and whether the various regulatory constraints are associated with tighter financing conditions.

7.2 Bank Constraints and Hedge Fund Financing Terms

The preceding results show that regulatory constraints predict the composition of financing banks offer to nonbank institutions. These results do not establish whether tighter constraints translate into tighter financing conditions for hedge funds specifically. I examine this question using the SCOOS data described in Section 2, which provide direct information on the financing terms that banks offer to hedge funds.

I measure changes in hedge-fund financing conditions using banks' responses on financing terms. Banks report whether terms to hedge funds have tightened, eased, or remained unchanged since the preceding quarter. I calculate net tightening as the percentage of banks reporting tighter terms minus the percentage reporting looser terms. Because these responses are already measured as

changes over the quarter, I regress net tightening on the level of cross-bank average constraint measures:

$$NT_t = \alpha + \sum_{k \in \{RW, LEV, LIQ, STR\}} \beta_k TBC_t^k + \gamma' \Delta X_t + \varepsilon_t, \tag{9}$$

where ΔX_t contains changes in the VIX, the NFCI, and the BAA spread. This controls for changes in market volatility, financial conditions, and credit spreads that could potentially affect dealers' financing decisions. This regression tests whether periods of tighter regulatory constraints coincide with periods of more tightening in hedge-fund financing terms, conditional on aggregate financial conditions. Inference uses a block bootstrap of the TBC measures.

The first two columns of Table 16 report the results for net tightening of hedge-fund financing terms. Both risk-weighted capital and leverage constraints are associated with greater net tightening. A one-standard-deviation increase in risk-weighted capital constraints is associated with a 9.1 percentage point increase in reported net tightening ($p < 0.001$). Leverage constraints are also associated with greater net tightening; a one-standard-deviation increase in leverage constraints is associated with a 3.4 percentage point increase in reported net tightening ($p = 0.042$). Both relations remain positive and statistically significant after controlling for changes in aggregate financial conditions. In contrast, liquidity and stress-test constraints are not statistically significantly associated with net tightening.

The last two columns of Table 16 provide complementary evidence that this relationship operates through banks' balance-sheet capacity. The first two columns alone do not rule out the possibility that banks tighten their financing terms for reasons unrelated to regulatory constraints; the relationship could arise as a result of common shocks that affect both reported constraints and tighter financing terms. If constraints do indeed affect financing through banks' balance-sheet capacity, they should also be associated with dealers identifying balance-sheet or capital availability as their reason for tightening. The SCOOS asks banks to identify their reasons for tightening financing terms to hedge funds, including "the availability of balance sheet or capital at your institution." Consistent with this, tighter risk-weighted capital and leverage constraints are in fact associated with dealers citing this reason more frequently. Therefore, the same constraints that are associated with net tightening are also associated with dealers attributing tightening to balance-sheet or capital pressures.

These results show that although leverage and risk-weighted capital constraints have opposite effects on banks' use of secured versus unsecured financing, both are associated with tighter financing

terms for hedge funds. The difference is that the financing composition results capture how banks allocate financing, whereas the results in this section capture whether dealers are tightening the terms conditional on the financing they do provide. The opposing effects are not contradictory, but rather reflect different dimensions of banks' adjustment to regulatory constraints. These results suggest that risk-weighted capital and leverage constraints are related to both the overall structure of financing to nonbank institutions and the financing conditions faced by hedge funds specifically. Robustness results are given in Table A15.

Having established that bank constraints are associated with tighter terms for hedge funds, I next examine how hedge funds adjust their risk-taking when faced with tighter financing pressures.

Table 16: Bank Constraints and Hedge-Fund Financing Terms

	Net tightening, HF price terms		**Reason: own balance sheet/capital**	
	No controls	Δ controls	No controls	Δ controls
Risk-weighted capital (RW)	0.091***	0.064***	0.019***	0.013*
	[<0.001]	[<0.001]	[0.006]	[0.054]
Leverage (LEV)	0.034**	0.041**	0.020***	0.020***
	[0.042]	[0.010]	[0.004]	[0.006]
Liquidity/funding (LIQ)	−0.004	−0.008	−0.003	−0.002
	[0.788]	[0.604]	[0.668]	[0.771]
Stress tests (STR)	0.024	0.020	−0.001	−0.003
	[0.103]	[0.135]	[0.870]	[0.636]
T	58	58	58	58

Estimates of equation (9). In the first two columns, the outcome is SCOOS net tightening of price terms offered to hedge funds. In the last two, it is the share of dealers that cite the availability of balance sheet or capital at their own institution as a reason for tightening. Constraint measures are cross-bank averages of each theme (equation 2), in levels. Δ controls are changes in the VIX, NFCI, and BAA spread. Block-bootstrap p-values are in brackets. Sample: 2011Q3–2025Q4. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

7.3 Hedge Fund Responses to Tighter Financing Terms

The preceding subsection shows that tighter bank constraints coincide with tighter financing terms for hedge funds. A natural and important follow-up question is whether bank constraints affect hedge funds' risk-taking through these financing terms. I investigate this channel by testing whether tighter hedge-fund financing terms are associated with lower leverage and higher cash holdings, which I use as proxies for hedge funds' risk-taking.

Using aggregate Form PF data described in Section 2, I estimate

$$\Delta Y_t = \alpha + \beta\, NT_t + \gamma' X_t + \varepsilon_t, \tag{10}$$

where NT_t is the SCOOS net tightening of hedge-fund financing terms described in the previous section, and ΔY_t is either the change in the log of hedge funds' gross notional exposure relative to net assets (a measure of leverage), or the change in the cash ratio of the ten largest hedge funds (a measure of liquidity holdings). Both outcomes provide proxies for risk-taking. When investors lower leverage, they are reducing their exposures relative to their capital. Similarly, higher cash holdings point to investors retaining more available liquidity, rather than deploying it into investments or holdings.

Table 17 reports the results. Quarters where banks tighten hedge-fund financing terms are quarters in which hedge funds reduce their leverage and the largest funds increase their cash holdings. A one-standard-deviation increase in net tightening is associated with a 0.70 standard deviation decline in leverage growth ($p = 0.001$) and a 0.28 standard deviation increase in the cash ratio ($p = 0.009$). These findings are consistent with hedge funds responding to tighter financing conditions by reducing leverage and increasing liquidity buffers. One potential concern is that the relationship could reflect changes in hedge funds' demand for financing rather than banks' constraints. However, a reduction in hedge-fund risk exposure should ease bank conditions, rather than tighten them.

Taken together, these results suggest that periods in which dealers tighten financing terms are also periods in which hedge funds reduce their exposures and maintain larger liquidity buffers. Combined with the previous subsection's evidence that tighter risk-weighted capital and leverage constraints coincide with tighter financing terms, these findings suggest that bank constraints may also limit hedge funds' capacity to bear risk.

Table 17: Hedge-Fund Financing Terms and Hedge-Fund Risk-Taking

	$\Delta \log$**(Gross notional/NAV)**			**Δ Cash ratio, top-10 funds**		
	Baseline	Δ controls	Ex-2020	Baseline	Δ controls	Ex-2020
	(1)	(2)	(3)	(4)	(5)	(6)
HF financing tightening	-0.70^{***}	-0.21^{*}	-0.58^{**}	0.28^{***}	0.40^{***}	0.27^{***}
	[0.001]	[0.050]	[0.015]	[0.009]	[0.002]	[0.007]
T	51	51	47	51	51	47

Estimates of equation (10). The outcomes are the change in the log ratio of hedge funds' gross notional exposure to net asset value, and the change in the cash ratio of the ten largest hedge funds, both from the OFR's aggregate Form PF statistics. The regressor is SCOOS net tightening of hedge-fund price terms, and coefficients are standardized. All specifications include the lagged outcome. The baseline and ex-2020 columns control for the levels of the VIX and NFCI, and the Δ controls columns use their changes instead. Standard errors are Newey–West with three lags. Brackets report one-sided p-values in the predicted direction from 1,999 phase-randomized surrogates of the regressor, Holm-adjusted across six predicted outcomes. Sample: 2013Q2–2025Q4. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

7.4 Hedge-Fund Financing and Treasury Cash-Futures Basis

The preceding sections show that different bank constraints are associated with different arbitrage spreads (Section 6) and financing decisions to nonbank intermediaries (Sections 7.1– 7.2). They also show that hedge funds adjust their risk-taking when faced with tighter constraints (Section 7.3). An open question is whether these financing responses can help explain why different bank constraints matter for different arbitrage prices. One potential explanation is that different arbitrage markets rely on different intermediation activities, so the constraints that restrict those activities also differ in their effects on arbitrage prices. This mechanism can operate even when banks do not hold the underlying arbitrage positions: bank constraints may transmit to prices through their effects on the financing and risk-taking of nonbank arbitrageurs.

To examine this channel, I study the Treasury spot-futures basis market. Existing literature provides evidence for hedge funds, not banks, being the marginal arbitrageurs in this market (Barth and Kahn (2025), Siriwardane et al. (2025)). Hedge funds finance these positions through repo financing, borrowing from banks to obtain the leverage needed to exploit these price differences (Glicoes et al. (2024), Barth and Kahn (2025)). Therefore, banks play an important role in this market even when they are not the marginal traders holding the underlying positions.

Earlier findings establish the first links in this mechanism. Table 15 shows that secured financing that banks offer to hedge funds, including repo, is sensitive to bank leverage constraints. Table 16 further shows that tighter bank leverage constraints are associated with tighter financing terms offered to hedge funds, while Table 17 shows that hedge funds respond to tighter financing conditions by reducing their borrowing and exposures. These findings together suggest a mechanism behind the relationship between leverage constraints and the Treasury spot-futures basis documented in Table 13. To examine this mechanism more directly, I extend the earlier financing analysis to the financing and positions of hedge funds engaged in relative-value strategies.

I use aggregate Form PF statistics for hedge funds that report relative value as their investment strategy. While the relative-value category is broader than the Treasury cash-futures basis I study, it provides a more targeted measure of potential arbitrageurs than the aggregate hedge-fund measures used in earlier sections.

Table 18 shows that relative-value hedge funds shrink their balance sheets when banks' leverage constraints tighten and when hedge funds are faced with tighter financing terms from banks. A one-standard-deviation tightening in the leverage constraint is associated with a 3.8 percent decline

Table 18: Leverage Constraints, Hedge-Fund Financing Terms, and Relative-Value Hedge Funds

	Bank leverage constraints		Hedge-fund financing terms	
	Est.	p	Est.	p
Relative-value hedge funds (Form PF)				
Gross notional exposure	−0.038	[0.028]	−0.32	[0.002]
Gross assets	−0.018	[0.080]	−0.40	[0.006]
Borrowing	−0.023	[0.068]	−0.34	[0.004]
Leverage: GNE/NAV	−0.032	[0.040]	−0.34	[0.017]
Leverage: GAV/NAV	−0.012	[0.138]	−0.39	[0.008]
All hedge funds				
Repo borrowing (Form PF)	−0.016	[0.050]	−0.20	[0.107]
Observations	51		51	

Outcomes are quarterly changes in logs of Form PF aggregates. Coefficients are standardized. Left: regressor is Δ LEV, the change in the binding severity of bank leverage constraints (Table 13). Controls are changes in the VIX, NFCI, and BAA spread; ex-2020 sample. Right: regressor is SCOOS net tightening of hedge-fund price terms; controls are the lagged outcome and changes in the VIX and NFCI; Newey–West standard errors (three lags). Sample: 2013Q2–2025Q4.

in the hedge funds' gross notional exposure ($p = 0.028$), about $100 billion at the sample mean. Their leverage falls as well: GNE/NAV declines 3.2 percent ($p = 0.040$), and GAV/NAV declines 1.2 percent. Results are similar when banks tighten their financing terms towards hedge funds.

Table 19 shows that hedge fund borrowing and repo financing are associated with wider spreads. The basis widens when relative-value funds borrow less (a 10 percent decline in borrowing goes with a 2.1 basis point wider basis, $p = 0.049$) and when repo borrowing falls (3.5 basis points per 10 percent, $p = 0.036$ excluding 2020).

Taken together, these findings provide suggestive evidence for why different bank constraints matter for different arbitrage spreads. Bank constraints differ in which activities they restrict, and arbitrage strategies depend on different intermediation activities. The Treasury cash-futures basis illustrates this mechanism: leverage constraints are associated with lower hedge-fund exposures and repo borrowing. Lower hedge-fund borrowing is, in turn, associated with wider spreads. Although these relationships do not establish a causal relationship, they are consistent with the view that which constraints are relevant for arbitrage prices depends on the underlying intermediation activity

Table 19: Relative-Value Hedge Funds and Treasury Spot-Futures Basis

Regressor	Estimate (bp)	Ex-2020	HKM, AEM	Obs.
Δ LEV	2.44	[0.050]	[0.042]	63
Hedge-fund positions (bp per unit change in log)				
RV borrowing	−21.3	[0.049]		51
Hedge-fund repo borrowing	−34.7	[0.036]		51
RV gross notional exposure	−13.1	[0.147]		51
CFTC leveraged-fund futures shorts	−2.0	[0.399]		62

The outcome is the quarterly change in the Treasury spot–futures basis, in basis points. The first row regresses the basis against the bank leverage constraint; the remaining rows are against positions of relative-value strategy hedge funds and are in quarterly change in logs. All regressions control for changes in the VIX, NFCI, and BAA spread. Block-bootstrap p-values in brackets.

that the arbitrage relies on.

8 Conclusion

This paper studies how different constraints on bank intermediation shape asset prices and financing decisions. Using conference-call transcripts of primary-dealer holding companies, I develop a new text-based constraint (TBC) measure that distinguishes risk-weighted capital, leverage, liquidity and funding, and stress-test constraints. I show that these measures capture economically distinct constraints and contain information beyond existing proxies for intermediary risk-bearing capacity.

I find that different constraints are associated with different arbitrage spreads and how banks provide financing to nonbank intermediaries. The specific constraints banks face determine which intermediation activities become costly, and I provide evidence that this in turn can explain why different constraints are associated with different arbitrages.

These findings highlight that intermediary risk-bearing capacity depends not only on how constrained banks are, but also on which constraints they face and how those constraints affect the intermediaries they finance. As risk-taking increasingly takes place outside bank balance sheets, understanding the effects of bank constraints on asset prices requires accounting for their transmission through the broader intermediation system. These findings suggest that evaluating the effects of bank regulation requires looking beyond its impact on banks' aggregate risk-bearing capacity to how specific constraints reshape intermediation activities and transmit through the broader financial system.

References

Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross-section of asset returns. The Journal of Finance 69, 2557–2596. doi:10.1111/jofi.12189.

Adrian, T., Shin, H.S., 2010. Liquidity and leverage. Journal of Financial Intermediation 19, 418–437. doi:10.1016/j.jfi.2008.12.002.

Baron, M., Muir, T., 2022. Intermediaries and asset prices: International evidence since 1870. The Review of Financial Studies 35, 2144–2189. doi:10.1093/rfs/hhab077.

Barth, D., Kahn, R.J., 2025. Hedge funds and the treasury cash-futures basis trade. Journal of Monetary Economics 155, 103823. doi:10.1016/j.jmoneco.2025.103823.

Boyarchenko, N., Eisenbach, T.M., Gupta, P., Shachar, O., Van Tassel, P., 2018. Bank-Intermediated Arbitrage. Technical Report 858. Federal Reserve Bank of New York. URL: https://www.newyorkfed.org/research/staff_reports/sr858.html, doi:10.2139/ssrn.3200041. revised July 2020.

Brunnermeier, M.K., Pedersen, L.H., 2008. Market liquidity and funding liquidity. Review of Financial Studies 22, 2201–2238. doi:10.1093/rfs/hhn098.

Brunnermeier, M.K., Sannikov, Y., 2014. A macroeconomic model with a financial sector. American Economic Review 104, 379–421. doi:10.1257/aer.104.2.379.

Bräuning, F., Stein, H., 2026. The effect of primary dealer constraints on intermediation in the treasury market. The Review of Financial Studies doi:10.1093/rfs/hhag043.

Bybee, L., Kelly, B., Manela, A., Xiu, D., 2024. Business news and business cycles. The Journal of Finance 79, 3105–3147. doi:10.1111/jofi.13377.

Bybee, L., Kelly, B., Su, Y., 2023. Narrative asset pricing: Interpretable systematic risk factors from news text. The Review of Financial Studies 36, 4759–4787. doi:10.1093/rfs/hhad042.

Choi, D.B., Holcomb, M.R., Morgan, D.P., 2020. Bank leverage limits and regulatory arbitrage: Old question-new evidence. Journal of Money, Credit and Banking 52, 241–266. doi:10.1111/jmcb.12742.

Cimon, D., Garriott, C., 2019. Banking regulation and market making. Journal of Banking amp; Finance 109, 105653. doi:10.1016/j.jbankfin.2019.105653.

Du, W., Tepper, A., Verdelhan, A., 2018. Deviations from covered interest rate parity. The Journal of Finance 73, 915–957. doi:10.1111/jofi.12620.

Gabaix, X., Maggiori, M., 2015. International liquidity and exchange rate dynamics *. The Quarterly Journal of Economics 130, 1369–1420. doi:10.1093/qje/qjv016.

Gilchrist, S., Zakrajšek, E., 2012. Credit spreads and business cycle fluctuations. American Economic Review 102, 1692–1720. doi:10.1257/aer.102.4.1692.

Glicoes, J., Iorio, B., Monin, P., Petrasek, L., 2024. Quantifying treasury cash-futures basis trades. FEDS Notes , None–Nonedoi:10.17016/2380-7172.3458.

Gromb, D., Vayanos, D., 2002. Equilibrium and welfare in markets with financially constrained arbitrageurs. Journal of Financial Economics 66, 361–407. doi:10.1016/s0304-405x(02)00228-3.

Haddad, V., Muir, T., 2021. Do intermediaries matter for aggregate asset prices? The Journal of Finance 76, 2719–2761. doi:10.1111/jofi.13086.

Haddad, V., Muir, T., 2026. Intermediaries and asset prices. Journal of Economic Literature 64, 876–906. doi:10.1257/jel.20251766.

Hassan, T.A., Hollander, S., Kalyani, A., van Lent, L., Schwedeler, M., Tahoun, A., 2025. Text as data in economic analysis. Journal of Economic Perspectives 39, 193–220. doi:10.1257/jep.20231365.

Hassan, T.A., Hollander, S., van Lent, L., Tahoun, A., 2019. Firm-level political risk: Measurement and effects*. The Quarterly Journal of Economics 134, 2135–2202. doi:10.1093/qje/qjz021.

He, Z., Kelly, B., Manela, A., 2017. Intermediary asset pricing: New evidence from many asset classes. Journal of Financial Economics 126, 1–35. doi:10.1016/j.jfineco.2017.08.002.

He, Z., Krishnamurthy, A., 2013. Intermediary asset pricing. American Economic Review 103, 732–770. doi:10.1257/aer.103.2.732.

Kruttli, M.S., Monin, P.J., Petrasek, L., Watugala, S.W., 2025. Ltcm redux? hedge fund treasury trading, funding fragility, and risk constraints. Journal of Financial Economics 169, 104017. doi:10.1016/j.jfineco.2025.104017.

Li, D., Monin, P.J., Petrasek, L., 2024. Credit Supply and Hedge Fund Performance: Evidence from Prime Broker Surveys. Technical Report 2024-089. Board of Governors of the Federal Reserve System. URL: https://www.federalreserve.gov/econres/feds/files/2024089pap.pdf, doi:10.17016/FEDS.2024.089.

Moskowitz, T.J., Ross, C.P., Ross, S.Y., Vasudevan, K., 2026. Risk, specialization, and covered-interest parity. Forthcoming .

Shleifer, A., Vishny, R.W., 1997. The limits of arbitrage. The Journal of Finance 52, 35–55. doi:10.1111/j.1540-6261.1997.tb03807.x.

Siriwardane, E.N., Sunderam, A., Wallen, J., 2025. Segmented arbitrage. The Journal of Finance 80, 2543–2590. doi:10.1111/jofi.13469.

A Details on FR Y-9C Data

Note: Because the FR Y-9C does not report high-quality liquid assets (HQLA), I construct an HQLA proxy by weighting assets by their HQLA level under the U.S. liquidity coverage ratio (LCR): 100% for Level 1 (cash, Treasuries, Ginnie Mae MBS), 85% for Level 2A (agency debt and agency MBS), 50% for Level 2B (municipal and other debt), and zero otherwise, and applying the LCR's caps on Level 2 assets.

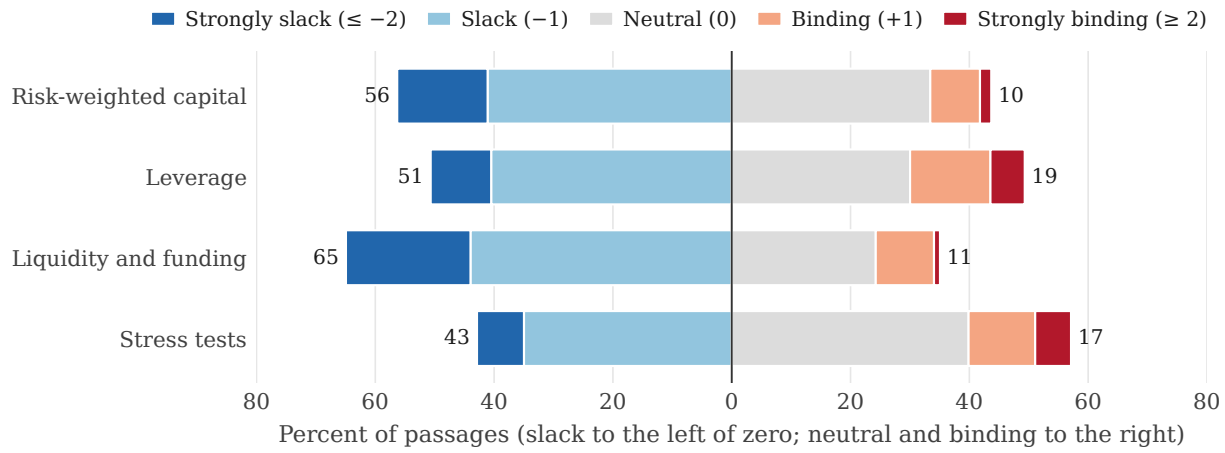
Codes in Table A1 are FR Y-9C items; trading securities come from Schedule HC-D. The HQLA share weights assets by their level in the U.S. liquidity coverage ratio (12 CFR 249.20–21), as described in the text. Payouts are reported year-to-date and converted to quarterly flows. Variables are measured for the bank holding company or, for foreign banks, the U.S. holding company. The sample is quarterly from 2010Q1, except for Credit Suisse, Mizuho, and UBS, whose U.S. holding companies begin filing in 2016Q3.

Table A1: FR Y-9C Variables

Variable	**Definition**	**FR Y-9C items**
Risk density	Risk-weighted assets / total assets	A223 / 2170
HQLA share	LCR-weighted liquid assets / (cash + securities + trading securities + reverse repo + loans): Level 1 at 100%, Level 2A at 85%, Level 2B at 50%, with the LCR caps	Level 1: cash 0081, 0395, 0397; Treasuries 0211, 1287, HC-D 3531; GNMA MBS G300, G303. Level 2A: agency and GSE debt 1289, 1293, 1294, 1298 (HT50, HT53 from 2018Q2), HC-D 3532; agency MBS G304, G307, G312, G315, K142, K145, K150, K153, HC-D G379, G380, K197. Level 2B: municipal and other debt 8496, 8499, 1737, 1741, 1742, 1746, HC-D 3533, G386. Denominator: securities 1754, 1773; reverse repo B987, B989; loans 2122
ST wholesale share	(Fed funds purchased + repo + commercial paper + other borrowed money $\leq$ 1 year) / total assets	(B993 + B995 + 2309 + 2332) / 2170
Payouts	(Common dividends + treasury stock purchases) / total equity	(4460 + 4783) / 3210
Secured financing	Fed funds sold + reverse repo + margin loans	B987 + B989 + 1545
Unsecured financing	Loans to nondepository financial institutions	J454
Capital ratios	CET1, Tier 1, leverage, and supplementary leverage ratios	P793, 7206, 7204, H036
Deposit share	Domestic and foreign deposits / total assets	(6631 + 6636, domestic and foreign offices) / 2170
Book equity share	Total equity / total assets	3210 / 2170

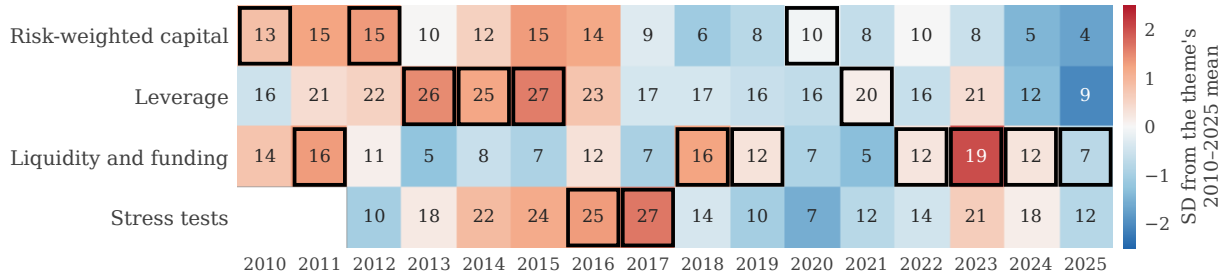
B TBC Measures: Descriptive Results

Figure A1: The Distribution of Binding Severity



This figure plots the distribution of passage-level binding severity for each constraint type in the post-2010 sample. The number on the left is the percentage of passages that are labeled as slack (the blue bars); the number on the right is the percentage labeled as binding (the red bars). The remaining are labeled as neutral.

Figure A2: Which Constraints are Most Binding Over Time



This figure plots the percentage of the theme's passages within a year that are described as binding, to give an idea of what constraints are the most binding over time. The percentages are labeled in each square, and the heatmap is standardized within each theme. In other words, red means that constraint is more binding than usual for that theme, blue is less. The outlined cell in each year is the theme that is furthest above its own average.

Table A2: Constraint Themes: Summary Statistics

	Full sample, 2006Q3–2025Q4				Post-2010, 2010Q1–2025Q4			
	RW	LEV	LIQ	STR	RW	LEV	LIQ	STR
How much banks talk about it								
Passages	16841	5005	4803	1076	16375	4730	4661	1061
Share of themed passages (%)	60.7	18.1	17.3	3.9	61.0	17.6	17.4	4.0
Bank-quarters discussing theme (%)	98.7	87.0	76.9	38.8	98.8	87.5	78.2	41.3
Passages per bank-quarter, if discussed	15.3	5.2	5.6	2.5	16.1	5.3	5.8	2.5
Banks ever discussing theme	24	23	23	16	20	20	19	15
How binding it is								
Mean binding severity (-3 to $+3$)	-0.59	-0.31	-0.73	-0.27	-0.60	-0.36	-0.74	-0.28
Binding passages (%)	10.6	21.3	11.3	17.4	10.3	19.3	10.8	17.2
Strongly binding, severity ≥ 2 (%)	2.0	6.9	1.4	5.9	1.9	5.8	1.0	6.0
Slack passages (%)	55.9	49.3	64.7	42.8	56.3	50.7	64.9	42.9
Share of total binding severity (%)	48.2	32.2	13.9	5.7	50.1	29.8	13.9	6.2
Direction								
Tightening (%)	14.1	20.6	11.3	4.9	13.8	18.8	11.0	4.9
Loosening (%)	20.1	18.7	27.4	9.9	20.2	19.0	27.2	9.9
Who raises it								
In Q&A (%)	41.0	42.6	43.9	73.3	41.0	43.1	44.3	73.8
Analyst-prompted (%)	17.8	14.9	15.6	37.8	17.8	15.1	15.7	38.1

This table describes the summary statistics of each of the four binding constraint themes. The first four columns give the full sample summary, whereas the next four columns are just the post-crisis sample.

C Transcript Corpus and Measure Construction

C.1 Transcript Corpus

I use the historical primary-dealer universe of He et al. (2017), which links dealers to their publicly traded holding companies and associated CRSP identifiers where available.[‡] Conference-call transcripts are indexed by Capital IQ (CIQ) company identifiers rather than CRSP identifiers. I therefore map the dealer universe to CIQ in two steps, producing a set of CIQ company identifiers for the dealer universe:

1. **PERMNO → GVKEY**: I map PERMNOs to GVKEYs using the CRSP–Compustat link table. I restrict the mappings to `LC`/`LU` links with `P`/`C` primacy. In the case of multiple matches, I prioritize `P` over `C`, `LC` over `LU`, and the most recent link start date.

2. **GVKEY → CIQ** `companyid`: Next I map the GVKEYs to Capital IQ company identifiers using the WRDS Capital IQ GVKEY bridge. Unmatched GVKEYs get dropped.

For each mapped `companyid`, I retrieve company-call metadata until December 31, 2025, including information about each conference call such as company identifier, date, and time. CapitalIQ sometimes stores multiple transcript versions of the same call, identified by the same `keydevid`. In these situations, I keep the version with the latest timestamp, breaking any remaining ties with the highest `transcriptid`. A call is only kept if the date falls within the dealer's active primary-dealer designation window.

Transcript text in CIQ is stored as an ordered sequence of components tagged with a speaker-role type, rather than as a single document. I retain the components belonging to the prepared remarks and Q&A, listed below, and exclude operator messages.

Document	**CIQ component types**	**Content**
Prepared remarks	2, 5	Presenter speech; Presentation Section
Q&A	3, 4, 8	Analyst question; answer; question/answer

The resulting sample contains 2,498 conference calls from 24 firms over 78 quarters, spanning 2006Q3 to 2025Q4. Coverage is relatively sparse in the early years because transcripts for events

[‡]The historical dealer list is constructed from New York Fed records, with dealers matched to their publicly traded holding companies using CRSP/Compustat for U.S. dealers and Datastream for foreign dealers. I thank Zhiguo He and Wei Wei for generously providing these data.

prior to 2008 were created retrospectively, whereas Capital IQ began creating transcript records systematically as calls concluded from 2008 onward.[§] Table A3 summarizes the distribution of transcripts and passages across firms, while Figure A3 shows the number of firms and passages represented over time. Summary statistics on these calls, such as average call duration and time of day, are given in Table A4.

[§]Wharton Research Data Services (WRDS), "WRDS Overview of Capital IQ Transcripts," accessed August 17, 2026, https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/compustat/capital-iq/transcripts/wrds-overview-capitaliq-transcripts-data/.

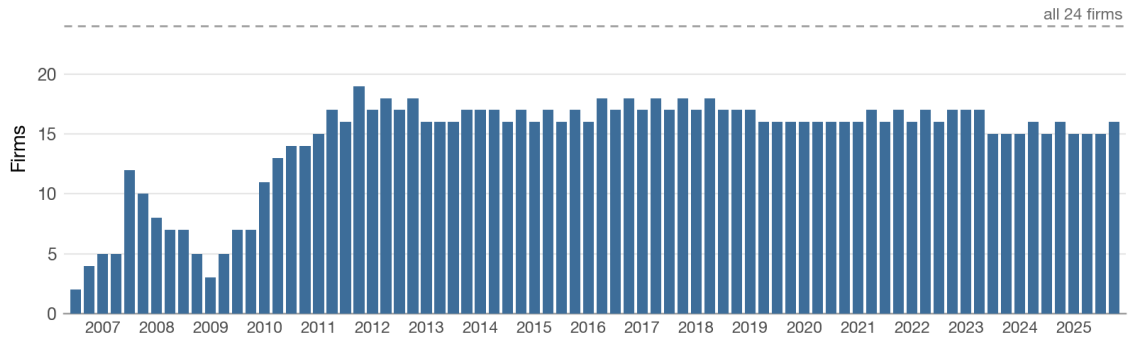
Table A3: Transcript Corpus by Firm

Firm	**Calls**	**Qtrs**	**Coverage**	**Passages**
Citigroup Inc.	231	77	2006Q4–2025Q4	2,787
JPMorgan Chase & Co.	207	74	2007Q3–2025Q4	1,989
Bank of America Corp.	192	74	2007Q3–2025Q4	1,915
Deutsche Bank AG	181	63	2007Q4–2025Q4	3,372
Goldman Sachs Group, Inc.	165	77	2006Q3–2025Q4	1,715
Morgan Stanley	164	75	2007Q1–2025Q4	1,456
Royal Bank of Scotland Group plc	161	63	2010Q2–2025Q4	2,399
Royal Bank of Canada	135	63	2010Q2–2025Q4	1,429
Barclays plc	133	65	2007Q3–2025Q4	2,552
Bank of Nova Scotia	130	57	2011Q4–2025Q4	1,342
Wells Fargo & Company	127	39	2016Q2–2025Q4	932
Credit Suisse Group AG	125	54	2007Q4–2023Q2	2,797
UBS AG	123	65	2007Q3–2025Q4	1,851
Bank of Montreal	118	57	2011Q4–2025Q4	888
HSBC Holdings plc	117	64	2007Q3–2025Q4	1,722
Nomura Holdings, Inc.	77	61	2010Q1–2025Q4	375
Jefferies & Company, Inc.	31	15	2009Q3–2013Q1	144
Jefferies LLC	28	23	2013Q2–2019Q1	41
Mizuho Financial Group, Inc.	26	25	2011Q2–2025Q4	126
Lehman Brothers Holdings Inc.	10	9	2006Q3–2008Q3	140
Merrill Lynch, Pierce, Fenner & Smith	8	8	2006Q4–2008Q3	68
MF Global Holdings Ltd.	5	4	2011Q1–2011Q4	85
Bear, Stearns & Co., Inc.	3	3	2007Q3–2008Q1	28
Countrywide Financial Corp.	1	1	2007Q3–2007Q3	7
Total	**2,498**		**2006Q3–2025Q4**	**30,160**

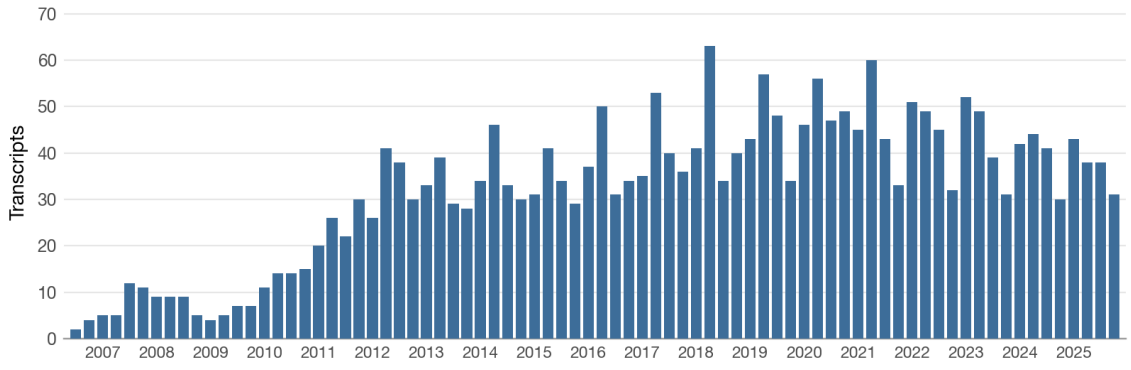
"Calls" is the number of retained Capital IQ transcripts, keeping the latest version of each call (`keydevid`). "Qtrs" is the number of calendar quarters with at least one call. "Passages" is the number of paragraphs classified as discussing the firm's own constraints after Stage 2 (Section 3). Lehman Brothers, Bear Stearns, Merrill Lynch, Countrywide, and MF Global leave the sample when they fail or are acquired. Jefferies appears under two legal entities after its 2013 reorganization.

Figure A3: Dealer Transcript Corpus

Panel A



Panel B



Panel A shows the number of primary dealers with at least one transcript in each quarter, and Panel B shows the number of transcripts. A firm can hold more than one call in a quarter. Transcripts are from Capital IQ and are kept only if the call falls within the firm's primary-dealer designation window. Sample: 2006Q3–2025Q4.

C.2 Transcript Sample

Table A4: Transcript Sample: Summary Statistics

	Earnings	Other	All
Panel A: Sample			
Transcripts	1,118	1,380	2,498
Firms	24	22	24
Firm-quarters	1,096	724	1,130
Panel B: Start time (US Eastern)			
Median start	8:00 am	9:15 am	8:45 am
Before 9:30 am open	71%	52%	60%
9:30 am–4:00 pm	28%	45%	38%
After 4:00 pm close	1%	3%	2%
Median start, US HQ	9:30 am	10:00 am	10:00 am
Canada HQ	8:00 am	9:30 am	9:00 am
Europe HQ	4:00 am	8:00 am	4:30 am
Japan HQ	5:30 am	3:15 am	5:30 am
Panel C: Timing within the quarter			
Days after fiscal qtr-end	25	55	34
Month 1 of calendar qtr	62%	20%	39%
Month 2	31%	35%	33%
Month 3	8%	45%	28%
Held Tue–Thu	74%	80%	78%
Panel D: Length and content			
Call length (min)	68	41	54
Prepared ('000 words)	3.8	1.6	3.0
Q&A ('000 words)	6.5	5.3	5.9
Constraint passages per call	14	6	9
Share from Q&A	44%	43%	44%
Analyst-prompted	19%	16%	18%

Notes: The sample is all 2,498 Capital IQ transcripts from September 2006 to December 2025, of which 2,332 contribute at least one passage to the constraint measure. "Earnings" are earnings calls; "Other" covers conference presentations (60%) and shareholder/analyst, fixed-income, investor-day, and special calls. Each call is assigned to the calendar quarter of its date, so an earnings call in quarter t usually reports results for $t-1$. Days after quarter-end use each firm's fiscal calendar. Start times are from Capital IQ and are missing for 51 calls. Entries are medians or shares.

C.3 Sample Counts at Each Stage

Table A5: Constructing the Measure: Counts at Each Step

Step 1: Screen transcript text		
Sentences screened	1,319,688	306,243 paragraphs
Candidate passages (anchor paragraphs)	43,041	14.1% of paragraphs
Step 2: Classify constraint statements		
Passages sent to the LLM	43,041	Claude Haiku 4.5, batch
Not about the dealer itself	12,859	29.9%
Unparseable	22	0.1%
Own-dealer constraint passages	**30,160**	**70.1%**
Binding / neutral / slack	14 / 32 / 54%	Sign of the score
Step 3: Consolidate and aggregate		
Distinct constraint labels	755	
Common topics ($\geq$200 mentions)	14	95.5% of passages
Firm $\times$ quarter $\times$ topic cells	8,730	14 topics
Firm $\times$ quarter observations	1,113	78 quarters, 2006Q3–2025Q4

Notes: The input is 2,498 transcripts from 24 primary dealers, 2006Q3–2025Q4. The right-hand column gives each count as a share of the relevant total from the previous step, or briefly describes the step.

C.4 Example Outputs from LLM

Table A6: From Transcript Text to the Constraint Measure: Worked Examples

Stage	Step	Output
Panel A. Tight (+2): standardized RWA becomes the binding constraint		
Screening	Source call	Citigroup Inc., 2017-07-20 (2017Q3); Q&A; Management (response)
	Retained paragraph `u011770`	Well, I think you've seen the – certainly, the growth in the standardized RWA, that matches the balance sheet growth. And that, if you noticed, it's the standardized RWA that, at least in this quarter, has now become our binding constraint. So right now, for us, it's CET1 measured on standardized RWA rather than CET1 measured on advanced approach RWA. That's the relevant ratio.
Classification	Own-firm constraint?	Yes — retained. *Management reports firm's own RWA growth and binding constraint*
	Constraint type	`rwa_density` (secondary: `cet1`)
	Binding severity	severity = +2 on $[-3, +3]$; confidence = 0.92. Evidence: "standardized RWA that, at least in this quarter, has now become our binding constraint"
Aggregation	Firm–quarter–topic cell	Citigroup Inc. × 2017Q3 × `rwa_density`: $n = 1$ passage; mean binding severity = +2.00
	Constraint measure	$TBC_{ikt} = +\mathbf{2.00}$
Panel B. Neutral (0): deposit funding unchanged		
Screening	Source call	Royal Bank of Scotland Group plc, 2024-10-25 (2024Q4); prepared; Management (prepared remarks)
	Retained paragraph `u038840`	Migration from noninterest-bearing to interest-bearing deposits continued at a slow pace as expected. And there was no material change in customer behavior following the first base rate cut. Noninterest-bearing balances remained at 32% of the total and term accounts remained at around 17%. The average rate of interest we pay on our customer deposit funding has remained flat, reflecting the lag effect on pass-through and small changes in mix.
Classification	Own-firm constraint?	Yes — retained. *RBS reports own deposit mix, rates, customer behavior*
	Constraint type	`deposit_funding` (secondary: `none`)

Table A6, continued

Stage	Step	Output
	Binding severity	severity = 0 on $[-3, +3]$; confidence = 0.85. Evidence: "Noninterest-bearing balances remained at 32% of total; average rate remained flat"
Aggregation	Firm–quarter–topic cell	Royal Bank of Scotland Group plc × 2024Q4 × `deposit_funding`: $n = 3$ passages; mean binding severity = $\frac{(0)+(-1)+(0)}{3} = -0.33$
	Constraint measure	$TBC_{ikt} = \mathbf{-0.33}$
Panel C. Significant headroom (−2): LCR comfortably above the requirement		
Screening	Source call	Citigroup Inc., 2012-10-24 (2012Q4); prepared; Management (prepared remarks)
	Retained paragraph `u010214`	While we are still awaiting final guidance on the Basel III liquidity coverage ratio, we believe that we are already comfortably in compliance given the proposed rules as we understand them, with an estimated LCR ratio of approximately 116%. In keeping with our estimates regarding Citi's excess liquidity, we currently expect that our LCR will decrease modestly as we manage to a level that is comfortably above the proposed 100% requirement.
Classification	Own-firm constraint?	Yes — retained. *Management reports Citi's own LCR ratio and liquidity management.*
	Constraint type	`lcr_hqla` (secondary: `none`)
	Binding severity	severity = −2 on $[-3, +3]$; confidence = 0.92. Evidence: "estimated LCR ratio of approximately 116%...comfortably above the proposed 100% requirement"
Aggregation	Firm–quarter–topic cell	Citigroup Inc. × 2012Q4 × `lcr_hqla`: $n = 2$ passages; mean binding severity = $\frac{(-2)+(-1)}{2} = -1.50$
	Constraint measure	$TBC_{ikt} = \mathbf{-1.50}$
Panel D. Exceptional slack (−3): $36bn excess capital, buybacks resume		
Screening	Source call	Bank of America Corporation, 2021-01-19 (2021Q1); prepared; Management (prepared remarks)

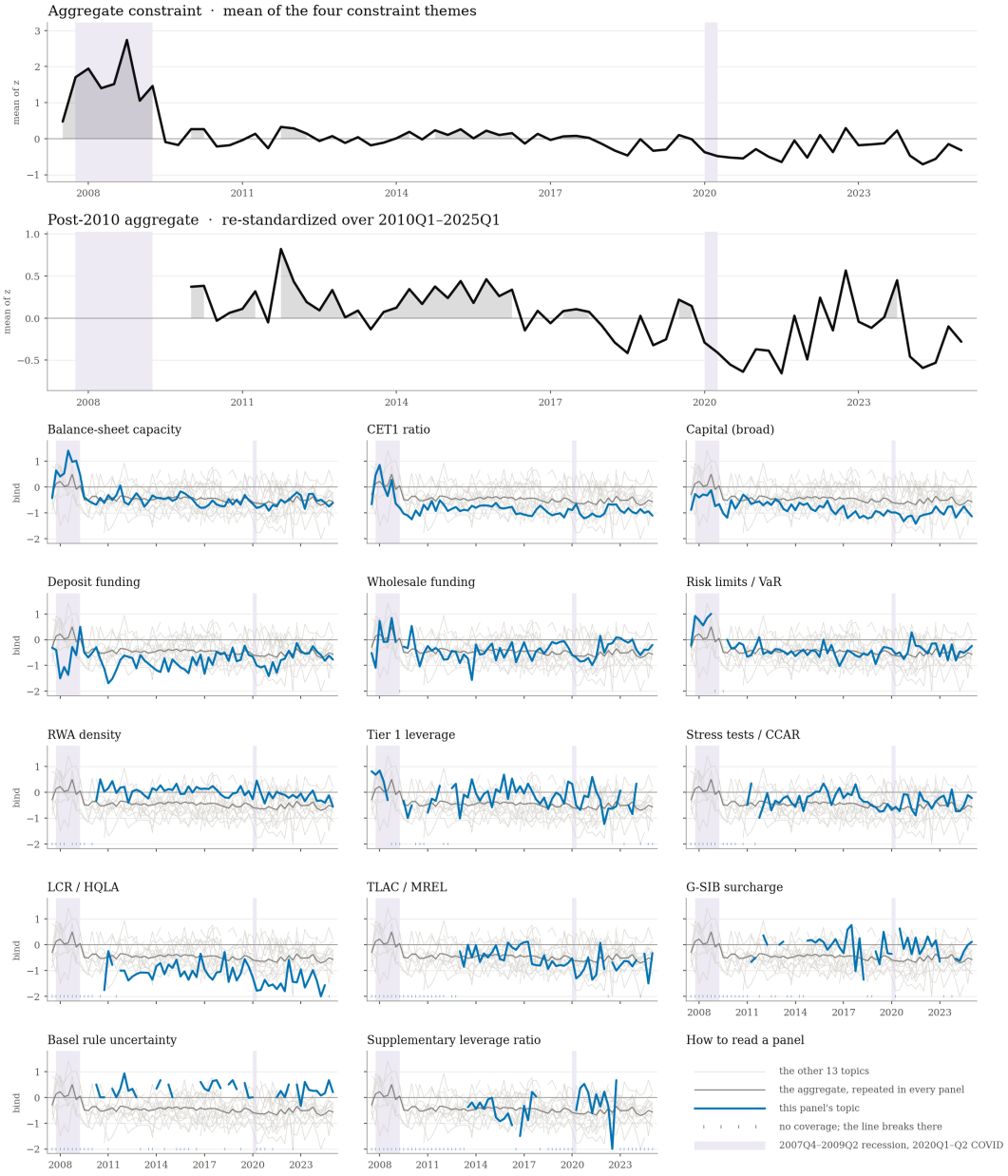
Table A6, continued

Stage	Step	Output
	Retained paragraph `u001886`	As we look at share count, it declined 7% driven by the momentum in shares bought as we moved in the second half of '19 and then in the first quarter of '20 prior to time of suspending share repurchases. With $36 billion in excess capital above our common CET1 minimum requirements and excess capital above – SLR reverting back to its normal calculation and completion of the CCAR exam, we'll once again begin repurchasing shares starting today.
Classification	Own-firm constraint?	Yes — retained. *Management reporting BofA's own CET1, SLR, and capital actions*
	Constraint type	`cet1` (secondary: `slr`)
	Binding severity	severity $= -3$ on $[-3, +3]$; confidence $= 0.95$. Evidence: "$36 billion in excess capital above our common CET1 minimum requirements and excess capital above SLR reverting back to its normal calculation"
Aggregation	Firm–quarter–topic cell	Bank of America Corporation × 2021Q1 × `cet1`: $n = 3$ passages; mean binding severity $= \frac{(-3)+(-1)+(-2)}{3} = -2.00$
	Constraint measure	$TBC_{ikt} = \mathbf{-2.00}$
Panel E. Dropped: analyst question, not a management statement		
Screening	Source call	Citigroup Inc., 2017-07-20 (2017Q3); Q&A; Analyst (question)
	Retained paragraph `u011712`	Just following up on Robert's question, roughly 2/3 of Citi's deposits are corporate, and out of that, TTS makes up the biggest chunk. How should we look at the stickiness of that deposit base at the – generally speaking?
Classification	Own-firm constraint?	**No — removed as a false positive.** *Speaker is analyst asking a question, overriding rule applies*
Aggregation	Firm–quarter–topic cell	None — the paragraph contributes to no measure.

Notes: Each panel follows one transcript paragraph through the three stages. In *Screening*, the paragraph is kept because Stage 1 flags at least one of its sentences (underlined). *Classification* first checks whether the paragraph is about the firm's own constraints, which removes false positives such as Panel E, and then assigns a constraint type and a binding-severity score from −3 (exceptional slack) to +3 (binding). *Aggregation* pools all retained passages for the same firm, quarter, and topic, and the constraint measure TBC_{ikt} is their mean binding severity, so higher values mean more binding constraints (Section 3.4).

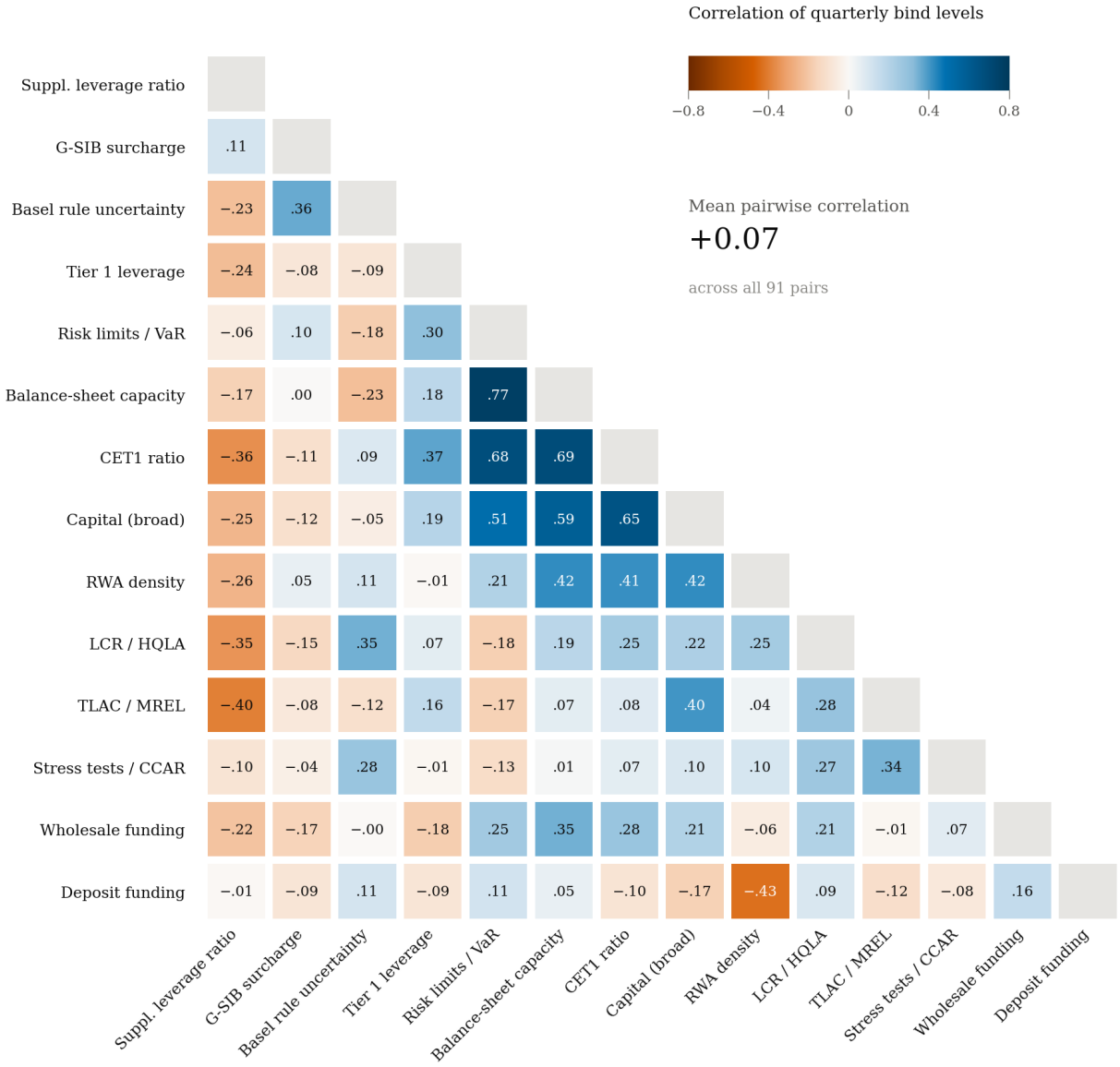
C.5 Full Set of Constraint Topics

Figure A4: Dealer Text-Based Constraint (TBC) Measures: All 14 Topics



The top panel plots the aggregate constraint measure, the equal-weighted average of the four constraint themes. The second panel re-standardizes over 2010Q1–2025Q1. Each of the 14 topics is also plotted. Each topic measure is the cross-bank average binding severity in that quarter, and higher values mean more binding constraints. Breaks in a line mark quarters with no coverage. Shading marks the 2007Q4–2009Q2 recession and 2020Q1–Q2.

Figure A5: Constraint Topic Measures — Pairwise Correlations



Pearson correlations between the quarterly levels of the 14 constraint topics, using quarters in which both topics are observed. Higher values mean more binding constraints. Sample: 2010Q1–2025Q4.

D Validating the Constraint Measure: Direction Placebo

Table A7: Direction Placebo: Past versus Future Balance-Sheet Adjustment

	Backward: $t-h,\ldots,t-1$			Forward: $t+1,\ldots,t+h$		
	$h=4$	$h=2$	$h=1$	$h=1$	$h=2$	$h=4$
Asset growth ($100\cdot\Delta\log$ assets)						
Two-way FE	-0.172	-0.491	-0.505^{**}	-0.750^{**}	-1.151^{***}	-2.100^{***}
Firm FE	$+0.002$	-0.550^{**}	-0.375^{*}	-0.393	-0.993^{***}	-2.119^{***}
Capitalization (Δ equity/assets, pp)						
Two-way FE	$+0.061$	$+0.034$	$+0.037$	$+0.104^{***}$	$+0.148^{***}$	$+0.266^{***}$
Firm FE	$+0.093^{*}$	$+0.069^{*}$	$+0.038$	$+0.096^{***}$	$+0.170^{***}$	$+0.350^{***}$

Each entry is the coefficient from regressing a bank's cumulative change in the outcome on its aggregate constraint measure, for the 12 banks in the FR Y-9C panel. The forward columns cumulate the outcome over the h quarters after the call, and the backward columns over the h quarters before it, using the same estimator, sample, and fixed effects. Two-way FE includes firm and quarter fixed effects, and firm FE includes firm fixed effects only. p-values are from 2,000 permutations, within quarter for two-way FE and within firm for firm FE. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

E Balance-Sheet Adjustments: Robustness

E.1 Leave-One-Out Robustness

The preceding results show that banks' balance-sheet adjustments align with the incentives associated with their reported regulatory constraints. An important question is whether this pattern is driven by a small number of observations, or reflects a general relationship across banks and adjustment margins. Table A8 tests the sensitivity of these results to excluding individual banks, outcomes, and predictions.

Panel A of Table A8 assesses the sensitivity of the results to excluding individual banks. The joint signed test remains statistically significant in all 14 specifications, with permutation-based p-values ranging from 0.001 to 0.016, compared with 0.006 in the main results. The true assignment ranks first among the 24 possible assignments in 9 of the 14 specifications, and second in the remaining five (when Bank of America, Bank of Montreal, HSBC, Morgan Stanley, or Wells Fargo is dropped from the sample). Together, these results suggest that no single bank drives the results.

Panels B and C assess the sensitivity of the results to excluding individual outcomes and predicted relationships, respectively. In Panel B, the joint signed test remains statistically significant when each outcome is excluded, with permutation-based p-values ranging from 0.008 to 0.014. The true assignment still ranks first among the 24 possible assignments in three of the four specifications, and second when the risk-density outcome is excluded. Panel C excludes individual predictions rather than entire outcomes. The results also remain robust to these exclusions. Together, these results suggest that no single outcome or prediction drives the results, supporting a broader pattern of constraint-specific balance-sheet adjustments.

Table A8: Leave-One-Out Robustness

All 14		
	p_{perm}	Rank
Baseline (six cells)	0.006	1
A. Leave one bank out		
Bank of America	0.001	2
Citigroup	0.005	1
Goldman Sachs	0.009	1
JPMorgan	0.010	1
Morgan Stanley	0.004	2
Wells Fargo	0.010	2
Bank of Montreal	0.006	2
Barclays	0.012	1
Credit Suisse	0.002	1
Deutsche Bank	0.003	1
HSBC	0.016	2
Mizuho	0.009	1
RBC	0.006	1
UBS	0.006	1
B. Leave one outcome out		
ΔHQLA share (2 cells)	0.014	1
ΔST wholesale share	0.008	1
Payout/equity	0.012	1
ΔRW^{fix} density (2 cells)	0.014	2
C. Leave one cell out		
LEV → ΔHQLA share	0.013	1
LIQ → ΔHQLA share	0.007	1
LIQ → ΔST wholesale share	0.008	1
STR → Payout/equity	0.012	1
LEV → ΔRW^{fix} density	0.008	1
RW → ΔRW^{fix} density	0.007	2

This table checks robustness of the balance-sheet adjustment results by leaving out individual banks, outcomes, and predictions. The joint signed test sums the t-statistics, each signed in the predicted direction, over the six predicted constraint–outcome cells. Rank is the position of the true assignment of constraints to predictions among all 24 possible assignments of the four themes, where 1 is the strongest alignment. p_{perm} comes from permutations that reassign each bank's full history of constraint measures to another bank.

E.2 Controlling for Banks' Own Condition

The bank-level results in Section 5 compare banks within a quarter, so quarter fixed effects absorb HKM, AEM, and every other aggregate series. A remaining concern is that the text proxies for a bank-level version of these measures: the bank whose leverage constraint tightens might simply be the bank with a low capital ratio. Table A9 re-estimates equation (5) with controls for each bank's condition at t: its own Tier 1, leverage, and book equity ratios; for the U.S. banks, its own HKM-style market capital ratio, market equity divided by market equity plus book debt, together with its stock return and volatility; and the levels of the balance-sheet ratios the outcomes are measured in. The joint test of the predictions remains significant with every set of controls (p_{perm} between 0.001 and 0.015 for U.S. banks and between 0.002 and 0.013 for all 14 banks), and the true assignment of constraints to predictions continues to rank first among all 14 banks. The wholesale-funding coefficient becomes larger and the payout coefficient is essentially unchanged. The leverage–HQLA coefficient shrinks when all controls are added (-0.64 to -0.48 for all 14 banks), but remains significant at the 10% level ($p_{perm} = 0.091$). The text's information about which constraint binds is therefore not contained in the bank's own reported ratios or market capitalization.

Table A9: Information in the Text Beyond Banks' Own Condition: Balance-Sheet Adjustments

	US6		**All 14**	
Bank-level controls at t	Joint p_{perm}	Rank	Joint p_{perm}	Rank
None (Table 9)	0.015	2	0.013	1
Own Tier 1, leverage, book equity ratios	0.010	2	0.003	1
Own market capital ratio, return, volatility	0.001	2		
Own levels of outcome ratios, size	0.015	2	0.002	1
All of the above[a]	0.007	2	0.003	1
Coefficients: no controls → all controls				
LEV → ΔHQLA	−0.37 → −0.22		−0.64 → −0.48	
LIQ → ΔST wholesale	−0.36 → −0.53		−0.33 → −0.67	
STR → Payout	−0.67 → −0.70		−0.35 → −0.29	
Observations	334		633	

This table re-estimates the balance-sheet adjustment regressions, which regress each outcome over the next four quarters on the four constraint themes with bank and quarter fixed effects, adding the indicated controls for each bank at quarter t. Controls are winsorized at 1% and 99% and standardized. Ratios are from the FR Y-9C. The market capital ratio is the HKM capital ratio computed for a single bank: CRSP market equity divided by market equity plus FR Y-9C book liabilities. Stock return is the quarterly log return, and volatility is annualized daily return volatility. [a]Market variables are available only for the six U.S. banks. The joint signed test sums the t-statistics, each signed in the predicted direction, over five predicted constraint–outcome cells (all except LEV → ΔHQLA), so the no-controls row differs from the six-cell joint test in Table 9. Rank is the position of the true assignment of constraints to predictions among all 24 possible assignments of the four themes, where 1 is the strongest alignment. Joint p_{perm} comes from permutations that reassign each bank's TBC measures to another bank while controls stay with their own bank. The bottom panel shows how the main coefficients change when all controls are added. Sample: 2010Q1 onward.

E.3 U.S. Bank Subsample

Tables A10 and A11 repeat the baseline balance-sheet adjustment estimates and the leave-one-out robustness analysis for the subsample of six U.S. banks.

Table A10: Different Constraints, Different Balance-Sheet Adjustments: U.S. Banks

US6 ($n = 334$)		
Predicted cell [sign]	b (t)	p_{perm}
LEV → ΔHQLA share [−]	−0.37 (−1.85)	0.263
LIQ → ΔHQLA share [+]	+0.39 (1.79)	0.225
LIQ → ΔST wholesale share [−]	−0.36 (−3.38)	0.024
STR → Payout/equity [−]	−0.67 (−3.53)	0.097
LEV → ΔRW^{fix} density [+]	+0.35 (2.42)	0.257
RW → ΔRW^{fix} density [−]	+0.25 (1.88)	0.212
Joint signed test, p_{perm}	0.011	
Rank of true mapping among 24 relabelings	2	

Estimates of equation (5) for the six U.S. banks, with bank and quarter fixed effects. Coefficients report the estimated percentage-point change in the outcome over the following four quarters associated with a one-standard-deviation tightening in the indicated constraint. t-statistics are in parentheses. The permutation-based p-value is based on 719 permutations that reassign each bank's full history of constraint measures to another bank. The joint signed test sums the t-statistics across the predicted constraint-outcome cells. Rank is the position of the true assignment of constraints to predictions among all 24 possible assignments of the four themes, where 1 is the strongest alignment. Sample: 2010Q1–2025Q4.

Table A11: Leave-One-Out Robustness: U.S. Banks

US6		
	p_{perm}	Rank
Baseline (six cells)	0.011	2
A. Leave one bank out		
Bank of America	0.042	7
Citigroup	0.008	2
Goldman Sachs	0.017	1
JPMorgan	0.050	4
Morgan Stanley	0.017	2
Wells Fargo	0.042	6
B. Leave one outcome out		
ΔHQLA share (2 cells)	0.017	3
ΔST wholesale share	0.019	3
Payout/equity	0.054	6
ΔRW^{fix} density (2 cells)	0.001	1
C. Leave one cell out		
LEV → ΔHQLA share	0.015	2
LIQ → ΔHQLA share	0.013	3
LIQ → ΔST wholesale share	0.019	3
STR → Payout/equity	0.054	6
LEV → ΔRW^{fix} density	0.007	2
RW → ΔRW^{fix} density	0.004	1

This table checks robustness of the balance-sheet adjustment results by leaving out individual banks, outcomes, and predictions for US banks. The joint signed test sums the t-statistics, each signed in the predicted direction, over the six predicted constraint–outcome cells. Rank is the position of the true assignment of constraints to predictions among all 24 possible assignments of the four themes, where 1 is the strongest alignment. p_{perm} comes from permutations that reassign each bank's full history of constraint measures to another bank.

F Arbitrage Spreads: Robustness and Alternative Explanations

F.1 Information Beyond Existing Measures

Table A12: Information in the Text Beyond Existing Measures: Market Outcomes

	Δ Average spread on four themes		Δ Average spread on aggregate		HF financing terms on four groups	
Controls	Text	Incumbents	Text	Incumbents	Text	Incumbents
Δ VIX, NFCI, BAA	0.23***		0.21***		0.25***	
	[0.002]		[0.001]		[<0.001]	
+ HKM, AEM	0.14***	0.17***	0.10***	0.16***	0.12***	0.13***
	[0.003]	[<0.001]	[0.002]	[<0.001]	[0.002]	[0.004]
+ EBP, federal funds rate	0.14***	0.17***	0.10***	0.16***	0.10***	0.18***
	[0.004]	[0.003]	[<0.001]	[0.004]	[0.005]	[0.002]
+ banks' reported capital ratios	0.10***	0.19**	0.07***	0.19**	0.09***	0.21***
	[0.009]	[0.011]	[0.004]	[0.013]	[0.002]	[0.001]
All of the above, excluding 2020	0.10**	0.23***	0.06**	0.22**	0.10**	0.24**
	[0.021]	[0.005]	[0.010]	[0.015]	[0.022]	[0.011]
Observations, all incumbents	60		60		55	

"Text" is the increase in R^2 when the TBC measures are added to a regression on the controls in that row. "Incumbents" is the increase in R^2 when the measures in that row and the rows above are added to a regression on the TBC measures and changes in the VIX, NFCI, and BAA spread. In the first pair of columns, the outcome is the change in the average of the seven strategies' standardized arbitrage spreads and the TBC measures are changes in the four constraint themes. The second pair is the same but with the aggregate constraint measure. The third pair regresses SCOOS net tightening of hedge-fund price terms on the four themes. Brackets report moving-block bootstrap p-values for the tested block (eight-quarter blocks, 1,999 draws). Sample: 2010Q2 onward. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

F.2 Alternative Explanations

Table A13 compares the constraint measure with dictionary-based "gloom" placebos constructed from the same transcripts, and Table A14 reports lead–lag tests between the constraint measure and arbitrage spreads.

Table A13: Constraint Measure versus "Gloom" Placebos

	Δ arbitrage spreads	
	Full sample	Post-2010
Panel A: each series on its own		
Constraint measure	$+0.558^{***}$	$+0.473^{***}$
Negative tone (LM)	$+0.558^{***}$	$+0.387^{**}$
Market stress	$+0.471^{***}$	$+0.243^{*}$
Macro uncertainty	$+0.407^{***}$	$+0.235$
Credit deterioration	$+0.203^{*}$	$+0.218^{*}$
Client activity	$+0.135$	$+0.182$
Panel B: horse race, constraint measure / placebo in the same regression		
vs. negative tone	$+0.445^{***}$ / $+0.445^{***}$	$+0.511^{***}$ / $+0.432^{***}$
vs. market stress	$+0.448^{***}$ / $+0.312^{***}$	$+0.510^{***}$ / $+0.305^{***}$
vs. macro uncertainty	$+0.511^{***}$ / $+0.334^{***}$	$+0.480^{***}$ / $+0.249^{**}$
vs. credit deterioration	$+0.586^{***}$ / $+0.265^{***}$	$+0.486^{***}$ / $+0.244^{**}$

Placebos are dictionary word counts per thousand words in the same transcripts. These measures are aggregated from firms using equal-weighted averages. Entries report standardized coefficients. Panel A enters each series on its own as univariate regressions. Panel B puts the constraint measure and respective placebo in the same regression. p-values are from 3,000 phase-randomized surrogates. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A14: Lead–Lag Tests

		forward		reverse		
link	k	F	p	F	p	n
Panel A. Granger test						
constraints → spread level	2	7.93	0.002^{***}	0.06	0.947	62
	4	3.81	0.005^{***}	0.92	0.464	60
Panel B. Toda–Yamamoto						
constraints → spread level	2	6.28	0.005^{***}	0.14	0.874	61
	4	3.56	0.018^{**}	1.04	0.384	59

Tests of predictability between the aggregate constraint measure and the average of the seven strategies' standardized spread levels. "Forward" tests whether constraints predict spreads, and "reverse" tests whether spreads predict constraints; k is the number of lags. Panel A reports Granger tests after removing a linear trend from both series. Panel B reports Toda–Yamamoto tests from a lag-augmented VAR in levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

G Hedge-Fund Financing Terms: Robustness

Table A15: Bank Constraints and Hedge-Fund Financing Terms: AR(1) Innovations

	Net tightening, HF price terms		**Reason: own balance sheet/capital**	
	No controls	Δ controls	No controls	Δ controls
Risk-weighted capital (RW)	0.088^{***}	0.057^{***}	0.018^{***}	0.012^{*}
	[<0.001]	[0.002]	[0.007]	[0.093]
Leverage (LEV)	0.034^{**}	0.037^{**}	0.016^{***}	0.015^{**}
	[0.041]	[0.013]	[0.009]	[0.017]
Liquidity/funding (LIQ)	0.002	0.002	0.001	0.004
	[0.889]	[0.890]	[0.822]	[0.538]
Stress tests (STR)	0.025	0.024	−0.000	−0.002
	[0.117]	[0.105]	[0.955]	[0.794]
T	58	58	58	58

Estimates of equation (9) using the AR(1) innovation in each constraint measure. In the first two columns, the outcome is SCOOS net tightening of price terms offered to hedge funds; in the last two, it is the share of dealers that cite the availability of balance sheet or capital at their own institution as a reason for tightening. Each cross-bank average theme measure is regressed on its own lag over 2010Q2–2025Q4, and the residual is scaled to unit standard deviation. Δ controls are changes in the VIX, NFCI, and BAA spread. Brackets report block-bootstrap p-values (eight-quarter blocks, 1,999 draws), resampling the four text series jointly. Sample: 2011Q3–2025Q4. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.