

The Macroeconomics of Regulatory Safe Asset Demand

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Abstract

This paper estimates the macroeconomic effects of regulatory safe asset demand. I construct a narrative series of plausibly exogenous changes in regulatory safe asset demand using announcements by regulatory agencies and quarterly bank-level data. Using this series as an instrument, I identify a regulatory safe asset demand shock. Regulations that increase safe asset demand raise banks' safe asset holdings persistently, increase the government funding advantage on impact, and tighten financial conditions temporarily before easing them in the long run. Output falls as banks shift away from bank credit to the private sector. A model in which banks face a regulatory portfolio constraint and funding costs that decrease in portfolio safety accounts for these responses. Counterfactuals imply that reforms permanently increasing banks' safe asset demand raise the funding advantage only temporarily. Varying the regulatory incentive to hold safe assets generates a Laffer curve in the government's interest savings, with current regulation near the peak of the curve.

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1 Introduction

Financial regulation can induce demand for safe assets by granting them preferential treatment on bank balance sheets. Treasuries and other safe assets carry a risk weight of zero under capital requirements and count in full toward the liquid asset holdings that liquidity standards require. Changes in these regulations can therefore alter the demand for safe assets through bank portfolios, and this regulatory safe asset demand can affect the economy along several dimensions. Larger safe asset holdings by banks may improve financial stability, while the additional demand for government debt may lower its yields relative to private claims and widen the government funding advantage. However, inducing banks to hold safe assets may crowd out bank credit to the private sector, with consequences for investment and output. Existing work provides little evidence on the magnitude of these effects or on their aggregate implications.

The fundamental identification challenge of estimating the causal effects of regulatory safe asset demand is that regulation is not random, as banking regulations have responded to macroeconomic conditions, especially during crises. Observed movements in financial and economic conditions around regulatory changes reflect both the effects of regulation and the conditions that motivated it. Identification therefore requires isolating regulatory changes that are not systematically shaped by the state of the economy.

I address this challenge by conducting a detailed narrative analysis of U.S. banking regulation. Using official regulatory documents, I identify 61 regulatory events over 1988–2025 that carry news about safe-asset-related requirements. I document each event’s regulatory context, motivation, and implementation details. Based on this information, I classify each event following the narrative approach ([Romer and Romer, 2010, 2023](#)). I label events as plausibly exogenous if they were driven by international harmonization calendars or long-term statutory agendas. Conversely, I exclude events if they responded to contemporaneous financial and economic conditions. Out of the 61 candidate events, I classify 38 as plausibly exogenous.

Building on this classification, I convert each announcement into a measure of the safe asset demand induced by the regulatory change. For each event, I use the information on the quantitative requirements in the announcement along with each bank’s pre-announcement balance sheet to compute the present value of the change in safe asset demand implied by the rule change. I validate these bank-level predictions in the cross-section of banks, showing that banks with higher predicted safe asset demand gradually accumulate more safe assets following the announcement. I then aggregate across banks and announcements within each quarter to obtain a quarterly series of regulatory safe asset demand news. I find no evidence that the resulting series is forecastable or correlated with other identified shocks. In particular, the series is uncorrelated with existing measures of financial regulation, suggesting

that the series captures news about safe asset demand without contamination from broader regulatory news. Using this series as an external instrument in a proxy structural vector autoregression (VAR) model, I identify a regulatory safe asset demand shock and estimate its dynamic causal effects.

I find that regulatory safe asset demand has significant effects on the economy. A one-standard-deviation shock raises the safe asset share of bank assets by 0.17 percentage points on impact, with a persistent effect that peaks at 0.34 percentage points. This corresponds to a 2.4 percent increase in safe asset holdings relative to the sample average, or roughly \$80 billion of safe asset accumulation at current balance sheets. The U.S. funding advantage, measured as the spread between AAA corporate yields and the 10-year Treasury yield, increases by 4.4 basis points on impact, with the effect remaining statistically significant for a year. Financial conditions tighten on impact and stay tight while the portfolio shift is underway, then ease and remain below their original level at longer horizons. Output falls temporarily, declining by 0.18 percent at the trough of responses. The contractionary effect gradually decays, with the decrease in output remaining statistically significant from the third to the fifth-quarter horizons. These results are robust along a number of dimensions, including the event set, the construction of the present value measures, the sample period, and the identification strategy.

The transmission of the shock operates through the recomposition of bank balance sheets. Banks absorb the induced demand by shifting the composition of their portfolios. Holdings of safe assets rise by over one percent on impact, with a peak increase of roughly 3 percent. In contrast, holdings of other securities decline. The shift comes at the expense of bank credit to the private sector, with total bank loans declining by 1.4 percent at the trough of responses. The contraction is particularly strong for bank lending to the financial sector, which declines by roughly 5 percent at the trough of responses. Nonbank credit does not increase to offset the decline in bank lending, suggesting little to no substitution toward nonbank financial institutions. Finally, the federal debt-to-GDP ratio increases by roughly 2 percentage points at the peak of responses, with the accompanying increase in primary deficits driven mainly by higher government transfers.

To interpret these findings, I develop a New Keynesian model in which a representative bank holds safe assets and the economy's claims on productive capital. The model builds on standard models of banking by adding two key ingredients. First, the bank faces a regulatory portfolio constraint over its assets. Second, households price the safety of the bank's portfolio into its funding cost. The identified shock maps into an innovation to the regulatory weight on safe assets in the bank's portfolio constraint. An increase in the regulatory weight on safe assets raises the regulatory value of safe assets relative to capital claims. The bank responds by adjusting its portfolio gradually and accepts lower yields on safe assets, which increases

the funding advantage on impact. Simultaneously, the bank requires a higher return on its claims to capital, crowding out investment. As the bank accumulates safe assets and rebuilds equity, funding costs fall and the funding advantage reverts to lower levels while the portfolio shift is still in place. The calibrated model accounts for the main features of the empirical impulse responses. It matches the impact response of the funding advantage while also capturing the estimated patterns of the accumulation of safe assets, a temporary decline in output, and muted responses of prices and the policy rate.

Using the model, I conduct a policy counterfactual based on proposed regulatory reforms and also examine to what extent the government can generate interest savings through regulatory safe asset demand. The counterfactual is motivated by recent policy changes to the supplementary leverage ratio, which requires that banks hold capital against their total assets regardless of risk. One proposed variant would have fully excluded Treasuries and central bank reserves from the calculation of the ratio, making safe assets cheaper for banks to hold. Proponents argued that this would lower Treasury yields by tens of basis points. I consider a reform that permanently raises bank safe asset holdings by magnitudes discussed in the policy discourse, and simulate the transition in the model. A regulatory change that permanently increases bank safe asset holdings raises the funding advantage during the transition. However, in the long run, the funding advantage settles slightly below its pre-reform level, as the permanently safer bank portfolio lowers the bank funding cost. Output falls during the transition as the reform crowds out investment, and recovers as banks rebuild equity. The transition involves a trade-off between the government’s interest savings and output in the near term. I find that this trade-off improves substantially under a phased implementation, which significantly reduces the transitional output costs. Across steady states, varying the regulatory incentive to hold safe assets generates a Laffer curve in the government’s annual interest savings. The model estimates imply that current regulation is close to the peak of the curve. Regulations that further increase safe asset demand would generate little additional interest savings while still lowering output in the transition.

Related literature and contribution. This paper contributes to the empirical literature on the financial and macroeconomic effects of financial regulation. A large part of this literature examines how capital and liquidity requirements affect bank portfolios and the supply of bank credit at the microeconomic level (Aiyar et al., 2014; Jiménez et al., 2017; Gropp et al., 2019; Fraisse et al., 2020; Favara et al., 2021; Irani et al., 2021; Roberts et al., 2023; Sundaresan and Xiao, 2024). A number of papers estimate the effects of financial regulation at the macroeconomic level, using cross-country variation (Akinci and Olmstead-Rumsey, 2018; Richter et al., 2019; Jordà et al., 2021; Sufi and Taylor, 2022; Albuquerque et al., 2025) or variation within the United States over time (Eickmeier et al., 2018; Cascaldi-Garcia and

Iacoviello, 2026). Within this literature, this paper is most closely related to Drechsel and Miura (2026), who identify shocks to U.S. bank regulation and estimate their macroeconomic effects. The authors implement a high-frequency approach using bank stock price movements around speeches that discuss banking regulation. Their design is agnostic about the content of regulation, as the speeches span the full range of regulatory communication, including during episodes of banking stress. I contribute to this literature by focusing on a specific channel concerning regulations that impact banks' demand for safe assets and estimating the aggregate effects of this safe asset demand channel.

This paper is also related to the literature on safe asset demand and the convenience yield on government debt. A large body of work studies the premium at which government debt trades relative to comparable private claims, and how this premium varies with the supply of government debt, the level of interest rates, and the demand of investors and financial intermediaries (Bansal and Coleman, 1996; Krishnamurthy and Vissing-Jorgensen, 2012, 2015; Greenwood et al., 2015; Nagel, 2016; Caballero et al., 2017; Gorton, 2017; He et al., 2019; van Binsbergen et al., 2022; Acharya and Laarits, 2023; Krishnamurthy and Li, 2023; Brunnermeier et al., 2024; Jiang et al., 2024). Related work examines the international demand for U.S. safe assets (Jiang et al., 2021; Choi et al., 2022; Engel and Wu, 2023). Within this literature, this paper is most closely connected to work that links the premium on government debt to financial regulation. This work shows that the regulatory constraints of financial intermediaries affect the pricing of Treasuries (Jermann, 2020; Duffie, 2020; He et al., 2022; Favara et al., 2022), and that regulation creates captive demand for government debt that sustains the government funding advantage (Reinhart and Sbrancia, 2015; Payne and Szöke, 2025). This literature focuses mainly on financial outcomes, measuring how the premium on government debt is determined. I contribute to this literature by estimating not only the financial effects, but also the aggregate effects of regulatory safe asset demand. To the best of my knowledge, this paper provides the first estimates of the macroeconomic effects of regulatory safe asset demand.

The methodology of this paper draws extensively from the literature on the identification of macroeconomic shocks using narrative methods and external instruments (Stock and Watson, 2018). These approaches have been implemented in a variety of settings, including monetary policy (Romer and Romer, 2004; Gertler and Karadi, 2015), fiscal policy (Romer and Romer, 2010; Ramey, 2011; Mertens and Ravn, 2013), and oil supply (Känzig, 2021). The baseline analysis of this paper is most closely related to the methodology in den Besten et al. (2026), who construct a narrative series of exogenous tariff changes and use it as an external instrument in a proxy VAR. Following Ramey (2011), who measures news about government spending as the present value of expected changes in defense spending, I quantify each regulatory event using a present value measure. I contribute to this literature by

providing a novel application to financial regulation concerning safe assets, constructing a new narrative series of plausibly exogenous regulatory changes.

The model draws on the literature on regulated bank intermediation and the government funding advantage. It builds on macroeconomic models with financial intermediaries (Gertler and Kiyotaki, 2010; Gertler and Karadi, 2011; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014) and banks that serve as producers of safe and liquid claims (Diamond and Dybvig, 1983; Gorton and Pennacchi, 1990; Stein, 2012; Diamond, 2020). Within this literature, the most closely related paper is Payne and Szőke (2025), who are the first to treat the government funding advantage as an equilibrium object that depends on financial regulation. They develop a model in which regulation creates captive bank demand for government debt, and show that this captive demand has historically underpinned the U.S. funding advantage. The model also borrows features from quantitative models of bank regulation in which households value bank deposits (Van den Heuvel, 2008; Begenau, 2020) and liquid banks are less likely to fail (Van den Heuvel and Villalvazo, 2026), with the modification that households price the safety of the bank’s portfolio into its funding cost. Relative to these papers, I develop a quarterly New Keynesian model in which bank equity and bank portfolios adjust gradually, which generates the transition dynamics that the empirical analysis estimates. More broadly, the model relates to quantitative models of bank regulation and bank liquidity management (De Nicolò et al., 2014; Mendicino et al., 2018; Corbae and D’Erasmus, 2021; Elenev et al., 2021; Begenau and Landvoigt, 2022; Bianchi and Bigio, 2022) and to work on financial repression and government funding costs (Chari et al., 2020; Gómez-Cram et al., 2026). I contribute to this literature by providing empirical estimates that can discipline these classes of models.

Roadmap. The rest of the paper proceeds as follows. Section 2 describes the institutional setting and the narrative approach. Section 3 describes the methodology to construct the instrument. Section 4 validates the instrument. Section 5 describes the econometric approach. Section 6 presents the aggregate effects and the transmission channels. Section 7 presents the model and examines policy counterfactuals. Section 8 concludes.

2 Institutional Context and Narrative Approach

2.1 Institutional Context

Federal bank regulation in the United States is determined primarily by three federal agencies: the Federal Reserve Board, the Office of the Comptroller of the Currency (OCC), and the Federal Deposit Insurance Corporation (FDIC). The agencies typically act jointly, su-

pervising individual banks and issuing the rules that apply across the banking system. The rules govern how much capital banks must hold, which assets they must keep on hand, and to which banks each requirement applies. Many of the standards they adopt follow international standards that are set by the Basel Committee on Banking Supervision, a group of central banks and supervisory authorities. Congress also occasionally sets requirements directly through banking legislation.

Many of these requirements treat safe assets preferentially. Throughout the paper, safe assets refer to Treasury securities, debt and mortgage-backed securities (MBS) issued by government-sponsored agencies, cash, and central bank reserves, unless otherwise stated. Regulation classifies these assets as the safest and most liquid assets that banks can hold. In this paper, I focus on four main types of regulation that affect the demand for safe assets. Although financial regulation encompasses many types of regulation and requirements may affect banks across multiple dimensions, I classify and use the four types, as they are the most salient types of regulation that are related to safe asset demand.

First, capital requirements determine how much equity a bank must hold against its risk-weighted assets. The requirements assign a risk weight for each type of asset. Since 1988, safe assets have been assigned zero or low risk weights, while most loans have been assigned full risk weight ([Basel Committee on Banking Supervision, 1988](#)). Consequently, a capital-constrained bank can meet higher requirements by tilting its portfolio toward safe assets.

Second, liquidity rules require banks to hold a sufficient amount of liquid assets, with regulations assigning safe assets the highest liquidity classification. For example, the Liquidity Coverage Ratio (LCR) requires covered banks to hold enough high-quality liquid assets (HQLA) to cover all expected cash outflows during a severe 30-day stress event ([Basel Committee on Banking Supervision, 2010](#)). Treasuries and reserves count toward HQLA at full value and without any limit. In contrast, other eligible assets, such as investment-grade corporate bonds, are counted with a haircut and are subject to a cap on their share of the total stock. The Net Stable Funding Ratio (NSFR) is another liquidity rule that extends the same logic as the LCR to a one-year horizon ([Basel Committee on Banking Supervision, 2014](#)).

Third, leverage rules require banks to hold capital in proportion to their total assets, with every asset counted equally regardless of risk. These rules work in the opposite direction from the first two types of regulation, since they tax safe assets at the same rate as risky assets. A leverage tightening therefore reduces covered banks' demand for safe assets. Leverage rules are a subset of capital requirements, but I make a distinction in this paper, as the method to calculate the induced safe asset demand differs significantly between traditional capital requirements and leverage rules.

Lastly, scope rules determine which banks are covered under each rule. For example, the Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) of 2018 raised the asset threshold above which banks face stricter regulation from \$50 billion to \$250 billion. Subsequently, the Federal Reserve’s 2018–2019 tailoring framework sorted banks into categories with progressively lighter requirements. Scope rules interact with the three other types of regulation by changing which banks must comply, which affects the aggregate amount of banks’ safe asset holdings.

This paper focuses on the effects of regulatory changes on the slow-moving component of bank safe asset demand. The quarterly event series and the quarterly macroeconomic data capture the gradual reallocation of bank portfolios and its effects over quarterly horizons. A separate strand of literature studies how regulation affects the capacity of dealer banks to intermediate within much shorter time frames. Balance sheet constraints such as the leverage ratio limit the capital that dealers can devote to arbitrage trades, and the resulting limits to arbitrage appear in negative swap spreads, deviations from covered interest parity, and Treasury market dislocations under stress (Du et al., 2018; Boyarchenko et al., 2018; Jermann, 2020; Duffie, 2020). These effects materialize within much shorter time frames and reflect how a given balance sheet is allocated across trades, whereas the effects I estimate reflect the level of safe asset holdings that regulation requires. The two effects are not mutually exclusive, as a single rule such as the SLR can change both the required stock of safe assets and the cost of intermediation. The quarterly design of this paper is suited to the first effect, and the estimates should be read as the effects of regulation on the slow-moving demand for safe assets.

Figure 1 plots U.S. commercial banks’ safe asset holdings as a share of their total assets over 1973–2025. The share varies substantially over time. Banks’ safe asset share fell by half between the early 1990s and 2008, then nearly tripled by 2021. This variation reflects multiple factors, including but not limited to macroeconomic conditions, monetary policy, and the regulatory changes that are the subject of this paper. Furthermore, these factors are not independent of one another. Regulation can respond to macroeconomic conditions, while regulatory changes may themselves carry macroeconomic consequences. Movements in safe asset holdings around regulatory changes therefore confound the effects of regulation with the conditions that prompted it. This simultaneity issue motivates the narrative approach of the paper, which isolates plausibly exogenous regulatory changes.

2.2 Narrative Approach

The narrative approach aims to identify policy changes that were not taken in response to contemporaneous or prospective economic conditions. It examines the historical record surrounding each policy event to establish its motivation, and only retains the events whose

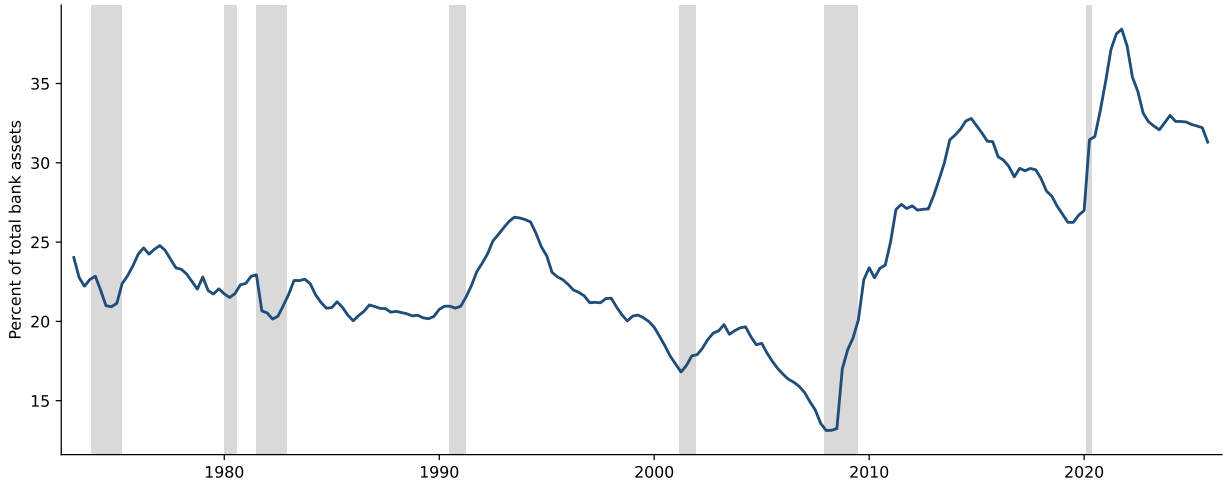


Figure 1: The safe asset share of U.S. commercial bank assets, 1973–2025

Notes: This figure shows safe asset holdings as a share of the total assets of U.S. commercial banks, aggregated from the Federal Reserve’s H.8 release. Safe assets are defined as Treasury securities, agency debt, agency mortgage-backed securities, and cash assets (including reserve balances at the Federal Reserve). Shaded areas mark NBER recessions.

motivation was unrelated to economic conditions at the time (Romer and Romer, 2010, 2023). Romer and Romer (2010) apply this approach to postwar tax changes, separating those driven by long-run considerations from those responding to the business cycle. I implement this in the context of U.S. banking regulation. The timing of the events follows Ramey (2011), who assigns the shocks to the dates that policy changes are announced, rather than when they take effect, to account for anticipation effects. The regulatory changes I use share this feature, since requirements are announced years before they bind. I therefore date each event according to the timing of announcements. The remainder of this section describes the documents from which the events are drawn, the criteria for including an event, and the classification that distinguishes between exogenous and endogenous events. I perform a series of diagnostic checks on the resulting event series in Section 3 following Ramey (2016). I find no evidence of serial correlation or predictability using macroeconomic or financial variables.

Sources and inclusion criteria. To identify a candidate set of announcements, I examine four types of documents from 1985 to 2025. These consist of (i) the joint press releases of the federal banking agencies in their rulemaking categories; (ii) the proposed and final rules in the Federal Register that amend the parts of the Code of Federal Regulations governing capital, liquidity, and enhanced prudential standards; (iii) Basel Committee publications

regarding international standards;¹ and (iv) U.S. banking legislation that affects quantitative requirements.

An announcement must satisfy four criteria to be included in the list of candidate events. First, the event must change or reveal news about a quantitative requirement. This excludes announcements without rule content, single-bank enforcement actions, and procedural rules. Second, the requirement must be related to safe asset demand through one of the four types of regulation described above. Third, the rule must apply to an identifiable set of banks, so that its coverage can be reconstructed in the bank-level data. Lastly, the event must have a well-defined public announcement date on which the expected path of regulation changed. Applying these criteria yields 61 candidate events between July 1988 and June 2025.

In addition to the primary documents, I draw on a range of sources to establish the motivation behind each policy change. These include contemporaneous government communications, press coverage of the announcements, congressional records, retrospective accounts by regulators and researchers, and historical accounts of banking regulation (Goodhart, 2011). Corroborating each event’s motivation from multiple sources ensures an accurate reading of the historical record, providing the basis for the classification that follows.

Classification. Following Romer and Romer (2010), I classify each candidate event by the primary motivation established from these sources. I classify an event as exogenous only if its motivation and timing are plausibly unrelated to contemporaneous or prospective economic conditions. The exogenous events fall into two groups.

The first group consists of events where the timing was determined by preexisting schedules (e.g., comment periods, Basel schedules, and elections). The motivations behind these events include international harmonization of banking standards, long-standing statutory agendas, and administration change. Examples include the 1988 Basel Accord, the 1996 Market Risk Amendment, and the 2004 Basel II framework. Each event is the outcome of international negotiations running for years with a schedule set well in advance. Elections are of course not independent of the economy over long horizons, but what identification requires is that events be orthogonal to the shocks of the announcement quarter rather than to slow-moving political trends. This is consistent with Romer and Romer (2010), who classify ideologically motivated tax changes as exogenous on the same grounds.

The second group consists of structural reforms adopted in response to a previous crisis and implemented with multi-year lags. Examples include the Basel III framework, the LCR, and the NSFR. Although these events are responding to economic conditions, they are responding to conditions from multiple years before the announcement. Given that the

¹These cover Basel I, Basel II, and Basel III, the LCR, the NSFR, the leverage ratio, and the framework for global systemically important banks (G-SIBs).

estimation of the macroeconomic effects conditions on lagged economic variables, a reform motivated by a crisis years earlier does not confound identification. As mentioned earlier, the identification requires that events be unrelated to the shocks of the announcement quarter rather than to past economic conditions.

I classify an event as endogenous when its timing or content responds to contemporaneous conditions. Regulators take such actions to support the flow of credit during downturns, to stabilize financial markets under stress, or to restore confidence in banks during and after failures. For example, reserve requirement cuts in 1990 and 1992 eased credit conditions in response to contemporaneous financial conditions, and the April 2020 temporary exclusion of Treasuries and reserves from the Supplementary Leverage Ratio (SLR) addressed a lack of liquidity in the Treasury market during the COVID pandemic. These regulatory changes act as a policy tool to stabilize the economy, and thus I exclude them from the sample.

Out of the 61 candidate events between 1988 and 2025, I classify 38 events as exogenous.² Appendix A lists the exogenous events along with relevant information.

2.2.1 Examples of exogenous and endogenous events

I present three examples from the set of candidate events, consisting of two exogenous events and one endogenous event. These examples illustrate the classification approach and why these events can be interpreted as news about regulatory safe asset demand.

The 1988 Basel Accord. In July 1988, the central bank governors of the Group of Ten approved the Basel Capital Accord. This was the first international risk-based capital standard ([Basel Committee on Banking Supervision, 1988](#)). It required banks to hold total capital of at least 8 percent of risk-weighted assets by the end of 1992. Cash, central bank reserves, and claims on OECD central governments carried a risk weight of zero, while claims on private borrowers carried a risk weight of 100 percent. These risk weights made holding safe assets the cheapest way to comply. The timing and content of this announcement were plausibly exogenous with respect to contemporaneous and prospective U.S. economic conditions in mid-1988. The stated motivation behind this international standard was to promote the soundness of the international banking system and competitive equality among banks of different countries. Moreover, the Accord concluded a negotiation process that had run for most of the decade.

The 2010 Liquidity Coverage Ratio. On December 16, 2010, the Basel Committee published the original LCR standard as part of the Basel III framework ([Basel Committee](#)

²The 23 excluded events are either endogenous, inconclusive in their exogeneity, or fail to have clear quantifiable effects on safe asset demand.

on [Banking Supervision, 2010](#)). The LCR mandated that covered banks hold a stock of HQLA at least as large as their projected net outflows over a 30-day stress scenario by the beginning of 2015. The standard counted reserves and Treasuries toward the required stock at full value and without limit. In contrast, it admitted corporate bonds only at a haircut and subject to a cap. A contemporary industry study estimated that complying with the standard would require the U.S. banking industry to accumulate about \$1.5 trillion of additional liquid assets, mostly composed of reserves and Treasuries ([The Clearing House, 2011](#)). The timing and content of this announcement were plausibly exogenous. The stated motivation was to reduce the likelihood and severity of future banking crises by strengthening the liquidity of bank balance sheets. The publication followed the timetable of the reform program that the Group of Twenty had mandated in 2009.

The 2020 Supplementary Leverage Ratio exclusion. On April 1, 2020, the Federal Reserve announced the temporary exclusion of Treasuries and reserves from the SLR denominator ([Board of Governors of the Federal Reserve System, 2020](#)). Under the exclusion, banks no longer needed to hold capital against their Treasury and reserve holdings, which lowered the cost of holding these safe assets and constituted positive news for safe asset demand. The Board estimated that the exclusion would allow banks to hold around \$1.6 trillion of additional assets without raising new capital ([Board of Governors of the Federal Reserve System, 2020](#)). The timing and content of the rule, however, were direct responses to contemporaneous conditions. The release states that the change was made “to ease strains in the Treasury market resulting from the coronavirus.” In addition, the announcement occurred within days of the CARES Act, the largest fiscal package in U.S. history ([U.S. Congress, 2020](#)), as well as the introduction of multiple emergency lending facilities ([Clarida et al., 2021](#)). I therefore classify this event as endogenous. Movements in safe asset holdings and in the economy following the announcement would reflect the pandemic and the policy response to it rather than the regulatory change.

3 Measuring Regulatory Safe Asset Demand

Using the list of exogenous events from Section 2, I construct a quarterly series that measures the intensity of each policy change. I first describe the data, then document the methodology that converts each announcement into a present-value measure of the safe asset demand that it induces. I then conduct diagnostic checks to assess the validity of the event series.

Data. I construct a measure of intensity for each event using the Consolidated Report of Condition and Income, also known as Call Reports. All federally insured U.S. commercial

banks must file a Call Report with the Federal Financial Institutions Examination Council (FFIEC) every quarter, providing details of their balance sheet, cash flows, and overall financial health. The quarterly panel covers 1984Q1 to 2025Q2, containing roughly 1.5 million bank-quarter observations. The Call Report dataset is widely used in the finance literature on banking (Kashyap and Stein, 2000; Drechsler et al., 2017). For each bank, I measure holdings of safe assets, defined as Treasury securities, agency debt and MBS, cash, and central bank reserves. This definition is largely consistent with the classifications used in the literature on safe assets and in bank regulation (Gorton et al., 2012; Gorton, 2017; Basel Committee on Banking Supervision, 2010).³ Appendix B describes the construction of the bank-level series in more detail.

Summary of methodology. The methodology to measure the intensity for each event involves three main steps. I first document the specific changes in the quantitative requirements that banks face, interpreting the announcements as a revision to the path of requirements that regulated banks expect to face. I then convert these revisions into an expected path of safe asset demand induced by the announced regulatory changes. This involves using the Call Reports to apply the requirements of each rule to the balance sheets of regulated banks. Finally, I collapse the demand path for each event into a single number to get an intensity measure corresponding to each event. In the baseline methodology, I collapse the demand path by taking the present value of the induced safe asset demand. I then aggregate the present values across events into a quarterly series.

Expected requirement paths. I represent every event as a revision to the expected path of the relevant requirement. For each event e , I construct the path expected just before the announcement, $m_e^{pre}(h)$, and the path expected just after, $m_e^{post}(h)$, at each quarterly horizon h since the announcement. The $m_e(h)$ refers to policy parameters that vary by event, as it represents the specific quantitative requirement that the announcement changes. For an LCR event, for example, $m_e(h)$ is the required ratio of liquid asset holdings to projected funding outflows that banks expect to face h quarters after the announcement. I base the paths on the rules' own phase-in calendars, as well as accounts of what was expected around the announcements. I then define the revision corresponding to the event e at horizon h as $\Delta m_e(h) = m_e^{post}(h) - m_e^{pre}(h)$. I take revisions of expected paths as the measure of news to account for anticipation, as forward-looking banks respond to the changes in the requirements they expect to face. For example, a final rule that confirms a proposal already priced in carries zero news, and thus would have $\Delta m_e(h) = 0$ for all horizons h .

³For example, the LCR counts central bank reserves, Treasuries, and MBS guaranteed by the Government National Mortgage Association at full value, while the debt and MBS of the government-sponsored enterprises count at a 15 percent haircut (Basel Committee on Banking Supervision, 2010).

Demand paths. Using the path of requirement revisions for each event, I construct a path of induced safe asset demand. For each covered bank i , I apply the requirements of each rule, stated channel by channel below, using information from the bank’s balance sheet. I denote the safe asset demand induced by the regulation changes from event e for bank i at quarterly horizon h as $\Delta d_{i,e}(h)$. I then aggregate the bank-level news across the set of covered banks C_e to obtain the demand path corresponding to the event, $D_e(h) = \sum_{i \in C_e} \Delta d_{i,e}(h)$. This provides a sequence of induced safe asset demand for each event, with one value $D_e(h)$ at every horizon from $h = 0$ in the announcement quarter to the horizon H_e at which the rule is fully phased in. The induced demand measures the additional stock of safe assets that banks must hold, and therefore remains at its terminal value $D_e(H_e)$ after the end of the phase-in period.

Present values. I collapse the path of induced safe asset demand to a single value for each event by taking the present value of the demand path. I calculate the present value for event e using the following equation:

$$\text{PV}_e = \sum_{h=0}^{H_e} \beta^h [D_e(h) - D_e(h-1)], \quad (1)$$

where I set $D_e(-1) = 0$ for all events, and β is the quarterly discount factor. I use $\beta = 0.99$ in the baseline methodology. I hold the discount factor fixed across events, so that variation of the resulting series is not contaminated by differences in the level of interest rates across announcements. I perform a series of robustness checks that vary the level of β in Appendix C.

I then aggregate across events within each quarter and scale by the lagged aggregate total assets of U.S. commercial banks to obtain a quarterly series z_t :

$$z_t = \frac{\sum_{e: t_e=t} \text{PV}_e}{\text{TA}_{t-1}}, \quad (2)$$

where TA_{t-1} denotes the aggregate total assets of U.S. commercial banks in the previous quarter. Scaling keeps the series stationary across the sample, during which time bank balance sheets grew tenfold. I use the aggregate total assets from the preceding quarter to ensure that the scaling does not respond to the announcements themselves. I also provide an alternative scaling using nominal GDP in Appendix C. Both the use of present values and the scaling by a lagged aggregate follow Ramey (2011).

Calculation of demand paths by regulatory channel. I now describe the methodology to calculate the induced demand paths for each of the four main regulatory channels described

in Section 2. For all types of regulation, event e is announced in quarter t_e and applies to the coverage set of banks C_e . I characterize C_e following the corresponding level at which each requirement operates, given that regulations apply either at the level of consolidated holding companies or for each insured commercial bank directly. Regulations that apply at the holding-company level are restricted to large institutions, where the thresholds that define applicability are based on the total assets of the consolidated holding company. For these rules, I approximate the size of each holding company by the combined assets of its member commercial banks, and compare this size with the rule’s threshold. I identify the eight U.S. global systemically important banks (G-SIBs) directly for the rules that apply to them specifically. The coverage set C_e then collects the member commercial banks of every qualifying holding company, and a bank without a holding parent enters based on its own assets. Regulations that apply to each insured commercial bank, such as the Basel capital minimums, place every bank in C_e .

I measure each bank’s exposure to a rule using its own balance sheet from the Call Reports. This matches how the requirements apply in practice. Capital rules bind at the level of each insured commercial bank, and the liquidity rules and the enhanced supplementary leverage ratio also apply to the large depository subsidiaries of the covered holding companies.⁴ I measure each bank’s exposure based on the quarter preceding the announcement. This ensures that the exposures are predetermined at the time of each event.

In the following paragraphs, I detail the steps to calculate the induced safe asset demand for each of the four regulatory channels. For all channels, I calculate $\Delta d_{i,e}(h)$, the safe asset demand induced by event e for bank i at quarterly horizon h . I then take the sum of $\Delta d_{i,e}(h)$ across the covered banks in C_e to estimate the demand path $D_e(h)$. For the sake of notational brevity, the pre-event exposures enter the equations with only the bank subscript. For example, an exposure written x_i denotes the pre-event average $\bar{x}_{i,e}$ for the event at hand.

Risk-weight and capital events. Capital requirements determine the minimum amount of equity a bank must hold in proportion to its risk-weighted assets. The risk weights vary from 0 percent to 1,250 percent. Most commercial and corporate loans carry a risk weight of 100 percent, while safe assets such as Treasuries carry a risk weight of zero. Assets with the highest risk, such as subordinated tranches of securitized assets, carry the highest risk weights. A bank can meet higher capital requirements either by raising new capital or by shifting the portfolio toward assets with lower risk weights, including safe assets.

⁴For example, the LCR and the NSFR apply to each depository subsidiary with at least \$10 billion in assets within the covered holding companies. A limitation of measuring exposures at the bank level is that positions held in nonbank affiliates are omitted. This is unlikely to be a cause for concern, as the covered holding companies hold the large majority of their consolidated assets in their commercial bank subsidiaries. See Avraham et al. (2012) and Cetorelli and Prazad (2025) for relevant discussions.

I assume that banks fully pass through the changes in requirements to the capital ratios they target. When an announcement raises the required capital ratio by one percentage point, each bank consequently raises its target for the capital ratio by one percentage point. This reflects how banks manage their capital in practice. U.S. banks hold voluntary buffers of several percentage points above every capital minimum, and they keep these buffers roughly constant when requirements change (Berrospide and Edge, 2010).

For an event that changes the required ratio of capital to risk-weighted assets, denoted as $m_e(h)$, bank i 's targeted level of capital changes by $\Delta m_e(h) \cdot \text{RWA}_i$, where RWA_i is the bank's risk-weighted assets. The induced demand is estimated as

$$\Delta d_{i,e}(h) = \varphi \cdot \Delta m_e(h) \cdot \text{RWA}_i, \quad (3)$$

where φ is the dollars of safe assets that banks acquire per dollar of newly required capital. I set $\varphi = 0.2$, in line with the empirical estimates of banks' asset-side responses to changes in capital requirements (Aiyar et al., 2014; Gropp et al., 2019). I show robustness with respect to the value of φ in Appendix C.

Liquidity events. Liquidity requirements determine the amount of liquid assets a bank must hold in proportion to its potential funding outflows. The Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) make up the two main types of liquidity requirements in the sample. The LCR requires banks to hold a sufficient amount of high-quality liquid assets (HQLA) based on their projected net cash outflows over a 30-day stress period. The NSFR requires banks to maintain a sufficient amount of stable funding to support their long-term assets and activities over a one-year period.

For LCR events, the requirement path $m_e(h)$ is the required ratio of HQLA to projected net cash outflows. The required HQLA at horizon h is $m_e(h) \cdot \text{NCO}_i$, where NCO_i denotes bank i 's projected net cash outflows. Given that Call Reports do not report net cash outflows directly, I estimate NCO_i following the methodology from Roberts et al. (2023) and Sundaresan and Xiao (2024). I measure the bank's stock of HQLA with its safe asset holdings SA_i . The safe asset holdings closely track eligible HQLA, since the definition covers the assets that the LCR counts at its highest quality levels.⁵ The induced demand is estimated as

$$\Delta d_{i,e}(h) = \max(0, m_e^{\text{post}}(h) \cdot \text{NCO}_i - \text{SA}_i) - \max(0, m_e^{\text{pre}}(h) \cdot \text{NCO}_i - \text{SA}_i). \quad (4)$$

The max operators set the induced demand to zero for banks already holding more safe assets than the requirement. The difference between the required level $m_e(h) \cdot \text{NCO}_i$ and SA_i is the bank's shortfall. This gap between the required level and the safe asset holdings

⁵See Appendix C for robustness checks that restrict the safe asset measure to Level 1 HQLA.

the bank already has reflects the safe asset demand induced by the requirement.

The NSFR is defined similarly to the LCR, but concerns long-term funding stability. I estimate required stable funding RSF_i and available stable funding ASF_i by applying the weights of the standard to each bank's assets and funding. The estimated induced demand for safe assets is

$$\Delta d_{i,e}(h) = \frac{\max(0, m_e^{post}(h) \cdot RSF_i - ASF_i) - \max(0, m_e^{pre}(h) \cdot RSF_i - ASF_i)}{0.8}. \quad (5)$$

The shortfall is very similar to the formulation for the LCR, with RSF_i and ASF_i being the NSFR analogs to NCO_i and SA_i , respectively. The estimation for the NSFR involves an extra step, which is that I divide the shortfall by 0.8 to convert it into safe asset purchases. The conversion factor reflects the weights of the standard, under which shifting one dollar from loans to safe assets lowers the required stable funding by 0.8 dollars (85 percent against 5 percent). Closing a one-dollar shortfall in the NSFR therefore requires 1.25 dollars of safe asset purchases.

A number of liquidity events in the sample change the definition of eligible HQLA rather than the level of the requirement. For example, the January 2013 revision of the LCR admitted certain corporate bonds and equities as eligible HQLA up to a cap. Such regulations lower the demand for the previously eligible safe assets, as banks can now meet part of the requirement with other types of assets.

For these events, the regulatory parameter $m_e(h)$ is the fraction of the requirement that the newly admitted assets are allowed to cover. For example, a revision that allows corporate bonds to cover at most 5 percent of the LCR raises $m_e(h)$ from zero to 0.05 for the horizons where the revision applies. I estimate the induced negative demand as

$$\Delta d_{i,e}(h) = -\Delta m_e(h) \cdot \min(SA_i, a \cdot NCO_i). \quad (6)$$

Banks can substitute safe assets with the newly admitted assets up to the fraction $m_e(h)$. The phase-in level of the LCR at the time of announcement is denoted by a , and $\min(SA_i, a \cdot NCO_i)$ reflects the amount of the bank's safe asset holdings up to the LCR requirement. Building on the earlier example, when a revision allows corporate bonds to cover up to 5 percent of the LCR, a bank that meets the LCR requirement exactly can replace up to 5 percent of its safe asset holdings with corporate bonds. Therefore, the bank's demand for safe assets falls by 5 percent of its safe asset holdings.

Leverage events. Leverage ratios determine the minimum amount of capital a bank must hold as a proportion of its total assets. Unlike the capital requirements discussed earlier in this section, the leverage ratios do not involve any risk weighting. Events related to leverage

ratios in the sample include the introduction of the U.S. minimum leverage ratio in 1990 and the changes to the supplementary leverage ratio for the largest banks. As leverage ratios treat all assets equally regardless of the risk associated with them, holding safe assets incurs the same capital charge as risky assets without the higher returns.

For these events, the regulatory parameter $m_e(h)$ is the required ratio of a bank's capital to its total exposure. The estimated induced demand for safe assets is

$$\Delta d_{i,e}(h) = -\psi \cdot \Delta m_e(h) \cdot \text{LevExp}_i, \quad (7)$$

where LevExp_i is the bank's on-balance-sheet leverage exposure (e.g., total assets), and ψ is the reduction in safe asset holdings per dollar of newly required capital. I set $\psi = 0.30$ based on estimates from the literature, which documents that banks facing binding leverage requirements decreased their safe assets by 20 to 40 cents per dollar of newly required capital (Duffie, 2020; Favara et al., 2022). I show robustness with respect to the value of ψ in Appendix C.

A number of leverage events change the definition of the leverage exposure LevExp_i rather than the leverage ratio. For example, the 2014 revision of the supplementary leverage ratio adjusted the denominator of the leverage ratio to add a set of off-balance-sheet items (e.g., credit derivatives, repo-style transactions) to the leverage exposure.

For these events, the regulatory parameter $m_e(h)$ is the share of the banks' leverage exposure that the regulation adds or removes. Adding a set of items to the leverage exposure would correspond to $m_e(h) > 0$, and removing a set of items would correspond to $m_e(h) < 0$. I calculate this share using the aggregate balance sheets of the covered banks. The estimated induced demand for safe assets is

$$\Delta d_{i,e}(h) = -\psi \cdot a \cdot \Delta m_e(h) \cdot \text{LevExp}_i, \quad (8)$$

where a is the level of the leverage ratio at the time of the event and ψ is the same parameter as in Equation 7. Adding a share $\Delta m_e(h)$ to the leverage exposure raises the bank's required capital by $a \cdot \Delta m_e(h) \cdot \text{LevExp}_i$.

Scope events. Scope events change the set of banks that a requirement covers. For example, the 2018 EGRRCPA raised the total asset threshold for enhanced prudential standards from \$50 billion to \$250 billion. All scope events in the sample concern the set of banks covered under various liquidity requirements.

For scope events, the induced safe asset demand is determined by the changes in the set of covered banks. A bank that enters the set of covered banks for a given regulation would adjust its safe asset holdings, if necessary, to comply with the regulation. A bank that

is removed from the set of covered banks would no longer need to maintain the safe asset holdings that the regulation required. The estimated induced demand for safe assets is

$$\Delta d_{i,e}(h) = \mathbb{1}_{i,e}^+(h) \cdot \max(0, \text{Req}_i - \text{SA}_i) - \mathbb{1}_{i,e}^-(h) \cdot \max(0, \min(\text{SA}_i, \text{Req}_i) - \text{SA}_i^0), \quad (9)$$

where $\mathbb{1}_{i,e}^+(h)$ indicates that the scope event adds bank i under the requirement at horizon h , $\mathbb{1}_{i,e}^-(h)$ indicates that the scope event removes bank i from coverage at horizon h , Req_i is the required level of safe assets under the relevant regulation, and SA_i^0 is the level of safe assets that bank i would hold in the absence of the relevant regulation. I estimate SA_i^0 by multiplying the total assets of bank i by the average safe asset share among a comparable set of banks that the regulation does not cover.⁶ The first term with the max operator represents the safe asset shortfall for a bank that enters the set of covered banks. The second term with the min and max operators reflects the level of safe asset holdings that was induced by the requirement for a bank that is removed from the set of covered banks. This is measured as the holdings in excess of the level SA_i^0 , with a ceiling of the required level Req_i . The ceiling ensures that any holdings above the requirement are not counted toward the estimated decrease in demand for safe assets.

Some of the scope events determine whether a given requirement applies fully or partially. For example, the 2018–2019 tailoring framework categorized banks with total assets above \$100 billion based on size, risk, and complexity. The liquidity requirements applied fully to the largest systemically important banks, while the requirements applied at reduced levels for banks in other categories. For these events, I scale the indicators by the corresponding fraction of the requirement that applies for each bank.

Event series and diagnostics. I apply the methodology described above to the 38 exogenous events to obtain the event series z_t . The event series reflects the estimated quarterly measure of regulation-induced safe asset demand shown in Equation 2. The quarters with the largest values correspond to announcements of major regulatory standards. The announcement of Basel I in July 1988 is associated with \$15 billion of safe asset demand in present value terms. Similarly, announcements regarding the LCR in December 2010 and the NSFR final standard in October 2014 are associated with \$122 billion and \$112 billion of safe asset demand, respectively. These estimated magnitudes are consistent with existing estimates from the literature on the effect of liquidity regulation ([The Clearing House, 2011](#); [Roberts et al., 2023](#); [Sundaresan and Xiao, 2024](#)).

Figure 2 shows the cumulative regulatory safe asset demand, along with a series con-

⁶The set of comparable banks for each bank i is composed of the ten closest banks in total asset size that are not covered by the given requirement. The average safe asset share among this comparable set is calculated using the quarter preceding the announcement.

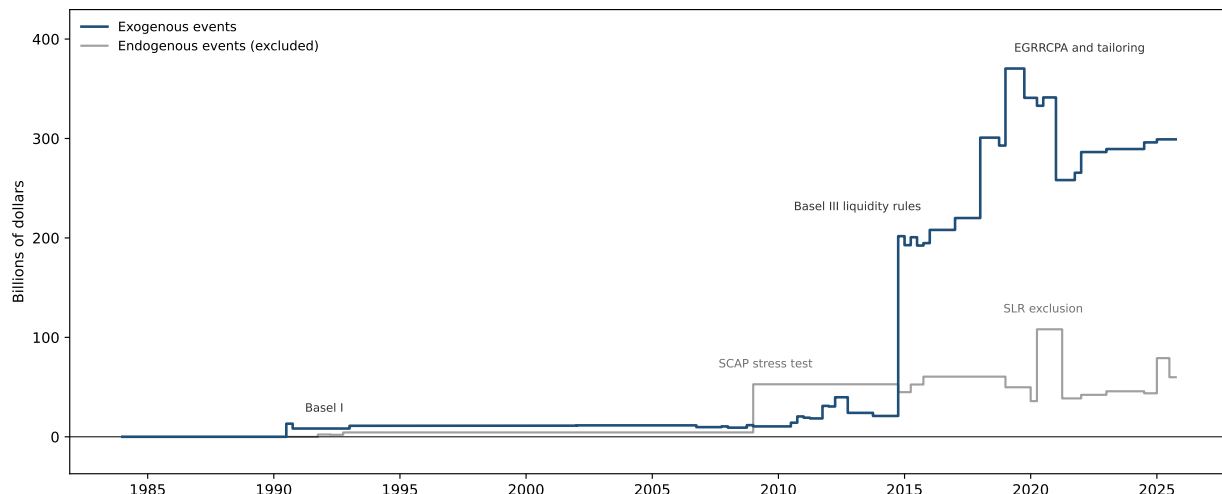


Figure 2: Cumulative regulatory safe asset demand, 1984–2025

Notes: This figure shows the cumulative regulatory safe asset demand, measured by summing each event’s path of induced safe asset demand in calendar time. The paths are summed in undiscounted levels, before each path is collapsed into a single measure by taking its present value. The dark blue line aggregates the 38 exogenous events, and the gray line aggregates the endogenous events.

structured under the same methodology using the endogenous events. I aggregate the predicted safe asset accumulation paths across the events. The cumulative demand reaches about \$10 billion after the Basel I phase-in and remains modest until 2014, when the Basel III regulations induce a sizeable increase. The exogenous series peaks at around \$370 billion in early 2019 before the tailoring framework reverses some of the accumulated demand. The endogenous series remains small throughout the sample, with the largest changes coming from the Supervisory Capital Assessment Program (SCAP) stress test in 2009 and the temporary SLR exclusion in 2020.

For the event series to be a valid measure of the news associated with exogenous events, the series must be uncorrelated with other shocks and unforecastable (Ramey, 2016). I conduct a series of diagnostic checks on the event series, and conclude that there is no evidence to suggest that the event series is correlated with other shocks or forecastable.

I first test for correlation between the event series and a number of identified shocks from the literature. I find no evidence that the event series is picking up other shocks. One of the key threats to identification in this paper is that the event series may be picking up news about general financial regulation, rather than news specifically about regulatory safe asset demand. I find that the series is uncorrelated with existing measures of financial regulation, including the bank regulation shocks from Drechsel and Miura (2026). This provides supporting evidence that the event series is not contaminated by news about broader financial regulation. I present the corresponding results in Appendix C.

In addition to correlation with other shocks, I test for predictability of the event series. I

	Exogenous events	Endogenous events
Event series (own lags)	0.80	0.44
<i>Macroeconomic variables</i>		
Real GDP	0.21	0.10
Industrial production	0.25	0.40
GDP deflator	0.37	0.48
Unemployment rate	0.60	0.04
<i>Financial variables</i>		
Funding advantage	0.76	0.84
Financial conditions (NFCI)	0.27	0.01
Excess bond premium	0.46	0.42
Term spread	0.23	0.05
Shadow federal funds rate	0.25	0.58
<i>Government and banking</i>		
Federal debt to GDP	0.60	0.01
Bank safe asset share	0.45	0.00
Joint	0.83	0.00

Table 1: Forecastability of the event series

Notes: This table reports p -values of Granger causality tests of the quarterly event series using a set of economic and financial variables. All variables are transformed to be stationary before estimation. Each row reports the p -value for the joint significance of two lags of the corresponding variable. The final “Joint” row tests all listed variables jointly, excluding the own lags of the series.

conduct a series of Granger causality tests using a number of economic and financial variables. I find no evidence that the event series is predictable. Table 1 shows the results for the event series using the 38 exogenous events and for the series using the 23 excluded events. The series with exogenous events is not systematically forecastable. The p -values are above 0.2 for all variables, and the joint p -value using all of the variables is 0.83. In contrast, the series with endogenous events is forecastable, suggesting that the events are responding to economic and financial conditions. The p -values are below 0.05 for the unemployment rate, the National Financial Conditions Index (NFCI), the debt-to-GDP ratio, and the bank safe asset share, with a joint p -value that is less than 0.001. I also test for serial correlation of the event series, and find no evidence that the event series exhibits serial correlation. I report the autocorrelation plots in Appendix C.

Alternative methods. I also use three alternative methods to construct the event series. The first alternative orthogonalizes the existing event series with respect to measures of general financial regulation from the literature. The second alternative replaces the step of taking present values by using the first principal component to collapse the demand paths.

The third alternative replaces the measure by only using the timing and sign of each event, following the methodology from [Boer and Lütkepohl \(2021\)](#) and [den Besten et al. \(2026\)](#). I compare the results using these alternative methods in Appendix C.

The first alternative method addresses the concern that the event series reflects not only news about regulatory safe asset demand, but also news about overall changes in banking regulation. I construct a version of the event series that is orthogonal to measures of financial regulation from the literature, following the methodology from [Miranda-Agrippino and Ricco \(2021\)](#) and [Bauer and Swanson \(2023\)](#). I regress the baseline event series z_t on each financial regulation measure, and remove the component of the series that the measure explains. I denote this orthogonalized event series as $z_t^\perp$. I use three measures of financial regulation from [Cascaldi-Garcia and Iacoviello \(2026\)](#), [Drechsel and Miura \(2026\)](#), and [Baker et al. \(2016\)](#). The measures explain little of the variation in the baseline event series z_t , and the correlation between $z_t^\perp$ and z_t ranges from 0.94 to 0.99 across the three measures. Appendix C details the methodology, along with the comparison of the results.

The second alternative method alters the step of collapsing the estimated demand path to a single number for each event. Rather than taking the present value of the demand paths, I use principal component analysis. I first aggregate the bank-event level safe asset demand paths to the event level, which results in an aggregate safe asset demand path for each event. I then scale each path using the total asset value of all U.S. commercial banks in the quarter preceding the event. Stacking the demand paths across all events results in a matrix, where each row corresponds to an event and each column corresponds to a quarterly horizon. I extend events with shorter demand paths by holding the demand at its terminal value beyond the end of the phase-in period.⁷ I then perform principal component analysis and use the score on the first principal component as the alternative measure of regulatory safe asset demand for each event. I compute the principal component without demeaning, as this maintains a value of zero for an event with no news. The first principal component accounts for roughly 90 percent of the variation across the demand paths. I aggregate the scores on the first principal component across events within each quarter to obtain a quarterly series. For ease of comparison, I finally scale the quarterly series to match the average volatility of the baseline series z_t constructed using the present value method. I denote this alternative series using principal component analysis as z_t^{pca} . The series is highly correlated with the baseline series, with a correlation of 0.99.

The third alternative method forgoes all of the steps used to measure the magnitude of regulatory safe asset demand. Following the methodology discussed in [Boer and Lütkepohl \(2021\)](#), I assign each event a +1 or -1 based on whether the event induces increases or

⁷This does not require any additional assumptions, as the induced demand to the stock of safe assets remains at its terminal level after the completion of any phase-in path.

decreases in safe asset demand. Under this alternative method, the identifying variation comes only from the timing of the announcements and the direction in which they move safe asset demand, with no role for the magnitude of the induced demand. I then aggregate to the quarterly level by taking the sum across events within each quarter. I denote this series using only signs as z_t^{sign} . The correlation between z_t^{sign} and z_t is 0.71.

4 Cross-sectional Validation

This section validates the methodology used to construct the event series z_t by testing its predictions in the cross-section of banks. Although the event series discussed in Section 3 is a quarterly aggregate series, it is constructed from bank-level measures. Each announcement corresponds to a predicted path of safe asset demand for each bank before these bank-level paths are aggregated to the quarterly level. I estimate stacked event studies that examine the response of safe asset holdings across banks around the regulatory events using the bank-level predictions. Banks with one additional dollar of predicted safe asset demand end up holding roughly one additional dollar of safe assets, while showing no differential trends before the announcements.

4.1 Event-Study Design

I estimate stacked event studies on the exogenous events discussed in Section 3 using the following specification for each horizon h :

$$\Delta y_{i,e,h} = \alpha_{e,h} + \beta_h \cdot PV_{i,e} + \varepsilon_{i,e,h}, \quad (10)$$

where $\Delta y_{i,e,h} \equiv y_{i,e,t+h} - y_{i,e,t-1}$ is the change in bank i 's holdings of safe assets from the quarter before the announcement of event e to h quarters after the announcement; $PV_{i,e}$ is the present value of the predicted safe asset demand for bank i corresponding to event e ; and $\alpha_{e,h}$ is the event fixed effect. Banks that are unaffected by an event have a $PV_{i,e}$ of zero. The sample of banks includes all commercial banks with over \$100 million in total assets. Both $\Delta y_{i,e,h}$ and $PV_{i,e}$ are in dollars, meaning that a coefficient of one implies that at horizon h , banks have accumulated safe assets that are equal to the present value of the predicted safe asset accumulation.

I use event fixed effects to follow the approach of [Cengiz et al. \(2019\)](#), in which each event is evaluated against its own contemporaneous controls through event-specific fixed effects. This specification also maps to the local projections difference-in-differences framework of [Dube et al. \(2025\)](#), in which differencing the outcome from its pre-treatment level removes unit heterogeneity without introducing unit fixed effects. Including bank fixed effects may

absorb part of the treatment effect itself, as a bank fixed effect estimated across the stacked events absorbs each bank’s average response.⁸ This concern is especially salient in this context, as the treatment effects are likely to be persistent.

Note that the identifying variation in this exercise is different from that of the main analysis. The event-study specification includes event fixed effects at each horizon, so the estimates compare banks within the same announcement and the event fixed effects absorb everything that banks experience in common. This validation exercise examines whether the cross-sectional variation in the predicted accumulation of safe assets corresponds to observed accumulation, while the main analysis in Section 5 estimates the aggregate responses.

4.2 Event-Study Results

Figure 3 shows the event-study estimates. Banks with larger predicted acquisitions show no differential trends in the pre-event periods. After the announcement, safe asset holdings increase gradually and settle just above the full-compliance prediction. The accumulation at the one-year horizon is \$0.14 per dollar of predicted present value accumulation. This rises to \$0.54 at the two-year horizon, and rises above \$1 at the three-year horizon. The effect levels off after the three-year horizon at roughly \$1.2 for the remainder of the estimated five-year horizon. The estimates are statistically significant from the two-year horizon onward. Overall, a bank with one additional dollar of predicted safe asset demand in present value terms accumulates just over one additional dollar of safe assets.

As the announcements often involve a phase-in schedule of a regulation over several years, full compliance does not imply an immediate response that corresponds to a coefficient of one. I conduct a joint test examining whether the estimated coefficients differ from the coefficients implied by full-compliance based on the estimated path of safe asset accumulation. The test imposes the full-compliance prediction as the null hypothesis at every horizon, and I compute the joint distribution of the horizon-level t -statistics using a wild cluster bootstrap with clustering at the event level. The resulting p -value is 0.58 for the full set of horizons, meaning that the test fails to reject the null hypothesis that the estimated coefficients equal the full-compliance predictions. Treating the full-compliance predictions as fixed, rather than an estimate with error, is the more conservative approach for this particular statistical test, as this understates the variance of the difference and makes rejection more likely.

⁸Goodman-Bacon (2021) shows that the two-way fixed-effects estimator with staggered treatment can attenuate long-run estimates. See Sun and Abraham (2021); Borusyak et al. (2024) for related discussions.

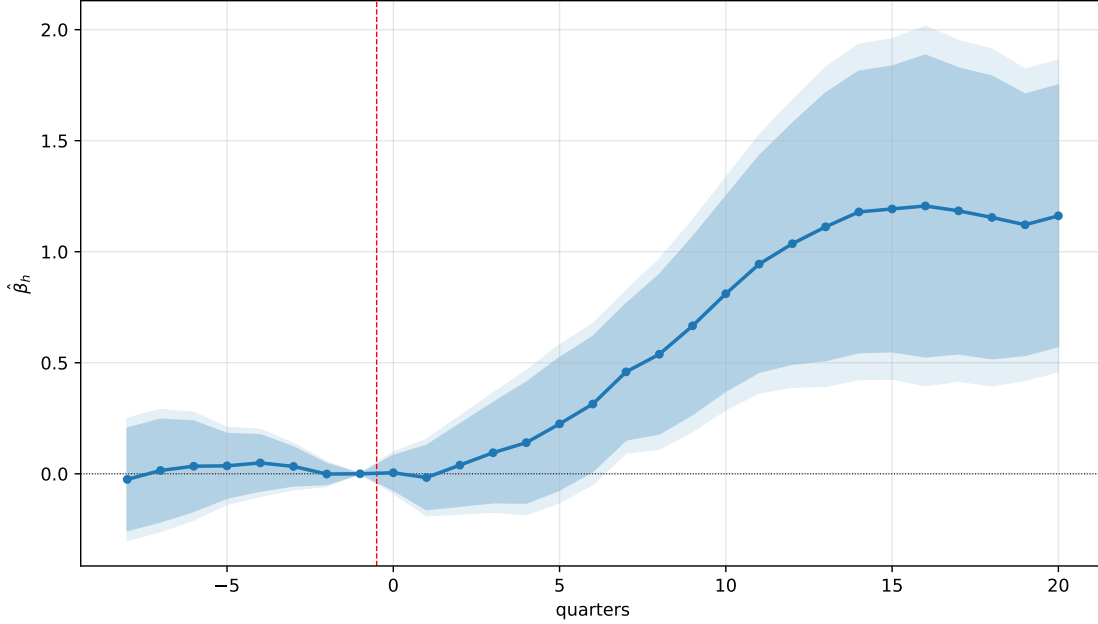


Figure 3: Event-study pass-through of predicted acquisitions

Notes: This figure shows the stacked event-study coefficients β_h of Equation 10. The solid blue line represents the point estimates; the dark and light shaded areas correspond to the 90 and 95 percent confidence intervals. I use wild cluster bootstrap standard errors clustered at the event level. The vertical red dashed line marks the announcement quarter.

5 Econometric Estimation

The baseline estimation of this paper employs the proxy VAR approach, using the quarterly event series z_t as an external instrument to identify regulatory safe asset demand shocks. In addition to the baseline methodology, I perform a number of robustness checks and estimate local projections using the identified shock to gain a better understanding of the transmission channels.

5.1 External Instrument VAR

To estimate the aggregate effects of regulatory safe asset demand shocks, I use quarterly data of six macroeconomic and financial variables in the baseline analysis. These consist of the safe asset share of bank assets, the U.S. funding advantage, the NFCI, real GDP, the GDP deflator, and the federal funds rate. I define the safe asset share as the aggregate holdings of Treasury and agency securities by U.S. commercial banks as a share of their aggregate total assets. This measure is narrower than the safe asset definition used to construct the event series, which also includes cash and central bank reserves. I use this narrower measure, as

this variable is a consistently defined series for all commercial banks from 1973 onward.⁹ I also use this narrower definition in the VAR, as this measures the quantity of government-backed securities that banks absorb, which is more directly related to the funding advantage and the safe asset object discussed later in the model section of this paper. I use the broader definition for the event series, as the induced demand is only well-defined for the broad class of safe assets based on the definition of the regulations. I define the funding advantage as the spread between the AAA corporate bond yield and the 10-year Treasury yield, following [Krishnamurthy and Vissing-Jorgensen \(2012\)](#). Although more sophisticated measures of the U.S. funding advantage exist, this measure is available at the quarterly frequency for the full sample from 1973 to 2025. I obtain the quarterly series for the NFCI, real GDP, and the GDP deflator from FRED. Finally, for the federal funds rate, I use the shadow federal funds rate series from [Wu and Xia \(2016\)](#) to account for the periods at the zero lower bound. Appendix B provides the full list of data sources and their corresponding variables.

Using the data described above, I estimate the following reduced-form VAR in levels from 1973Q1 to 2025Q2:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \mathbf{B}_1 \mathbf{y}_{t-1} + \dots + \mathbf{B}_p \mathbf{y}_{t-p} + \boldsymbol{\Gamma} \mathbf{d}_t + \mathbf{u}_t, \quad (11)$$

where $\mathbf{y}_t$ is the $n \times 1$ vector of endogenous variables, i.e., the safe asset share of bank assets, the AAA–10Y Treasury spread, the NFCI, log GDP, log GDP deflator, and the federal funds rate. $\boldsymbol{\alpha}$ is an $n \times 1$ vector of constants, and $\mathbf{B}_1, \dots, \mathbf{B}_p$ are $n \times n$ coefficient matrices. $\mathbf{d}_t$ is a 4×1 vector of four separate dummy variables for each of the four quarters of 2020, and $\boldsymbol{\Gamma}$ is the corresponding $n \times 4$ matrix of coefficients. The dummy variables account for the extreme observations during the COVID pandemic, following the methodology from [Mori and Peersman \(2026\)](#). I set the lag length p equal to four quarters in the baseline analysis. Finally, $\mathbf{u}_t$ is the $n \times 1$ vector of reduced-form innovations with covariance matrix $\boldsymbol{\Sigma}$.

I assume that there is a linear mapping between the reduced-form innovations $\mathbf{u}_t$ and an $n \times 1$ vector of mutually uncorrelated structural shocks $\boldsymbol{\varepsilon}_t$:

$$\mathbf{u}_t = \mathbf{S} \boldsymbol{\varepsilon}_t, \quad (12)$$

where $\mathbf{S}$ is a nonsingular $n \times n$ matrix mapping the structural shocks to the reduced-form innovations. This assumes that the VAR is invertible, meaning that the VAR contains the information required to recover the structural shocks ([Stock and Watson, 2018](#); [Plagborg-Møller and Wolf, 2021](#)).¹⁰ As the structural shocks are mutually uncorrelated by definition,

⁹The Call Report panel I use to construct the event series begins in 1984Q1, following a major revision to the reporting framework.

¹⁰Only the shock of interest must be invertible for identification using external instruments. Relaxing the invertibility assumption requires the instrument to satisfy a lead-lag exogeneity condition ([Stock and](#)

the covariance matrix of $\boldsymbol{\varepsilon}_t$, denoted $\boldsymbol{\Omega}$, is a diagonal matrix. Combined with the assumption from Equation 12, the covariance matrix of the reduced-form innovations can be expressed as $\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'$.

I assume that one of the structural shocks is a regulatory safe asset demand shock, denoted ε_t^{SA} . Without loss of generality, I denote this shock as the first element of $\boldsymbol{\varepsilon}_t$, so that $\varepsilon_{1,t} = \varepsilon_t^{SA}$. Under this set of assumptions, the first column of $\mathbf{S}$, denoted $\mathbf{s}_1$, represents the effect of ε_t^{SA} on $\mathbf{u}_t$, and consequently on $\mathbf{y}_t$. Therefore, identifying $\mathbf{s}_1$ allows me to estimate the macroeconomic effects of regulatory safe asset demand shocks.

To identify $\mathbf{s}_1$, I use the event series z_t of Equation 2 as an external instrument for ε_t^{SA} . I use the series as an instrument rather than as a direct measure of the shock, as z_t is an imperfect and incomplete estimate of the shock. The set of events does not capture every relevant piece of regulatory news, and the induced safe asset demand calculated in Section 3 may be measured with error. The external instrument approach accounts for such measurement error (Stock and Watson, 2018). Given that the instrument starts in 1988, while the VAR sample starts in 1973, there is no identifying variation prior to 1988. The use of an instrument sample that is shorter than the estimation sample is common in the proxy VAR literature, as the longer sample allows for more precise estimates of the reduced-form coefficients (Gertler and Karadi, 2015).

For z_t to be a suitable instrument, the instrument must be valid and relevant, expressed as the following:

$$\text{Validity/Exogeneity: } \mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] = \mathbf{0}, \quad (13)$$

$$\text{Relevance: } \mathbb{E}[z_t \varepsilon_{1,t}] \neq 0, \quad (14)$$

where $\boldsymbol{\varepsilon}_{2:n,t}$ is the $(n-1) \times 1$ vector consisting of all structural shocks excluding the regulatory safe asset demand shock $\varepsilon_{1,t} = \varepsilon_t^{SA}$.

The exogeneity condition in Equation 13 requires that z_t is uncorrelated with other contemporaneous structural shocks. Note that this condition concerns the structural shocks at time t rather than the history of economic conditions. This condition motivates the narrative approach that excludes any of the events classified as endogenous in Section 2. Moreover, the series of diagnostic checks in Section 3 provides supporting evidence for the exogeneity condition, showing that the instrument cannot be predicted using observable macroeconomic and financial conditions.

The relevance condition in Equation 14 can be directly tested using a first-stage test. The heteroskedasticity-robust first-stage F -statistic is 14.2 in the baseline analysis, which is above the conventional threshold of 10 (Stock et al., 2002; Montiel Olea and Plagborg-Møller,

Watson, 2018).

2021).

If the assumptions stated in Equations 11 to 14 hold, then $\mathbf{s}_1$ can be identified up to sign and scale by running the regression

$$\mathbf{y}_t = \tilde{\boldsymbol{\alpha}} + \tilde{\mathbf{B}}(L) \mathbf{y}_{t-1} + \mathbf{s}_1 y_{1,t} + \tilde{\mathbf{\Gamma}} \mathbf{d}_t + \tilde{\mathbf{u}}_t \quad (15)$$

via equation-by-equation two-stage least squares, using z_t as the instrument for $y_{1,t}$. The lag polynomial $\tilde{\mathbf{B}}(L)$ has the same number of lags as Equation 11. The point estimates of this regression are equivalent to estimates from the regression

$$\hat{\mathbf{u}}_t = \boldsymbol{\delta} + \mathbf{s}_1 \hat{u}_{1,t} + \boldsymbol{\eta}_t, \quad (16)$$

using z_t as the instrument for $\hat{u}_{1,t}$. This is perhaps a more intuitive specification, given that $\mathbf{s}_1$ captures the effect of ε_t^{SA} on $\mathbf{u}_t$.

I scale $\mathbf{s}_1$ such that a one-unit positive shock of ε_t^{SA} corresponds to a one-standard-deviation increase in the identified shock. I apply this scaling to the point estimate and separately to each bootstrap replication, using the standard deviation of the shock implied by that replication.¹¹ Using the estimated structural impact vector $\hat{\mathbf{s}}_1$ and the coefficient matrices $\hat{\mathbf{B}}_1, \dots, \hat{\mathbf{B}}_p$, I compute the impulse responses to a regulatory safe asset demand shock. I provide a detailed explanation of this external instruments approach in Appendix D. To conduct inference, I use residual-based moving block bootstrap confidence bands with 10,000 replications (Jentsch and Lunsford, 2019).

5.2 Local Projections

To gain a deeper understanding of the transmission channels, I also use local projections to examine the dynamic causal effects on a wider range of outcome variables (Jordà, 2005).

I first extract the regulatory safe asset demand shock from the quarterly VAR:

$$\hat{\varepsilon}_t^{SA} = \hat{\mathbf{s}}_1' \hat{\boldsymbol{\Sigma}}^{-1} \hat{\mathbf{u}}_t, \quad (17)$$

where $\hat{\mathbf{s}}_1$ is the structural impact vector, $\hat{\boldsymbol{\Sigma}}$ is the covariance matrix of $\hat{\mathbf{u}}_t$, and $\hat{\mathbf{u}}_t$ is the vector of reduced-form innovations (Stock and Watson, 2018). I standardize the extracted shock series to unit variance.

¹¹The impact response of the bank safe asset share is therefore the estimated standard error of the shock. This is in contrast to a unit normalization of the impact response, under which the band collapses to the point estimate at that horizon by construction.

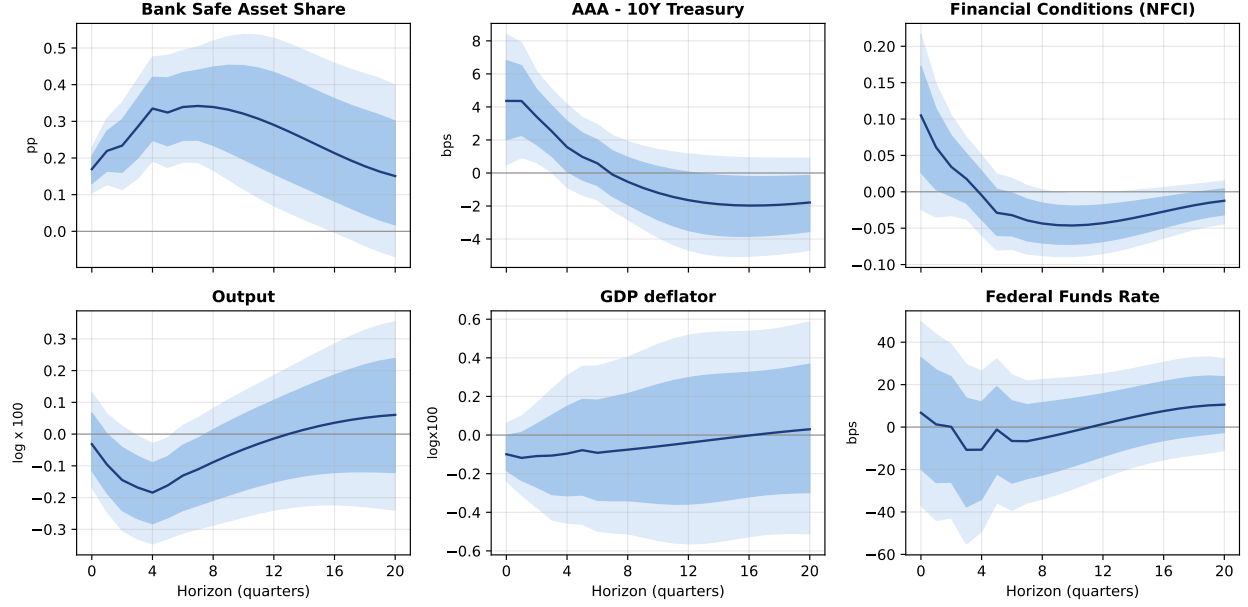


Figure 4: Impulse responses to a regulatory safe asset demand shock

Notes: This figure shows the impulse responses to a regulatory safe asset demand shock estimated using the external instruments approach. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. Standard errors are computed using residual-based moving block bootstrap from [Jentsch and Lunsford \(2019\)](#) with 10,000 replications.

I then estimate the effect on outcome i at horizon h using local projections:

$$y_{i,t+h} = \alpha_h^i + \phi_h^i \hat{\varepsilon}_t^{SA} + \beta_{h,1}^i y_{i,t-1} + \dots + \beta_{h,p}^i y_{i,t-p} + \xi_{i,t,h}, \quad (18)$$

where ϕ_h^i is the coefficient of interest, as it captures the impulse response to the regulatory safe asset demand shock for outcome i at horizon h . I use four lags of the outcome in the baseline specification, and estimate the effects for horizons of up to 20 quarters. I conduct inference using a residual-based wild bootstrap with 10,000 replications.¹²

6 Results

6.1 Aggregate Effects

I present the results from the baseline analysis in Figure 4. The figure shows the impulse responses to the regulatory safe asset demand shock for the six variables in the VAR. The solid lines correspond to the point estimates, while the dark and light shaded regions correspond to the 68 and 90 percent confidence intervals, respectively.

¹²The bootstrap confidence bands account for the fact that the shock series $\hat{\varepsilon}_t^{SA}$ from Equation 17 is a generated regressor.

A one-standard-deviation regulatory safe asset demand shock results in a 0.17 percentage point increase in the bank safe asset share on impact. The effect is persistent with a peak of 0.34 percentage points. The funding advantage increases on impact by 4.4 basis points, and the effect remains significant for a year as it gradually decreases. The funding advantage decreases over time, with a decrease of roughly 2 basis points at long horizons. The NFCI increases by 0.11 index points on impact, meaning that financial conditions tighten immediately after the shock. Financial conditions subsequently ease at later horizons, with negative effects on the NFCI from the fourth quarter onward. Output declines temporarily with a hump-shaped response. The negative effect is statistically significant from the third to the fifth quarter, with a trough of -0.18 percent in the fourth quarter. The effects on both the GDP deflator and the federal funds rate are statistically insignificant for all horizons. The GDP deflator decreases by roughly 0.1 percent and the effect gradually subsides. The federal funds rate declines by roughly 10 basis points within a year of the shock, consistent with a monetary policy response to the decline in output.

Overall, the baseline analysis suggests that regulatory safe asset demand shocks raise bank safe asset holdings persistently, increase the government’s funding advantage temporarily, and have significant real effects through tightening financial conditions and a decline in output. I find that the baseline results are robust across a number of dimensions, including the event set, the method of constructing the external instrument, and the identification strategy. I discuss each of the robustness checks and report their results in [Appendix E](#).

6.2 Transmission Channels

To examine how regulatory safe asset demand shocks propagate through the economy, I estimate impulse responses using local projections following [Equation 18](#) for a number of outcome variables. I focus on transmission channels concerning bank balance sheets, credit supply, the funding advantage, and fiscal variables. The estimates show that banks respond to the regulatory safe asset demand shock by changing the composition of their portfolios. Bank holdings of safe assets increase, while bank lending to the private sector decreases. The increase in the funding advantage is driven mainly by decreases in Treasury yields. The government responds with higher levels of government transfers, contributing to increases in debt and deficits.

Bank balance sheets. [Figure 5](#) shows the impulse responses for the consolidated balance sheet of U.S. commercial banks. Total assets and total liabilities have minimal responses on impact, and both decrease by roughly 1 percent at the trough of responses. The lack of significant responses for liabilities on impact provides supporting evidence that the identified shock is not picking up any deposit-funding shock or a general credit contraction, as

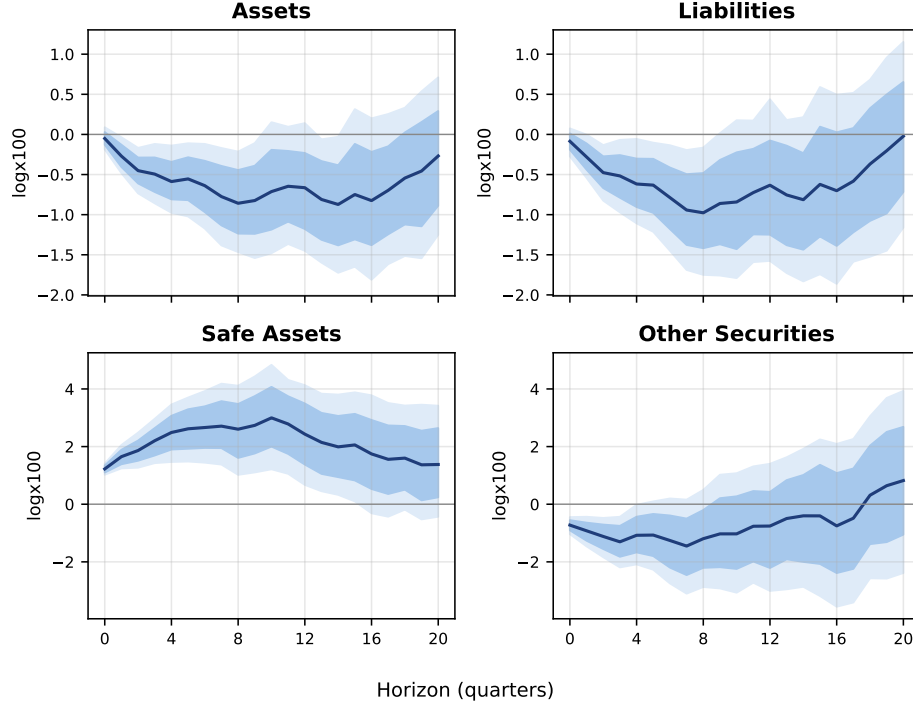


Figure 5: Consolidated bank balance sheet responses

Notes: This figure shows the impulse responses to a regulatory safe asset demand shock estimated using local projections. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively.

such shocks would decrease liabilities on impact. Holdings of safe assets increase by over 1 percent on impact with statistically significant effects that peak at roughly 3 percent after ten quarters. In contrast, other securities holdings decrease with a statistically significant effect on impact.

Credit supply. Figure 6 shows the impulse responses for variables related to credit supply. Total bank loans decrease significantly, with a decrease of 1.4 percent at the trough of responses. This decline in bank loans is consistent with the findings in [Drechsel and Miura \(2026\)](#), who find that tighter bank regulation contracts lending and activity. Total bank credit also decreases, but by lower magnitudes. The contraction in bank loans is particularly strong when focusing on the financial sector, with a decrease of 5 percent at the trough of responses. Nonbank credit to the nonfinancial sector shows insignificant negative responses, suggesting that there is little to no substitution of lending from banks to nonbank financial institutions (NBFIs). This is consistent with evidence that NBFIs depend heavily on banks for funding ([Acharya et al., 2026](#)).

I estimate impulse responses for more granular types of lending and show the results in Appendix E. Bank credit to the private nonfinancial sector decreases significantly, declining

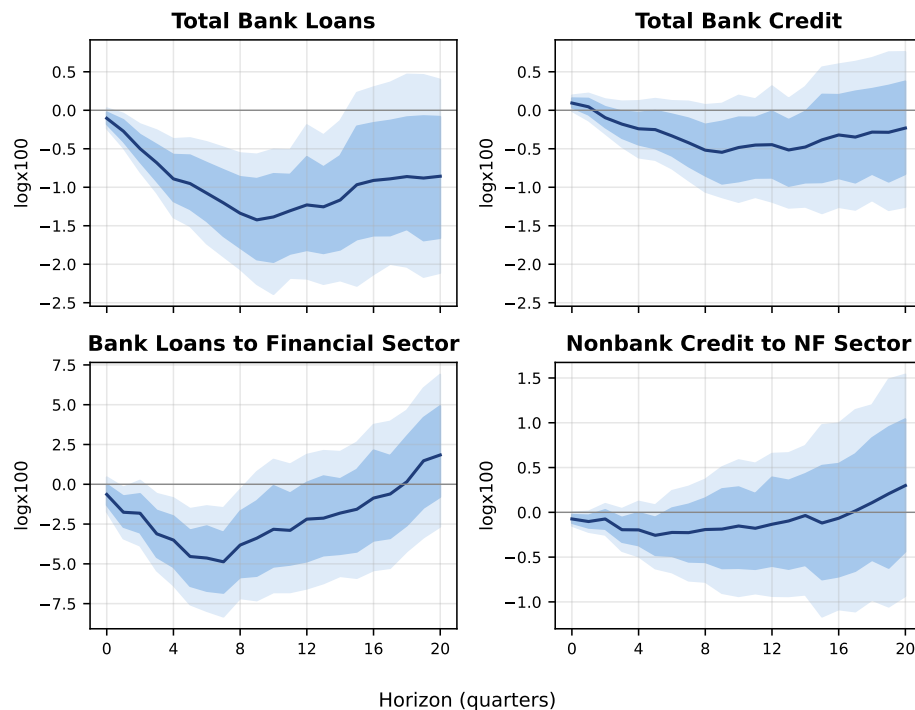


Figure 6: Credit supply responses

Notes: This figure shows the impulse responses to a regulatory safe asset demand shock estimated using local projections. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively.

by 0.8 percent at the trough of responses. The results show that the decline in lending is concentrated in loans to firms. Nonfinancial corporate loans experience a statistically significant decrease of 1.8 percent at the trough of responses. In contrast, corporate debt securities and home mortgages show no significant responses. Examining the responses by the type of bank loans shows the largest declines for commercial and industrial loans, which have a statistically significant decrease of 2.4 percent at the trough of responses. Real estate loans and consumer loans also decrease, but by lower magnitudes.

Funding advantage. Figure 7 shows the impulse responses for variables related to the funding advantage. The AAA–10Y Treasury spread rises by roughly 5 basis points on impact, which is consistent with the estimates from the baseline VAR. I also examine the response of the Baa–10Y Treasury spread, which increases by 7 basis points on impact. The shape of the responses is very similar to that of the AAA–10Y Treasury spread. To decompose the effects on the funding advantage, I estimate the impulse responses of the AAA yield and the 10-year Treasury yield separately. The 10-year Treasury yield decreases significantly on impact, while the responses of the AAA yield are insignificant for the entire horizon. This suggests that the increases in the funding advantage are driven by increases in safe asset

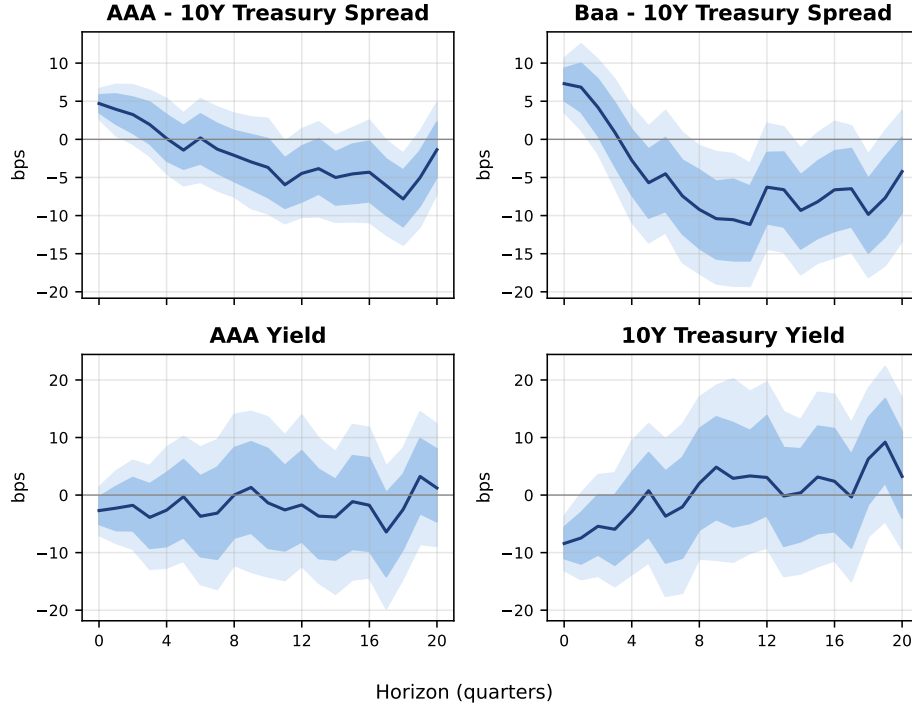


Figure 7: Funding advantage responses

Notes: This figure shows the impulse responses to a regulatory safe asset demand shock estimated using local projections. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively.

demand.

Fiscal variables. Figure 8 shows the impulse responses for fiscal variables. The federal debt-to-GDP ratio increases significantly, with a peak response of 2 percentage points. The debt measure used for the ratio is the par value of gross federal debt, so the estimated responses are not contaminated by revaluation effects. The primary deficit also shows statistically significant increases, although the estimates are noisier. I decompose the effects on deficits and expenditures by examining the responses in government transfers and purchases. I find that government transfers respond significantly more in magnitude relative to government purchases, suggesting that the increases in deficits are driven by increased transfers. This is consistent with the contractionary effect I find with respect to output, as transfers may be increasing through a combination of automatic stabilizers and discretionary spending in response to the recession. In terms of magnitudes, the government transfers-to-GDP ratio increases by roughly 0.4 percentage points at the peak of responses. In contrast, the responses for government purchases are minimal, with a peak increase of roughly 0.05 percentage points.

I examine the debt response further by estimating impulse responses for additional mea-

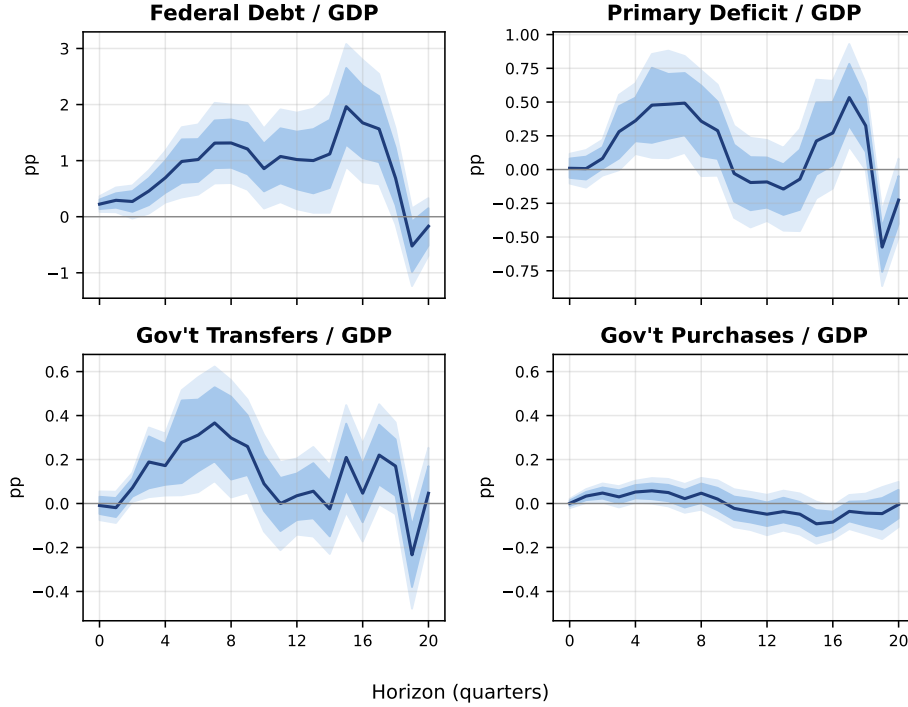


Figure 8: Fiscal responses

Notes: This figure shows the impulse responses to a regulatory safe asset demand shock estimated using local projections. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively.

asures of the federal debt. I show the results in Appendix E. The market value measure of federal debt increases faster and by a larger magnitude, which is consistent with the fact that Treasury yields fall in response to the identified shock. The par value of debt increases by 1.8 percent at the peak of responses, which is consistent in magnitude with the cumulated response of primary deficits.

Exchange rates. Finally, I also examine how exchange rates respond to the identified shock. I show the estimated impulse responses in Appendix E. The real broad dollar index appreciates by roughly a quarter of a percent on impact, with statistically significant effects for the first few horizons.¹³ The response is otherwise insignificant, with a combination of positive and negative responses. The nominal dollar index responds similarly, with statistically insignificant increases for most horizons. The dollar appreciation response on impact is consistent with evidence from the existing literature. Jiang et al. (2021) find that increases in the convenience yield that foreign investors assign to U.S. safe assets result in dollar ap-

¹³The real broad dollar index combines the discontinued trade-weighted U.S. dollar index (1973–2019) with the real broad dollar index (2006–present). Similarly, the nominal dollar index combines the discontinued nominal major currencies U.S. dollar index (1973–2019) with the nominal broad U.S. dollar index (2006–present).

preciation, while [Engel and Wu \(2023\)](#) show that the relative liquidity yields on government bonds account for a significant share of variation in exchange rates.

7 Model

To understand the mechanisms behind the estimated effects and to evaluate policy counterfactuals, I develop a model with a banking sector subject to safe asset regulation. The model combines two financial features in an otherwise standard New Keynesian model. First, the model includes a regulatory portfolio constraint on bank assets, which can provide incentives for banks to hold more safe assets. Second, the model features a pricing mechanism for the banks' funding cost. Households have preferences over the safety of the bank claims they hold as deposits, resulting in lower funding costs for banks when they hold more safe assets.

The key intuition of the model is as follows. When a new policy raises the regulatory weight on safe assets, the regulatory value of holding safe assets rises. Banks therefore become more willing to hold safe assets at lower yields, widening the government's funding advantage on impact. As the banking sector accumulates more safe assets, the yield on safe assets falls relative to the policy rate, as the supply curve of safe assets is upward sloping in prices. Conversely, lending to firms becomes more expensive, as loans now provide relatively less regulatory value. Banks thus demand a higher return on their loans, and this increased cost of credit lowers investment and output. As banks accumulate more safe assets, the market accepts lower deposit rates that reflect the safer portfolio, and the bank's funding costs fall. Over time, banks adjust their portfolio and bank equity is rebuilt, which contributes to a recovery in output and a decrease in the funding advantage. Overall, the effect on the funding advantage is temporary while the effect on bank portfolios is persistent, matching the dynamics of the estimated responses.

In this section, I present the model, then calibrate the model using the estimated empirical impulse responses. Using the calibrated model, I conduct two counterfactual exercises. The first examines the consequences of a permanent increase in the regulatory weight on safe assets, motivated by recent policy discourse. The second maps a regulatory Laffer curve by comparing steady-state characteristics across varying levels of the regulatory weight on safe assets. I provide detailed derivations and additional results in [Appendix F](#).

7.1 Setup

The model consists of a representative household, a continuum of monopolistically competitive intermediate-goods firms with sticky prices, a competitive capital producer, a representative bank, a monetary authority, and a government that supplies safe assets to the banking

sector. The household can save through bank deposits and a riskless claim at the policy rate. The bank holds all of the safe assets and the claims on productive capital in the economy. The supply of safe assets to the bank slopes upward, so the yield on safe assets falls relative to the policy rate when the bank accumulates more safe assets. The bank is subject to a regulatory portfolio constraint with the weight on safe assets characterizing the extent to which regulation privileges safe assets relative to other assets. I interpret the regulatory safe asset demand shock to be an innovation to this weight.

Households. The representative household chooses consumption C_t , labor N_t , deposits D_t , and a riskless claim A_t to maximize

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \psi_N \frac{N_t^{1+\varphi_N}}{1+\varphi_N} + \varphi_D \gamma(\ell_t) D_t \right] \quad (19)$$

subject to the budget constraint

$$C_t + D_t + A_t \leq W_t N_t + (1 + r_{t-1}^d) D_{t-1} + (1 + r_{t-1}) A_{t-1} + \Pi_t^{div} - T_t, \quad (20)$$

where r_t^d is the rate on bank deposits, r_t is the policy rate (the return on a riskless claim in zero net supply that stands for money market instruments that households can save in), Π_t^{div} is the dividend from the bank and firms, and T_t is a lump sum tax. The final term of the utility function represents the non-pecuniary value of holding bank deposits. For every dollar held in bank deposits, the household receives a marginal non-pecuniary value $\varphi_D \gamma(\ell_t)$, which reflects the liquidity services of deposits net of the cost of exposure to the banking sector. This value is increasing in the safety of the bank's portfolio represented by $\ell_t = S_t/D_t$, where S_t and D_t are the levels of the bank's safe asset holdings and deposits, respectively. The household is atomistic and takes the banking sector's liquidity ratio ℓ_t as given, and in equilibrium its deposit holdings coincide with the deposits the bank issues. This is motivated by the household demand for deposits in [Gorton and Pennacchi \(1990\)](#) and the deposits-in-utility formulation of [Van den Heuvel \(2008\)](#) and [Begenau \(2020\)](#). I specify the function $\gamma(\ell_t)$ in detail later in this section. Note that this deposits-in-utility feature provides the feedback from regulation to bank funding costs. Regulation that incentivizes banks to hold more safe assets makes bank portfolios safer, and the household prices this safety into the deposit rate. This feature is not required for generating the funding advantage, which arises solely from the regulatory constraint.

The first order condition for the riskless claim is the Euler equation on the policy rate

$$C_t^{-\sigma} = \beta (1 + r_t) \mathbb{E}_t C_{t+1}^{-\sigma}. \quad (21)$$

The first order condition for deposits is

$$C_t^{-\sigma} - \varphi_D \gamma(\ell_t) = \beta (1 + r_t^d) \mathbb{E}_t C_{t+1}^{-\sigma}. \quad (22)$$

This condition requires deposits to earn enough to cover the time value of consumption net of the marginal non-pecuniary value of holding deposits. The two conditions price deposits relative to the policy rate, and the deposit rate together with the safe asset rate determines the bank funding cost. I discuss this in detail later in the section.

Labor. The household supplies differentiated labor through a continuum of unions, and each union resets its nominal wage with probability $1 - \theta_w$ each quarter, following [Erceg et al. \(2000\)](#). Wage inflation π_t^w follows the standard wage Phillips curve

$$\log(1 + \pi_t^w) = \kappa_w \log(mrs_t/W_t) + \beta \log(1 + \pi_{t+1}^w), \quad \kappa_w = \frac{(1 - \theta_w)(1 - \beta\theta_w)}{\theta_w (1 + \varepsilon_w \varphi_N)}, \quad (23)$$

where W_t is the real wage, $mrs_t = \psi_N N_t^{\varphi_N} C_t^\sigma$ is the marginal rate of substitution between consumption and labor, ψ_N is the weight on the disutility of labor, φ_N is the inverse Frisch elasticity of labor supply, and ε_w is the elasticity of substitution across labor types. Under fully flexible wages, the labor supply curve collapses to $W_t = mrs_t$.

Production and capital. The production process in the model consists of a continuum of monopolistically competitive intermediate goods firms, a competitive final goods aggregator, and a competitive capital producer. Intermediate firms, each denoted by j , produce according to the production function $Y_t(j) = Z K_{t-1}^{\alpha_k} N_t(j)^{1-\alpha_k}$, and rent capital and labor in competitive markets. Intermediate firms set nominal prices à la Calvo, with each firm resetting its price with probability $1 - \theta_p$ each quarter. A competitive final goods firm aggregates the intermediate varieties with constant elasticity ε_p . This results in the standard log-linear New Keynesian Phillips curve

$$\log(1 + \pi_t) = \kappa_p \log(mc_t/\overline{mc}) + \beta \log(1 + \pi_{t+1}), \quad \kappa_p = \frac{(1 - \theta_p)(1 - \beta\theta_p)}{\theta_p}, \quad (24)$$

where π_t is price inflation, mc_t is the real marginal cost of intermediate firms, and $\overline{mc}$ is its steady-state value.

A capital firm builds capital subject to quadratic adjustment costs with curvature ϕ_I . This implies Tobin's $q_t = 1 + \phi_I g_t$ where $g_t = K_t/K_{t-1} - 1$. The realized gross return on capital is denoted by R_{t+1}^k . All capital claims in the economy are held by the bank, and consequently priced by the required return for banks.

Banks. The representative bank holds a portfolio consisting of safe assets S_t and claims on productive capital $q_t K_t^b$, funded by deposits D_t and inside equity E_t . In each period, the bank chooses its levels of safe asset holdings, capital claims, and deposits to maximize expected profits $\mathbb{E}_t \Pi_{t+1}$, where

$$\Pi_{t+1} = r_t^s S_t + (R_{t+1}^k - 1) q_t K_t^b - r_t^d D_t, \quad (25)$$

subject to the balance sheet constraint

$$S_t + q_t K_t^b = D_t + E_t \quad (26)$$

and the regulatory portfolio constraint

$$\varrho D_t \leq \Upsilon_t \equiv \left[\kappa_t S_t^\alpha + (1 - \kappa_t) (q_t K_t^b)^\alpha \right]^{1/\alpha}. \quad (27)$$

The profit consists of the returns on safe assets, at the safe asset rate r_t^s , and capital claims minus the interest on deposits. The balance sheet constraint equates total assets with the sum of total liabilities and equity. The regulatory portfolio constraint is a CES aggregator over the bank's portfolio with regulatory weight κ_t on safe assets and curvature $\alpha < 1$. The regulatory constraint applies to a proportion ϱ of the bank's deposits.

The bank pays out only a proportion of its profits and equity as dividends in each period. The bank follows a dividend distribution schedule such that bank equity accumulates according to the following law of motion

$$E_t = (1 - \delta_e) E_{t-1} + \zeta \Pi_t, \quad (28)$$

where ζ is the proportion of retained profits and δ_e is an equity payout rate set so that the bank's leverage ratio is stationary in steady state.¹⁴ Equity is therefore a slow-moving state that is predetermined within each period.

The bank's first order conditions for S_t and K_t^b are

$$[S] \quad s_t \equiv r_t^d - r_t^s = \mu_t \left[\kappa_t (\Upsilon_t / S_t)^{1-\alpha} - \varrho \right], \quad (29)$$

$$[K] \quad s_t^k \equiv \mathbb{E}_t R_{t+1}^k - (1 + r_t^d) = \mu_t \left[\varrho - (1 - \kappa_t) (\Upsilon_t / q_t K_t^b)^{1-\alpha} \right], \quad (30)$$

where μ_t is the multiplier on the regulatory portfolio constraint. The first order condition for S determines the safe asset holdings of the bank, where s_t is the spread between the bank

¹⁴Every stock variable in the balance sheet constraint is an end-of-period value chosen or realized in quarter t , following the timing convention from [Gertler and Kiyotaki \(2010\)](#) and [Gertler and Karadi \(2011\)](#). See Appendix F for a discussion.

funding cost r_t^d and the safe asset rate r_t^s . The bank is willing to accept negative returns from holding safe assets as long as s_t does not exceed the safe asset's marginal regulatory value. The first order condition for K determines the price of lending, where s_t^k is the spread between the return on capital R_{t+1}^k and the gross bank funding cost $1+r_t^d$. The bank requires the capital claim to earn the sum of the funding cost and the marginal regulatory cost of holding capital claims.

The regulatory constraint represents a reduced form of the main types of regulations discussed in Section 2. An increase in κ_t raises the regulatory value of safe assets relative to loans, exactly as a risk-weight tightening, a liquidity requirement, or a leverage exclusion would. The identified regulatory safe asset demand shock therefore corresponds to an innovation to κ_t in the model.

The sum of the two spreads, s_t and s_t^k , is the funding advantage χ_t in the model

$$\chi_t \equiv \mathbb{E}_t R_{t+1}^k - (1 + r_t^s) = s_t + s_t^k. \quad (31)$$

The bank portfolio adjusts to changes in κ_t gradually. The bank pays a quadratic transaction cost with slope ϕ_S on net changes in its securities holdings. Because the portfolio adjusts slowly, the bank cannot satisfy the requirement exactly at every date. Therefore, the constraint is enforced as a penalty on violations whose steepness ψ is set in the calibration. Appendix G presents the portfolio adjustment costs in detail. This friction only impacts the transition dynamics of the model, and does not change any of the steady-state values. I also present a version with flexible wages and no portfolio adjustment costs in Appendix F.

Bank funding cost. The funding cost that the bank pays on its deposits is determined by household preferences reflecting the non-pecuniary value of bank deposits. The household first order condition for deposits in Equation 22 and the Euler equation in Equation 21 imply the following spread between the deposit rate and the policy rate:

$$s_t^d \equiv r_t^d - r_t = -\varphi_D \gamma(\ell_t) (1 + r_t) C_t^\sigma, \quad (32)$$

where ℓ_t is the ratio of the bank's safe asset holdings to deposits, S_t/D_t .¹⁵ The deposit spread that the bank pays is the negative of the household's marginal non-pecuniary value of deposits in consumption units. Households demand compensation for holding bank deposits according to the riskiness of the bank's assets. I specify the non-pecuniary value as a constant

¹⁵The condition holds exactly even under uncertainty, because both rates are known at date t , so the expectation term $\mathbb{E}_t C_{t+1}^{-\sigma}$ is common to the two first order conditions and cancels.

liquidity value of deposits net of the expected loss from a failure of the bank,

$$\gamma(\ell) = \gamma_0 - \eta \left[1 - \Phi((\ell - \bar{\ell})/\sigma_s) \right], \quad \Phi(x) = \frac{1}{1 + e^{-x}}, \quad (33)$$

where Φ is the logistic CDF and $\bar{\ell}$ is the steady-state level of ℓ_t . Parameters γ_0 , η , and σ_s respectively govern the level, scale, and sensitivity of the mapping between ℓ_t and the non-pecuniary value of deposits. Substituting this specification into Equation 32 delivers the equilibrium deposit spread

$$s_t^d = \left[s_0 + \xi \left(1 - \Phi((\ell_t - \bar{\ell})/\sigma_s) \right) \right] \cdot \frac{(1 + r_t) C_t^\sigma}{(1 + \bar{r}) \bar{C}^\sigma}, \quad (34)$$

with $s_0 \equiv -\varphi_D \gamma_0 (1 + \bar{r}) \bar{C}^\sigma$ and $\xi \equiv \varphi_D \eta (1 + \bar{r}) \bar{C}^\sigma$. The term $1 - \Phi((\ell_t - \bar{\ell})/\sigma_s)$ can be interpreted as a term that is proportional to the perceived probability that the bank fails, decreasing in the safety of its portfolio. η can be interpreted as a parameter that is proportional to the perceived loss per deposit dollar in the case of bank failure. σ_s is the dispersion of the perceived hazard, and γ_0 reflects a constant liquidity value of deposits that is orthogonal to the bank portfolio. At the calibrated steady state the expected loss from failure slightly exceeds the liquidity value, so the net non-pecuniary value of deposits is negative and the bank pays a positive spread over the policy rate. In [Van den Heuvel and Villalvazo \(2026\)](#), the failure event is a liquidity shortfall, and the hazard is the probability that a latent liquidity draw exceeds the bank's buffer of liquid assets. I use a broader specification, where the equilibrium spread reflects any failure risk that declines as the bank portfolio shifts toward safe assets.

In contrast to [Van den Heuvel and Villalvazo \(2026\)](#), where bank failures entail a resource cost that depends on the bank's portfolio, my specification involves a mechanism where the safety of the portfolio is reflected in prices through the bank funding cost. This pricing mechanism allows regulatory safe asset demand to ease financial conditions in the long run, as observed in the empirical estimates. Banks facing regulation to hold more safe assets become safer, resulting in cheaper funding costs that propagate to the rest of the economy. Although deposit rates do not fluctuate frequently to reflect the riskiness of bank portfolios in reality, I interpret the bank funding cost in the model to reflect banks' marginal cost of liabilities derived from a broader set of funding instruments. This reading follows the run models of [Gertler and Kiyotaki \(2015\)](#) and [Gertler et al. \(2020\)](#), in which household-held bank debt stands in for short-term wholesale funding. A complementary interpretation is that the bank funding cost reflects the total costs of deposits from the bank's perspective. This not only includes the interest on deposits, but also the other costs associated with building deposits such as establishing branches.

The safe asset rate is determined in the market for safe assets. The banking sector holds the stock outstanding, and the supply of safe assets available to the bank slopes upward:

$$\log(S_t/\bar{S}) = \varepsilon_S s_t^s, \quad s_t^s \equiv r_t - r_t^s, \quad (35)$$

where the scarcity premium s_t^s is the discount of the safe asset rate relative to the policy rate, $\bar{S}$ is the steady-state level of bank holdings, and ε_S is the elasticity of the supply to the banking sector with respect to the premium. The supply curve is a reduced form for the absorption of the rest of the market, which holds most of the stock of safe assets, as well as for the issuance response of the government. Inverting the supply gives the premium

$$s_t^s = \theta_S \log(S_t/\bar{S}), \quad \theta_S \equiv 1/\varepsilon_S, \quad (36)$$

where θ_S is the slope of the supply, the increase in the premium that induces the market to release one percent of bank holdings. The premium is zero at the steady state and rises when the bank absorbs safe assets. Note that the spread between the bank funding cost and the safe asset rate in the bank's first order conditions is the sum of the deposit spread and the premium, $s_t = r_t^d - r_t^s = s_t^d + s_t^s$. The funding advantage in Equation 31 can be decomposed to be the sum of three spreads, $\chi_t = s_t^d + s_t^k + s_t^s$. Appendix J discusses a version of the model with a perfectly elastic supply of safe assets, in which the scarcity premium is zero, as well as a version with household convenience demand for safe assets, which generates the scarcity premium through another mechanism.

The bank takes the deposit spread expressed in Equation 34 and the premium in Equation 36 as given, since depositors price the safety of the banking sector as a whole and the premium is a market price. Appendix I formalizes this assumption with a continuum of atomistic banks that take the sector-wide ratio as given and shows that the symmetric equilibrium coincides with the equilibrium described here. The same appendix develops an extension in which depositors price the funding cost independently for each bank, and banks internalize the schedule in their portfolio choice.

Monetary policy and the government. Monetary policy follows a Taylor rule,

$$i_t = \bar{r} + \phi_\pi \pi_t + \phi_y \log(Y_t/\bar{Y}), \quad (37)$$

where i_t is the nominal policy rate, $\bar{r}$ is the steady-state real rate, $\bar{Y}$ is steady-state output, and parameters ϕ_π and ϕ_y govern the responses to inflation and output. The policy rate is the nominal return on the riskless claim, and the Fisher equation delivers its real counterpart r_t .

The consolidated government issues safe assets and balances its budget with lump sum taxes,

$$B_t^g + T_t = (1 + r_{t-1}^s) B_{t-1}^g, \quad (38)$$

where $B_t^g = S_t$ is the stock of safe assets outstanding in the model, all of which the bank holds, and T_t is the lump sum tax. The government supplies safe assets to the banking sector along the supply curve of Equation 35, so that the quantity of safe assets is determined by the bank's demand and the yield adjusts along the supply.¹⁶ A higher regulatory weight makes the bank willing to hold safe assets at lower yields, raising the demand for Treasuries. The safe asset rate falls relative to the policy rate by the scarcity premium at which the market supplies the additional holdings. Because taxes are lump sum, Ricardian equivalence makes the timing of taxes irrelevant for equilibrium aggregate quantities and prices.

Equilibrium. An equilibrium is a set of paths for quantities, prices, and the multipliers such that the representative household, the capital producer, and the representative bank all optimize, wage and price setting follow the Phillips curves from Equations 23 and 24, the equity law of motion in Equation 28 holds, the deposit spread satisfies Equation 34, the scarcity premium satisfies Equation 36, monetary policy follows the Taylor rule in Equation 37, the government budget in Equation 38 holds, and the goods and asset markets clear. Appendix F fully characterizes the equilibrium.

7.2 Calibration and Estimation

I parameterize the model in three main steps. I first use standard parameter values from the existing literature for a set of commonly used preference, technology, and policy parameters. I then calibrate a set of parameters that determine the steady-state values for financial variables by setting them to match the average levels from the sample period. Finally, I estimate the remaining set of parameters that govern the dynamics of the model using impulse response matching. Table 2 reports all parameter values.

I use standard values for externally set parameters. I impose log utility, a Frisch elasticity of 1, a capital share of 0.33, quarterly depreciation of 0.025, Calvo pricing with an average price duration of four quarters, a 20 percent markup, a labor demand elasticity of 6, and Taylor coefficients of $\phi_\pi = 1.5$ and $\phi_y = 0.05$. I set the quarterly discount factor to be 0.995 to match a 2 percent annual real rate. In addition, I set five financial parameters externally.

¹⁶Bank safe asset holdings are small relative to the outstanding stock of Treasury securities throughout the sample, so demand shifts move holdings rather than the administered rate. [Lopez-Salido and Vissing-Jorgensen \(2023\)](#) and [Afonso et al. \(2025\)](#) estimate reserve demand and find evidence supporting the ample reserves regime in the sample period. The supply curve summarizes how the rest of the market, which holds most of the stock, releases safe assets to the banking sector.

The retention rate $\zeta = 0.5$ implies that bank profits are split evenly between dividend distributions and retained earnings in each quarter. The penalty steepness $\psi = 200$ determines the penalty for violating the bank portfolio constraint. The CES curvature parameter for the bank portfolio constraint is set to $\alpha = 0.75$. Finally, the hazard dispersion inside the function for the non-pecuniary value of deposits is set to $\sigma_s = 0.50$ as a normalization. The impulse responses identify only the local slope of the relationship between the bank share of safe assets and the bank funding spread, which corresponds to $\xi/(4\sigma_s)$ in the model. The slope of the supply of safe assets to the banking sector is set to $\theta_S = 0.107$ percentage points of premium per log unit of bank holdings. This is based on the response of the Aaa–Treasury spread to the log of debt to GDP estimated by [Krishnamurthy and Vissing-Jorgensen \(2012\)](#). They estimate a response of 0.75 percentage points per log unit of the stock, which I divide by 7 to account for the fact that the banking sector holds roughly one eighth of all Treasury debt in the sample period.¹⁷ A one percent increase in bank holdings therefore increases the scarcity premium by 0.107 basis points. The results of the model are robust to varying the values of these externally set parameters, which I discuss in Appendix F.

I calibrate a set of parameters such that the steady-state values of the financial variables match the average levels from the sample period used in this paper. The steady-state targets are the funding advantage, the bank safe asset share, and bank leverage. I set the funding advantage target to be $\bar{\chi} = 114$ basis points based on the 1973–2025 average of the AAA–10Y Treasury spread used in the VAR. I split the 114 basis points to consist of a bank funding spread of 30 basis points and a credit spread of 84 basis points. The funding spread target corresponds to the premium banks historically pay on uninsured and wholesale funding over Treasuries outside of crisis episodes.¹⁸ I then attribute the remaining part of the spread to the credit spread. The mapping treats the AAA yield as the observable counterpart to the required return on the bank’s capital claims, given that both represent the cost of funding for private firms with little to no default risk. The safe asset share of bank assets and bank leverage are targeted to be 0.14 and 9, respectively, with both based on their sample averages.¹⁹ The bank funding spread, the credit spread, the bank safe asset share, and bank leverage form the four targets that pin down the following four parameters. The regulatory parameters $(\bar{\kappa}, \varrho)$ are determined by the targeted spreads and the binding constraint, the equity payout rate δ_e is set to keep the bank leverage stationary, and s_0 from the function for the non-pecuniary value of deposits is set to match the funding spread target. The

¹⁷Seven eighths of the stock of Treasury debt is held outside the banking sector in the sample period, implying that a one percent rise in bank holdings requires the rest of the market to release one-seventh of a percent of its holdings.

¹⁸The 30 basis point target is in line with the historical spread between three-month interbank rates and Treasury bills during the sample period.

¹⁹The safe asset share target is the banks’ holdings of Treasury securities relative to total assets, as Treasury holdings are the closest empirical counterpart to safe assets in the model.

Parameter	Description	Value	Target / source / comments
<i>Panel A. Externally set parameters</i>			
σ	CRRRA	1	log utility
φ_N	Inverse Frisch elasticity	1	standard
β	Discount factor	0.995	2% annual real rate
α_k	Capital share	0.33	standard
δ	Depreciation (quarterly)	0.025	10% annual depreciation
θ_p	Calvo price stickiness	0.75	average price duration of four quarters
ε_p	Demand elasticity	6	20% markup
ϕ_π	Taylor rule, inflation	1.5	Taylor rule
ϕ_y	Taylor rule, output	0.05	Taylor rule
ε_w	Labor demand elasticity	6	symmetric with goods demand
ψ	Requirement penalty steepness	200	see Appendix G
ζ	Earnings retention	0.5	even split of retention and payout
α	CES curvature, regulatory aggregator	0.75	see Appendix F
σ_s	Hazard dispersion	0.50	normalization; only $\xi/(4\sigma_s)$ identified
θ_S	Slope of the supply of safe assets to banks	0.107	pp of premium per log unit of bank holdings; Krishnamurthy and Vissing-Jorgensen (2012) on the stock held outside banks
<i>Panel B. Steady-state targets and implied parameters</i>			
<i>Targets</i>			
$\bar{\chi}$	Funding advantage	114 bp	1973–2025 mean, AAA–10Y Treasury spread
$\bar{s}$	Bank funding spread	30 bp	wholesale/uninsured deposit premium
$\bar{s}^k$	Credit spread	84 bp	remainder of the funding advantage
$S/(S+qK)$	Safe asset share	0.14	bank safe asset share, 1973–2025 mean
D/E	Bank leverage	9	aggregate call-report leverage, 1984–2025
<i>Implied parameters</i>			
$\bar{\kappa}$	Weight on safe assets	0.4307	first order conditions at the targeted spreads
ϱ	Constraint scale	0.5710	binding constraint at the targeted balance sheet
s_0	Spread schedule level	−0.0203	delivers the funding spread target (Appendix F)
δ_e	Equity payout rate	0.0114	keeps bank leverage stationary
Z	Productivity level	0.4960	normalization $Y = 1$
ψ_N	Labor disutility weight	0.7061	normalization $N = 1$
<i>Panel C. Estimated by impulse response matching (standard errors in parentheses)</i>			
ξ	Loss scale, safety pricing	0.0420 (0.0029)	affects funding advantage response at long horizons
ϕ_I	Capital adjustment cost	0.0010 (0.9524)	robust to wide range of values
ϕ_S	Portfolio transaction cost	0.0327 (0.0114)	affects speed of the portfolio build-up
ρ_κ	Shock persistence	0.9440 (0.0214)	affects decay of the responses
ω	Impact fraction of a revision	0.5511 (0.1002)	affects split between surprise and phased versions
θ_w	Calvo wage stickiness	0.7869 (0.0864)	affects depth of the output response
	Shock scale	0.0898 (0.0124)	normalization of the shock size

Table 2: Model calibration and estimation

Notes: This table reports all model parameters. Panel A parameters are set externally. Panel B parameters are implied by the steady-state targets. Panel C parameters are estimated using impulse response matching. The standard errors in Panel C treat the bootstrap variances of the estimated responses as independent across horizons.

parameters estimated in the subsequent steps affect only the transition dynamics of the model, and leave the steady state unchanged. The steady-state targets therefore continue to hold exactly for any values of the estimated parameters.

The identified shock corresponds to an announcement about a new path of κ , the weight on safe assets in the regulatory bank portfolio constraint. The identified shock reflects a combination of regulatory announcements with varying amounts of time between the announcement and the regulation binding. To account for this, I calibrate the announced path of the key regulatory parameter κ to be a mixture of a surprise announcement that takes effect immediately and an announcement where the regulation phases in gradually over two years. A fraction $\omega \in [0, 1]$ determines the weight on the surprise announcement. Both the surprise and announced changes decay at ρ_κ , with the decay starting after full phase-in for the announced path. The decaying path reflects the fact that the identified regulatory safe asset demand shock is a news shock derived from repeated announcements regarding changes to regulation. Each event represents a deviation from the path of regulatory requirements that banks previously expected. Repeated announcements regarding a given change in regulation revise the path each time, including announcements that only change the phase-in schedule leading up to the same rule change. As a result, the average revision decays over the horizon of the expected path even though any individual rule may be permanent in isolation. For $\omega = 1$, the change in κ would bind immediately before decaying over time, while $\omega = 0$ would involve no change in κ on impact with the change fully phasing in after eight quarters. I estimate the fraction ω along with the remaining parameters.

I estimate the remaining parameters using impulse response matching (Rotemberg and Woodford, 1997; Christiano et al., 2005). The estimation selects values of the parameters that minimize the distance between the model's impulse responses and the empirical impulse responses estimated in Section 6. I match the responses of five out of the six variables in the VAR, which excludes the NFCI. I exclude the NFCI, as the model counterpart to the index would be the average of the funding and credit spreads. The dynamics of this variable would be identical to those of the funding advantage up to a unit conversion, and thus would not provide any additional information.

Let $\hat{m}$ be the 105×1 vector that contains the estimated impulse responses of the five matched variables at horizons zero through twenty, and let $m(\theta)$ be the corresponding vector of model responses under the announcement path described above. The estimator is

$$\hat{\theta} = \arg \min_{\theta} [\hat{m} - m(\theta)]' W [\hat{m} - m(\theta)], \quad (39)$$

where W is a diagonal weighting matrix containing the inverse pointwise variances of the

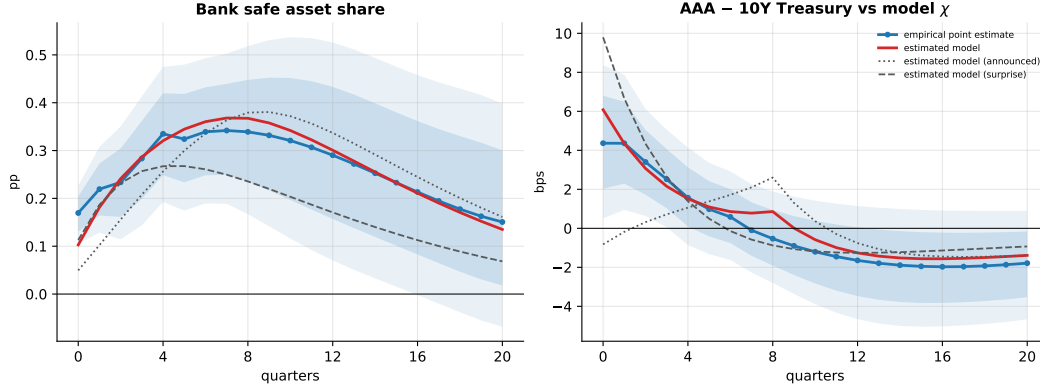
bootstrap distribution of the estimated responses.²⁰ The vector of parameters θ consists of the six remaining parameters $(\xi, \phi_I, \phi_S, \rho_\kappa, \omega, \theta_w)$ and the size of the shock. The shock scaling is a free parameter, given that the impulse responses are only identified up to sign and scale. The parameters are estimated jointly, although each parameter primarily influences a specific feature of the impulse responses. The persistence of the shock, denoted by ρ_κ , affects the decay of the impulse responses across all variables. The fraction of the surprise shock, ω , mainly affects the shape of responses in the funding advantage at shorter horizons. The wage stickiness θ_w influences the depth of the output response relative to the minimal response of prices. The ξ parameter, which determines the slope of the relationship between bank safe asset holdings and bank funding costs, primarily affects the shape of the funding advantage responses at long horizons. The bank portfolio adjustment cost ϕ_S mainly impacts the relative magnitudes of the responses in the bank safe asset share and the funding advantage.

The shock is estimated to have persistence of $\rho_\kappa = 0.944$, which corresponds to a half-life of roughly three years. The estimated fraction of the surprise path is $\omega = 0.55$, meaning that roughly half of the announced revision binds in the announcement quarter. The estimated wage stickiness is $\theta_w = 0.79$, implying an average wage spell of roughly five quarters. The estimated slope on the bank funding cost with respect to safe asset holdings is $\xi = 0.042$, which corresponds to a persistent one-percentage-point rise in the bank safe asset share decreasing the deposit spread by 8 basis points. The estimated bank portfolio adjustment cost is $\phi_S = 0.033$, and the capital adjustment cost is $\phi_I = 0.001$. The capital adjustment cost is driven to the lowest levels within its admissible range, resulting in investment adjustments being close to frictionless. The adjustment cost is still necessary in the model to generate any valuation effects of regulation on the bank's balance sheet. Without adjustment costs, the price of capital would be constant. Overall, the average deviation between the impulse responses of the calibrated model and the empirical point estimates is 0.4 standard errors, which is well within the confidence bands of the estimated impulse responses.

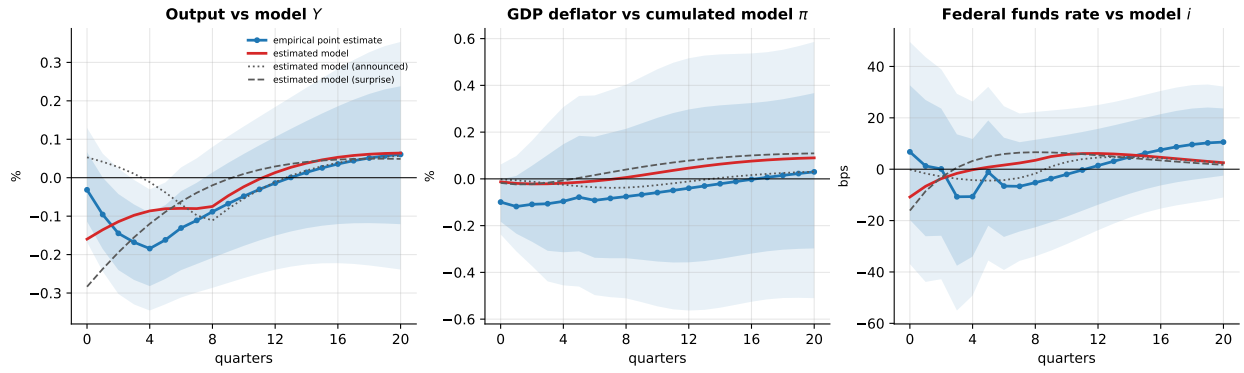
7.3 Transmission and Model Fit

The transmission mechanisms of a regulatory safe asset demand shock in the estimated model are as follows. When the regulatory weight on safe assets κ_t increases, the regulatory value of safe assets rises relative to capital claims, and the bank needs to adjust its portfolio to comply with the new requirement. The portfolio adjustment cost keeps the bank from adjusting its portfolio immediately. The bank accepts a lower return on safe assets, as the safe assets now have a higher marginal regulatory value. Conversely, the bank requires a

²⁰The weighting matrix puts more weight on the more precisely estimated horizons. I use diagonal weighting, as the optimal weighting matrix induces finite-sample bias in the estimator (Guerron-Quintana et al., 2017).



(a) The portfolio and the funding advantage



(b) Output, prices, and the policy rate

Figure 9: Model versus empirical impulse responses

Notes: This figure shows the impulse responses of the empirical and the model estimates. The solid blue line with dots shows the empirical impulse responses with the 68 and 90 percent confidence bands. The red line shows the estimated model. The dark gray dashed and dotted lines show the responses under a surprise path and an eight-quarter phase-in path, respectively. The model funding advantage χ is in annualized basis points, and model inflation is cumulated to a price level for comparison with the GDP deflator.

higher return on capital claims, as the capital claims now have a higher marginal regulatory cost. The funding advantage χ_t therefore jumps on impact, and the higher required return on capital crowds out investment. This crowding out effect, combined with price and wage rigidities, results in lower output and a small decrease in prices.

Over time, the bank adjusts its portfolio by increasing its safe asset holdings. As households price the fact that bank portfolios are now safer, the deposit spread decreases according to Equation 34. At the same time, the retained earnings rebuild bank equity, resulting in a recovery of investment, and consequently a recovery of output. The funding advantage then decreases and settles below its pre-shock level, consistent with the empirical result of both the funding advantage and financial conditions decreasing at longer horizons.

Figure 9 shows the comparisons of the impulse responses from the empirical estimates and the model estimates. I also show two additional versions of the model impulse responses,

where one version is responding to a surprise shock to κ ($\omega = 1$) and the other is responding to an announced phase-in path ($\omega = 0$). The estimated model matches the empirical responses closely. The safe asset share has a hump-shaped response that closely matches the empirical estimates for the entire twenty-quarter horizon. The funding advantage widens by 6 basis points on impact in comparison to 4 basis points in the empirical estimate. The model estimates match both the decaying pattern and the negative estimates at longer horizons. Output falls by similar magnitudes, although with slightly different shapes of responses. The model estimates an output decline of 0.16 percent on impact, while output decreases by 0.18 percent after one year in the empirical estimate. Although the timing of the output trough is different, the model estimates fall inside the 90 percent confidence bands of the empirical estimates at almost every horizon. The responses of prices and monetary policy are statistically insignificant for almost all horizons in the empirical estimates. That said, the model estimates still closely mirror the pattern for both prices and the federal funds rate. Appendix F examines the contribution of each feature of the model to the estimated dynamics.

7.4 Counterfactuals

I conduct two counterfactual exercises using the estimated model. The first exercise examines the consequences of a permanent increase in the regulatory weight on safe assets, motivated by recent policy debates. The second exercise examines the steady-state characteristics across varying levels of the regulatory weight on safe assets, which generates a regulatory Laffer curve.

7.4.1 Permanent increase in regulatory preference for safe assets

The first counterfactual examines a scenario involving a one-time permanent increase in the regulatory weight on safe assets κ . In contrast to the estimated shock, which captures a temporary deviation from the expected regulatory path, the counterfactual permanently increases the regulatory weight. Although this translates to permanent increases in the amount of safe assets that banks hold, the model predicts that the increase in the funding advantage would only be temporary.

This counterfactual exercise is motivated by a number of recent policy proposals and changes, most notably regarding the recalibration of the leverage framework. In April 2020, bank regulators temporarily excluded U.S. Treasuries and reserves from the denominator of the supplementary leverage ratio (SLR). The SLR defines the minimum ratio of bank capital to total leverage exposure, which is calculated regardless of asset risk. The exclusion lowered the banks' regulatory cost of holding safe assets, resulting in banks increasing their

safe asset holdings modestly during the exclusion (Bräuning and Stein, 2025). The exclusion expired in March 2021, and subsequently, policymakers proposed various changes to the leverage framework, including a permanent exclusion of Treasuries and reserves and the introduction of a countercyclical component.²¹ In June 2025, the regulators proposed a recalibration of the enhanced supplementary leverage ratio buffer for the largest banks, and the final rule adopting the recalibration followed in November 2025. The policy debates revolved around the amount of additional Treasuries and reserves that banks would absorb, along with estimated effects on government borrowing costs. The Treasury Secretary argued that reforming the leverage ratio could lower 10-year Treasury yields by tens of basis points (Bloomberg News, 2025). The various proposals differ in their specific designs, but many of the proposals involved permanently raising the regulatory value of safe assets relative to loans. Similar discussions have continued amid rising long-term Treasury yields, and a government facing higher borrowing costs may be more tempted to strengthen the regulatory demand for its own debt.

For the counterfactual, I consider a permanent increase in the regulatory weight on safe assets κ that raises bank safe asset holdings by \$250 billion in the steady state. The magnitude of the increase in safe asset holdings is based on estimates from the policy discourse.²² Using the 2025Q2 aggregate bank balance sheet of \$24.2 trillion, the accumulation of \$250 billion would correspond to a 1.03 percentage point increase in the bank safe asset share. I solve for the permanent level of κ that corresponds to a 1.03 percentage point increase in the safe asset share, and then compute the transition path following a surprise permanent increase in κ to that level. Figure 10 shows the results. I use the surprise path rather than the phase-in path for simplicity. I also examine scenarios with varying steady-state levels of safe asset holdings, along with phase-in paths, in Appendix K.

The key result is that a permanent increase in the regulatory weight on safe assets raises the funding advantage only temporarily. Because the bank adjusts its portfolio gradually, the regulatory value of safe assets rises, and the funding advantage increases by 29 basis points on impact. As the bank increases its safe asset holdings, the funding advantage declines and reaches its original level after six quarters. In the long run, the funding advantage is 7 basis points below its original level. This is a result of the permanent increase in safe asset holdings lowering the bank funding cost, as banks now have a safer portfolio. The effect on the funding advantage is therefore transitory, while the effect on bank portfolios is permanent.

²¹Proposals include Liang and Parkinson (2020) and Group of Thirty Working Group on Treasury Market Liquidity (2021), with Duffie (2020) documenting the role of the constraint in the March 2020 episode.

²²The \$250 billion scenario is roughly twice the observed response to the temporary 2020–2021 exclusion. Garvey and Platerink Kosonen (2025) estimate that broker-dealer and depository subsidiaries could add roughly \$3 trillion of Treasuries or reserves under a full exclusion.

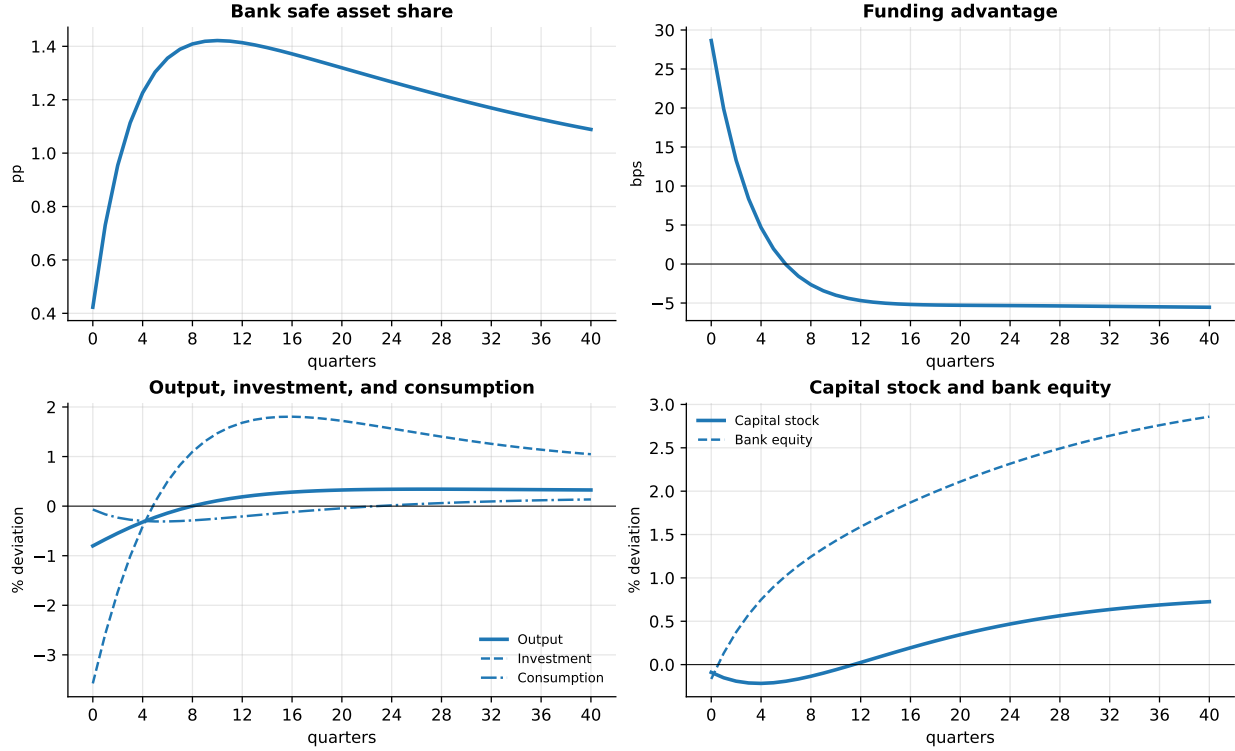


Figure 10: Permanent increase in the regulatory weight on safe assets

Notes: This figure shows the impulse responses to an unanticipated permanent increase in the regulatory weight, scaled to induce an increase in bank safe asset holdings of \$250 billion in the steady state. See Appendix F for additional results.

The permanent increase in κ is contractionary in the transition, but output recovers over time. Output falls by roughly 0.8 percent on impact due to the regulation change crowding out investment. Output then recovers, as the bank rebuilds equity and bank funding costs decrease. In the new steady state, the deposit spread decreases from 30 to 20 basis points, and output and the capital stock are 0.4 and 1 percent above the baseline, respectively.

The transition involves a trade-off between the government's interest savings and output. The immediate increase in the funding advantage contributes to higher interest savings for the government, but this comes at the cost of the contraction in output in the first few years. The interest savings represent the premium payments that the government avoids as a result of the induced regulatory demand. In each period, the interest savings are the product of the funding advantage and the safe asset holdings of the bank. I quantify the trade-off between interest savings and output across four different implementations of the increase in the regulatory weight. Along with the surprise permanent increase in the regulatory weight κ , I also consider a phase-in version where κ increases linearly over four quarters to reach the same full level of the regulatory weight. In addition, I consider both the surprise and phase-in versions of temporary increases in the regulatory weight. The temporary changes

Implementation	Interest savings (\$B, 2025)			Output (\$B, 2025)		
	2 years	5 years	10 years	2 years	5 years	10 years
Permanent, surprise	12.1	18.5	24.9	−240	−68	371
Permanent, phase-in	8.2	15.9	22.7	−89	48	480
Temporary, surprise	7.3	4.9	3.5	−241	−176	−137
Temporary, phase-in	7.2	4.9	2.6	−195	−130	−66

Table 3: Interest savings and output along the transition

Notes: This table reports the present value of the cumulative government interest savings and output effects along the transition of the counterfactual exercises, discounted at the steady-state real rate. Interest savings and output effects are converted to dollars with the 2025Q2 aggregate bank balance sheet and 2025 nominal GDP, respectively. The phase-in variants reach the full κ level after four quarters, and the temporary variants decay from the full κ level with a half-life of four quarters.

reach the same full level of the regulatory weight, but decay with a half-life of one year.²³ Table 3 reports the present value of the cumulative interest savings and output effects of each implementation over two, five, and ten-year horizons. The surprise permanent version results in roughly \$18 billion in interest savings over the first five years while incurring \$68 billion of forgone output. The output effects become positive by the ten-year horizon as the capital stock accumulates over time. The trade-off improves substantially for the phase-in version. The interest savings are slightly lower at \$15.9 billion, but the output effects are already positive by the five-year horizon. The temporary policies result in much lower interest savings, and their output effects remain negative at all horizons. The temporary policies come with transitional output costs, but without the long-run benefits of the accumulation of the capital stock as the bank builds up a safer portfolio and more equity.

I discuss a few limitations of the counterfactual results. First, the unanticipated change in the regulatory weight shown in this section is the upper bound for the increase in the funding advantage. Announced paths result in significantly lower increases in the funding advantage on impact. For example, the increase in the funding advantage on impact is less than half of the unanticipated change when using the announcement path estimated in Section 7.2. Second, the counterfactual exercise fails to capture any changes in dealer intermediation capacity or market functioning in stress, which is one of the key motivations behind the proposed policies. While such channels may influence the dynamics of both the funding advantage and output, I focus on the demand channel, through which regulation increases banks' safe asset holdings and affects the government funding advantage.

²³For comparison, the regulatory weight in the baseline calibration of the model decays with a half-life of roughly three years.

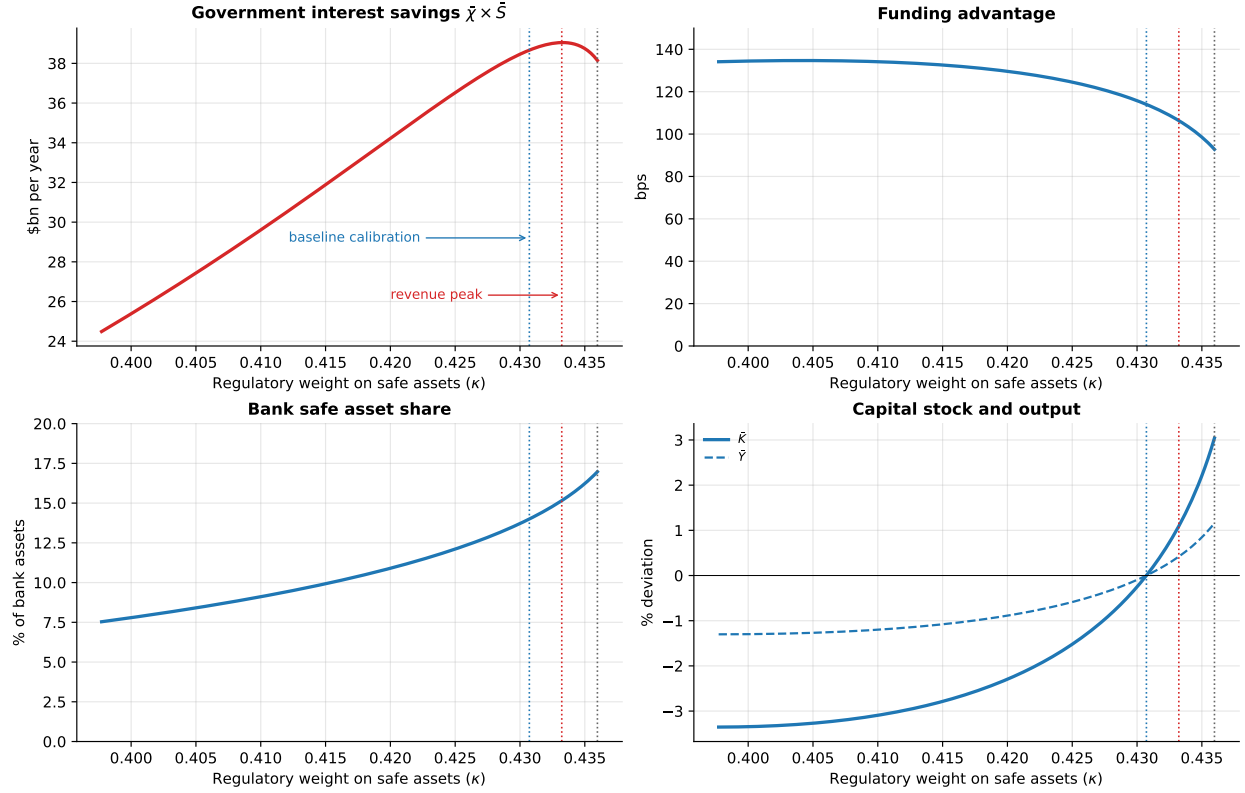


Figure 11: The regulatory Laffer curve

Notes: This figure shows the steady-state values for varying levels of the permanent regulatory weight on safe assets κ . The interest savings $\bar{\chi} \times \bar{S}$ are in dollars based on 2025 bank balance sheets. Dotted vertical lines show the level of κ corresponding to the baseline calibration, the revenue peak, and the capacity boundary at which the deposit spread over the policy rate reaches zero.

7.4.2 Regulatory Laffer curve

The second counterfactual examines how the government's annual interest savings vary with respect to the regulatory weight on safe assets κ across steady states. The interest savings are expressed as the product of the funding advantage and the safe asset holdings in steady state, $\bar{\chi} \times \bar{S}$, which is the premium the government avoids paying on the safe assets as a result of the induced regulatory demand. The funding advantage $\bar{\chi}$ represents the interest savings per dollar of induced safe asset demand, and the amount of safe asset holdings $\bar{S}$ represents the total quantity of induced safe asset demand. The interest savings across different levels of the regulatory weight form a regulatory Laffer curve. The usual Laffer curve involves the government setting a tax *rate* while the tax *quantity* (i.e., the tax base) responds. The regulatory Laffer curve in this paper works in reverse order. The regulation fixes the *quantity* of safe assets that banks must hold through the regulatory weight κ , and the market responds by determining the *rate* at which the government saves on interest payments.

Figure 11 shows the resulting Laffer curve along with a number of other relevant vari-

ables. There are two counteracting forces that affect government interest savings when the regulatory weight on safe assets increases. First, increasing the regulatory weight contributes to higher government interest savings through the effect on banks' safe asset holdings. The increase in the regulatory weight induces banks to hold more safe assets. Keeping the level of the funding advantage fixed, the higher total safe asset holdings increase government interest savings, as the interest savings are a product of the funding advantage and the quantity of safe asset holdings. In contrast, increasing the regulatory weight contributes to lower government interest savings through the effect on the funding advantage. Regulation that requires banks to hold more safe assets makes their portfolios safer. This additional safety is priced into cheaper bank funding costs, which translates to a lower funding advantage in the steady state. This reflects the decreasing marginal value of holding safe assets as bank portfolios become safer. Consequently, an increase in the regulatory weight decreases the interest savings per dollar of safe asset holdings. The latter effect intensifies as the regulatory weight increases. As a result, the Laffer curve peaks when the additional safe asset holdings induced by higher κ exactly offset the effect of the decrease in the funding advantage. The Laffer curve also ends at a specific level of κ , at which point the deposit spread over the policy rate approaches zero. Regulation cannot sustain any additional permanent holdings of safe assets beyond this level, as it would require the bank's marginal funding to be priced below the policy rate. Wholesale funders with direct access to the money market would not accept such a rate. The scarcity premium rises with the regulatory weight, to 2.8 basis points at this boundary, and adds to the interest savings, but it is too small to offset the compression of the deposit spread.

As the regulatory weight increases, the cheaper bank funding also lowers the required return on capital claims, resulting in higher levels of the capital stock and output. This response is consistent with [Begenau \(2020\)](#), who shows that higher capital requirements lower banks' equilibrium funding costs and can increase bank lending.

The baseline calibration shows that the observed regulation is close to the peak of the regulatory Laffer curve. The model implies that the maximum sustainable interest saving is about \$39 billion a year, or 0.13 percent of GDP.²⁴ For comparison, [Krishnamurthy and Vissing-Jorgensen \(2012\)](#) estimate that the convenience yield on the entire Treasury supply has saved the government about 0.25 percent of GDP per year at historical average debt levels, meaning that the regulatory safe asset demand accounts for roughly half of that total. The remaining share of the interest savings may represent other factors that influence the U.S. funding advantage, such as the liquidity or collateral value of Treasuries.

The peak of the Laffer curve is at a slightly higher level of the regulatory weight κ relative

²⁴Dollar figures convert the model's steady states through the observed 2025Q2 aggregate bank balance sheet of \$24.2 trillion, and the GDP share divides by 2025 nominal GDP of \$30.3 trillion.

to the baseline calibration. However, increases in κ would yield minimal improvements in interest savings. Further increases can induce additional safe asset holdings, but would involve lower interest savings beyond the peak of the curve. The exact location of the peak of this regulatory Laffer curve is fairly sensitive to the calibration of the model. However, the finding that current regulation is close to the peak of the curve is robust across a wide range of calibrations. I discuss this further in Appendix F.

Overall, the two counterfactuals show that while financial regulation that privileges safe assets can sustain a funding advantage, further increases in the regulatory preference raise the funding advantage only temporarily and generate minimal additional interest savings in the long run. While the temporary increases in the funding advantage can generate government interest savings, they come with transitory output costs.

8 Conclusion

The U.S. government’s funding advantage is partly sustained by financial regulations that privilege safe assets. This paper estimates the macroeconomic effects of this regulatory safe asset demand. I construct a series of plausibly exogenous regulatory safe asset demand news using a narrative approach, and use it as an instrument to identify regulatory safe asset demand shocks. I find that a shock that increases regulatory safe asset demand raises the safe asset share of bank portfolios persistently, widens the funding advantage temporarily, and lowers output through decreased bank lending. I develop a New Keynesian model with regulated banks that accounts for the estimated responses, and use the model to evaluate policy counterfactuals.

The results offer a number of policy implications. Reforms that permanently increase banks’ safe asset demand can increase the funding advantage, but the effect on the funding advantage is temporary and comes with an output cost. Comparing steady states across varying levels of the regulatory weight on safe assets creates a regulatory Laffer curve, with current regulation being close to its peak. Therefore, policies that privilege safe assets beyond current levels would result in only modest increases in government interest savings in the long run.

The findings of this paper motivate a number of avenues for future research. First, the model treats financial regulation as exogenous. Amid rising yields, the government may be tempted to increase regulatory preference for safe assets to induce demand for its debt, and debt issuance may in turn respond to the cheaper funding that regulation delivers. Endogenizing these policies would shed light on the interaction between financial regulation and fiscal policy, and the extended model could also be used to study regulatory responses during crisis periods. Second, this paper focuses on the aggregate effects, rather than the

distributional effects of the decline in bank credit. Combining the bank-level regulatory exposures measured in this paper with firm-level borrowing data could identify which types of firms are most severely impacted. A model with heterogeneous firms could then examine how the distributional effects contribute to aggregate fluctuations. Finally, future work could estimate the international spillovers of regulatory safe asset demand. Building on the estimated responses of exchange rates in the paper, the identified shocks can be used to estimate responses of capital flows and foreign safe asset holdings. A two-country extension of the model could then explore relevant spillover channels and their implications for the U.S. and foreign economies.

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Appendix

The Macroeconomics of Regulatory Safe Asset Demand

Takaaki Sagawa

A List of events

Table A.1 lists the 38 exogenous events with relevant information and a brief description for each event.

Table A.1: List of events

Date	Regulation	Channel	Sign	Description
1988-07-15	Basel I	Risk weight	+	Basel Committee publishes the Basel Capital Accord, setting an 8 percent risk-based capital ratio with zero risk-weights assigned to gov't securities.
1990-09-21	Leverage ratio	Leverage	+	OCC sets a minimum Tier 1 leverage ratio of 3 percent of total assets for national banks.
1996-01-04	Market Risk Amendment	Risk weight	+	Basel Committee amends the Capital Accord to require capital against market risk in the trading book from 1997.
2001-11-29	Recourse rule	Risk weight	+	Agencies issue the final rule on the capital treatment of recourse, direct credit substitutes, and residual interests in securitizations.
2004-06-26	Basel II	Risk weight	−	G10 governors endorse Basel II framework, introducing rating and model-based risk weights that lower required capital on low-risk private assets.
2006-09-05	Basel II	Risk weight	+	Agencies propose the U.S. Basel II advanced approaches with transitional capital floors and a delayed start relative to the Basel timetable.
2007-11-02	Basel II	Risk weight	−	Agencies finalize the U.S. Basel II advanced-approaches rule.
2009-12-17	LCR	Liquidity	+	Basel Committee consultative document first proposed the 30-day Liquidity Coverage Ratio at a 100 percent minimum.
2010-07-21	Dodd-Frank Act	Risk weight	+	Collins Amendment capital floor and enhanced prudential standards for bank holding companies above \$50 billion.
2010-12-16	Basel III capital	Risk weight	+	Basel Committee publishes final Basel III capital standard, raising the common equity minimum to 4.5 percent and adding a 2.5 percent conservation buffer.

Table A.1, continued

Date	Regulation	Channel	Sign	Description
2010-12-16	LCR	Liquidity	+	Basel Committee publishes the original Basel III liquidity standard, finalizing the LCR with strict HQLA categories and full compliance from 2015.
2011-11-04	G-SIB surcharge	Risk weight	+	Basel Committee finalizes the G-SIB methodology with capital surcharges of 1 to 2.5 percent of risk-weighted assets.
2011-11-22	Capital plan rule	Risk weight	+	The Federal Reserve requires annual stress-tested capital plans from bank holding companies above \$50 billion.
2012-06-07	Basel III capital	Risk weight	+	Agencies propose the U.S. implementation of the Basel III capital rules for all banks and bank holding companies.
2012-06-07	Basel 2.5 market risk	Risk weight	+	Agencies finalize the Basel 2.5 market risk rule.
2013-01-06	LCR	Liquidity	−	Basel Committee revises the LCR with a graduated phase-in to 2019, a broader HQLA pool, and lower run-off rates.
2013-07-02	Basel III capital	Risk weight	−	Agencies finalize the U.S. Basel III capital rule with relaxations for community banks relative to the 2012 proposal.
2013-07-09	eSLR	Leverage	+	Agencies propose an enhanced supplementary leverage ratio of 5 percent for the eight largest bank holding companies and 6 percent for their bank subsidiaries.
2013-10-24	LCR	Liquidity	+	Agencies propose a U.S. LCR stricter than the Basel standard, with full compliance by 2017 and a narrower HQLA definition.
2014-01-12	Basel III leverage ratio	Leverage	−	Basel Committee finalizes the leverage ratio framework.
2014-02-18	Enhanced prudential standards	Scope	+	The Federal Reserve finalizes Regulation YY, applying liquidity buffers, stress tests, and other enhanced standards to bank holding companies above \$50 billion.
2014-09-03	LCR	Liquidity	+	Agencies finalize the U.S. LCR with a modified LCR for bank holding companies between \$50 and \$250 billion.
2014-09-03	SLR exposure measure	Leverage	+	Agencies revise the supplementary leverage ratio exposure measure, expanding it by roughly 8 percent for some banks.
2014-10-31	NSFR	Liquidity	+	Basel Committee finalizes the Net Stable Funding Ratio, requiring available stable funding to cover required stable funding over one-year horizon.

Table A.1, continued

Date	Regulation	Channel	Sign	Description
2014-12-09	G-SIB surcharge	Risk weight	+	The Federal Reserve proposes a U.S. G-SIB surcharge with a second method based on short-term wholesale funding.
2015-10-30	TLAC	Risk weight	+	The Federal Reserve proposes total loss-absorbing capacity requirements of 16–18 percent of risk-weighted assets for U.S. G-SIBs.
2016-04-26	NSFR	Liquidity	+	Agencies propose the U.S. NSFR, at 100 percent for the largest banks and a 70 percent modified ratio for mid-sized firms.
2017-12-07	Basel III capital	Risk weight	+	Basel Committee publishes the revised Basel III framework, with revised standardized approaches.
2018-05-24	Tailoring Act	Scope	–	The Economic Growth, Regulatory Relief, and Consumer Protection Act raises the asset threshold for mandatory enhanced prudential standards from \$50 billion to \$250 billion.
2018-10-31	Tailoring Act	Scope	–	The Federal Reserve proposes a four-category tailoring framework.
2019-10-10	Tailoring Act	Scope	–	Agencies adopt the final tailoring framework, reducing liquidity and stress-testing requirements for Category III/IV firms.
2019-11-19	SLR	Leverage	–	Agencies finalize the Tailoring Act’s exclusion of central bank deposits from the SLR exposure measure for a set of custody banks.
2020-03-04	Stress capital buffer	Risk weight	+	Federal Reserve finalizes the stress capital buffer.
2020-10-20	NSFR	Liquidity	–	Agencies adopt the final U.S. NSFR, calibrated to the tailoring framework.
2021-03-19	SLR exclusion expiry	Leverage	+	The Federal Reserve announces that the temporary exclusion of Treasuries/reserves from SLR would expire as scheduled.
2023-07-27	Basel III capital	Risk weight	+	Agencies propose the U.S. implementation of the revised Basel III framework for banks above \$100 billion.
2024-09-10	Basel III capital	Risk weight	–	The Federal Reserve announces a re-proposal of the 2023 rule, excluding banks between \$100 and \$250 billion from most changes.
2025-06-25	eSLR recalibration	Leverage	–	Agencies propose replacing the fixed 2 percent eSLR buffer for G-SIBs with a buffer equal to half of each firm’s G-SIB surcharge.

B Data

Bank panel. The bank-quarter panel covers 1984Q1–2025Q2 from FFIEC Call Reports, with the pre-2001 Treasury series from the Chicago Fed archives, consisting of over 1.5 million bank-quarter observations. The safe asset components consist of cash and balances due, Treasury securities (held-to-maturity amortized cost plus available-for-sale fair value; pre-2001 data from RCFD0400), GNMA MBS, GSE agency debt, and GSE agency MBS. Shares are in percentage points of total assets.

Aggregate series. Table B.1 lists the aggregate variables used in the VAR and the local projections, along with their sources, frequencies, and sample periods.

Source	Variables	Frequency	Sample period
Federal Reserve Board, H.8	Treasury + agencies share of bank assets	Weekly	1973Q1–2025Q2
	Bank assets, liabilities, and securities	Weekly	1974Q1–2025Q2
	Bank credit and bank loans by type	Weekly	1974Q1–2025Q2
Federal Reserve Board, H.15	Federal funds rate	Daily	1973Q1–2025Q2
	Treasury yields	Daily	1973Q1–2025Q2
Federal Reserve Board, Z.1	Bank loans to the financial sector	Quarterly	1974Q1–2025Q2
	Corporate loans and debt securities	Quarterly	1974Q1–2025Q2
	Home mortgages	Quarterly	1974Q1–2025Q2
Federal Reserve Board, G.5	Trade-weighted dollar indexes	Monthly	1974Q1–2025Q2
Federal Reserve Bank of Chicago	NFCI and its subindices	Weekly	1973Q1–2025Q2
Federal Reserve Bank of Dallas	Market value of federal debt	Monthly	1974Q1–2025Q2
Wu and Xia (2016)	Shadow federal funds rate	Monthly	Zero lower bound
Moody's	AAA and Baa corporate bond yields	Monthly	1973Q1–2025Q2
Bureau of Economic Analysis	Real GDP and GDP deflator	Quarterly	1973Q1–2025Q2
	Nominal GDP	Quarterly	1974Q1–2025Q2
	Federal receipts, outlays, interest, and transfers	Quarterly	1974Q1–2025Q2
	Government consumption and investment	Quarterly	1974Q1–2025Q2
U.S. Department of the Treasury	Federal debt, gross and privately held	Quarterly	1974Q1–2025Q2
Bank for International Settlements	Credit to the nonfinancial sector by lender	Quarterly	1974Q1–2025Q2

Table B.1: Data sources

Notes: This table lists the aggregate variables used in the VAR and the local projections, along with the source, frequency, and the estimation sample. The variables in the VAR enter from 1973Q1, and the local projections use the identified shock from 1974Q1.

C Instrument construction and validation

C.1 Methodology

This section describes the calculation of the induced safe asset demand paths from Section 3 in more detail. I first describe the balance sheet inputs and the parameters that apply to every event, and then describe the calculation for each of the four regulatory channels.

Balance sheet inputs. For every event, C_e represents the set of commercial banks for which the bank regulation/rule applies. This is defined at the level of the consolidated holding company for rules with asset thresholds, and at the level of each insured bank for rules that apply to all banks. I measure the exposure of each covered bank with the Call Report balance sheet in the quarter preceding the announcement. The robustness checks use windows of one quarter and eight quarters. Risk-weighted assets are taken directly from the Call Reports when reported. Otherwise, I approximate risk-weighted assets by applying the Basel I risk buckets to the balance sheet. Tier 1 capital is replaced by equity capital in the years before it is reported.

Discounting/scaling. The present value of each demand path uses a quarterly discount factor of $\beta = 0.99$. I also use $\beta = 1.00$ and $\beta = 0.95$ in the robustness checks. The quarterly series scales the present values by the aggregate total assets of U.S. commercial banks in the preceding quarter. I also scale by nominal GDP or leave the series in billions of dollars as part of the robustness checks.

Capital events. I estimate the induced safe asset demand for capital events using Equation 3 with the assumption that the bank accumulates $\varphi = 0.20$ dollars of safe assets per dollar of newly required capital. This assumption is based on the evidence from the literature that banks meet higher risk-based requirements in part by shifting toward government securities (Haubrich and Wachtel, 1993; Furfine, 2001; Juelsrud and Wold, 2020; Bonner, 2016), while most of the adjustment in capital ratios comes through retained earnings (Cohen and Scatigna, 2016). Given that the literature does not provide a uniform and precise estimate for φ , so I test that the results are robust to a wide range of values for φ . Safe assets carry a zero risk weight, and thus shifting one dollar from loans to safe assets lowers risk-weighted assets one for one. There are a number of events that require a different treatment from the usual capital rules. For example, the 1988 Basel Accord and the 2015 proposal on total loss-absorbing capacity set requirements relative to the stock of capital that banks already held. For these events, the induced demand is φ times the change in the shortfall

$\max(0, m_e(h) \cdot \text{RWA}_i - \text{Cap}_i)$ between the pre-announcement and post-announcement paths. Cap_i here represents the bank’s Tier 1 capital.

Liquidity events. I estimate the induced safe asset demand for liquidity events using Equations 4 to 6. The projected net cash outflows NCO_i apply the run-off rates of the 2014 U.S. LCR rule to the categories available in the Call Reports. This construction follows [Hong et al. \(2014\)](#), who compute the LCR and the NSFR of U.S. commercial banks from the Call Reports, and [Roberts et al. \(2023\)](#) and [Sundaresan and Xiao \(2024\)](#), who build proxies for the LCR from public regulatory filings. I use the bank’s safe asset holdings as the measure for the stock of high-quality liquid assets. I check that this is robust to restricting the stock to Level 1 assets, consisting of cash, central bank reserves, Treasuries, and MBS guaranteed by the Government National Mortgage Association. For the NSFR, the available stable funding ASF_i applies factors of 100 percent to equity capital, 90 percent to retail deposits, 50 percent to wholesale funding, and zero to federal funds purchased and repurchase agreements. The required stable funding RSF_i applies factors of 5 percent to Level 1 assets, 15 percent to other safe assets, and 85 percent to all other assets. The conversion factor of 0.8 in Equation 5 is the difference between the factors on other assets and on Level 1 assets. The mapping of the NSFR factors to reported balance sheet categories follows [King \(2013\)](#) and [DeYoung and Jang \(2016\)](#), who estimate the ratio from public balance sheet data for international and U.S. banks, respectively.

Leverage events. I estimate the induced safe asset demand for leverage events following Equations 7 and 8. I use $\psi = 0.30$ dollars of safe assets shed per dollar of newly required capital. The value corresponds to the range of 20 to 40 cents documented in the literature, and the robustness checks use $\psi = 0.20$ and $\psi = 0.40$. The leverage exposure is the bank’s average total assets reported in the Call Reports.

Scope events. I estimate the induced safe asset demand for scope events using Equation 9. I identify the set of banks affected by changes in thresholds by directly observing the total asset levels under the old and new thresholds. For the 2018 EGRRCPA, the affected set of banks consists of holding companies with total assets between \$50 billion and \$250 billion. For the 2018 tailoring proposal and its 2019 final rule, the affected set of banks consists of holding companies between \$100 billion and \$700 billion. The induced demand is scaled by the fraction of the liquidity requirement that applies to each category.

C.2 Diagnostics

I conduct a series of diagnostic tests to examine the validity of the event series, which is used as the external instrument in the baseline analysis.

Forecastability of the instrument. In addition to the forecastability test I conduct in Section 3, I implement additional forecastability tests in Table C.1. The table shows the properties of the regressions of each instrument variant on four quarterly lags of relevant macro-financial variables. I estimate the regressions for not only the baseline present-value instrument, but also the sign-only versions. I also compare the results of the instrument constructed using the exogenous events with a present-value series constructed using crisis-response events. The crisis-response events are a subset of the endogenous events that are excluded from the baseline set of events, and consist of the SCAP 2009, the 1990–1992 reserve-requirement cuts, the 1991 FDICIA enactment, the April 2020 SLR exclusion, COVID capital relief, and the 2023 long-term-debt proposal.

The table shows p -values of 0.647 and 0.934 for the baseline instrument and the sign-only instrument, respectively. This provides evidence that the baseline present-value instrument and its sign-only version are both unforecastable. In contrast, the p -values of the crisis-response events are 0.000 and 0.483 for the baseline methodology and sign-only instrument, respectively.

Instrument variant	R^2	F	p -value
Z (baseline events)	0.107	0.85	0.6471
Z (± 1 sign-only)	0.073	0.56	0.9340
Z (crisis-response events)	0.423	5.21	0.0000
Z (crisis-response events, ± 1 sign-only)	0.122	0.99	0.4826

Table C.1: Forecastability of the present-value instrument

Notes: This table reports regressions of each instrument variant on four lags of the macro-financial state (real GDP growth, GDP deflator inflation, the NFCI, the shadow federal funds rate, and the safe asset share), quarterly, 1984–2025. The reported F statistic and p -values test the joint significance of all predictors. The crisis-response events appear here only for comparison, and are not part of the baseline set of events.

Serial correlation. I also test for autocorrelation of the instrument. Figure C.1 plots the autocorrelation function of the baseline present-value series at lags of up to 24 quarters. The coefficients are small throughout, with just two of the 24 coefficients falling outside the 95 percent threshold (with Bonferroni-correction that accounts for multiple hypothesis tests). Ljung–Box tests for the baseline event series also fail to provide evidence in favor of the instrument being autocorrelated, with no first-order dependence ($p = 0.91$) and no rejection at eight lags ($p = 0.19$).

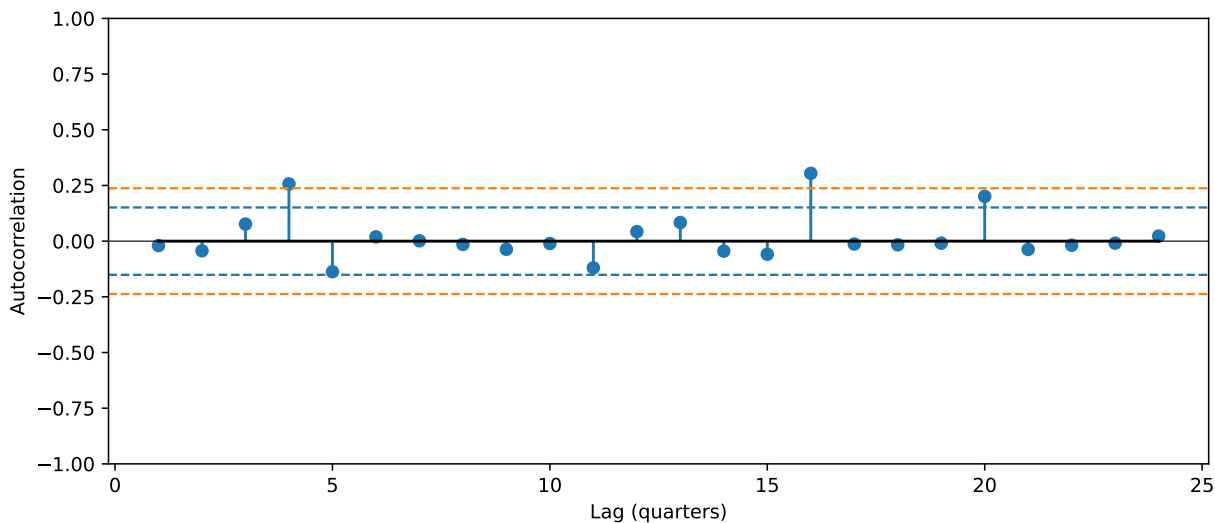


Figure C.1: Autocorrelation function of the present-value event series

Notes: This figure shows the autocorrelation function of the baseline present-value event series at lags of one to 24 quarters, 1984–2025. The blue dashed lines mark the pointwise 95 percent threshold under the null of no autocorrelation, and the orange dashed lines mark the Bonferroni-corrected 95 percent threshold that adjusts for testing 24 lags jointly.

Correlation with other shocks. I also examine whether the instrument is correlated with other identified shocks from the literature. Table C.2 reports the correlation between the series z_t and nineteen series from the literature, covering financial regulation, monetary policy, fiscal policy, uncertainty, oil, and trade. I find no evidence that the event series is correlated with any of the other identified shocks. None of the correlations in the table is significant at the 5% level. The largest correlation in absolute value is 0.24 for the narrative tariff series from [den Besten et al. \(2026\)](#) with a p -value of 0.13.

Importantly, the instrument is not correlated with measures of financial regulation. This provides supporting evidence that the event series is specifically measuring the safe asset demand channel induced by each announcement and that the series is not contaminated by overall changes in banking regulation. The financial regulation and financial deregulation indices of [Cascaldi-Garcia and Iacoviello \(2026\)](#) measure newspaper coverage of regulation being tightened or loosened in the financial sector, based on a large language model classification of articles from 1960 onward. The bank regulation news shock of [Drechsel and Miura \(2026\)](#) measures surprises in bank stock prices in narrow windows around Federal Reserve speeches on banking and its regulation. The financial regulation uncertainty index is the financial regulation category of the news-based policy uncertainty index of [Baker et al. \(2016\)](#). The event series is uncorrelated with each of these measures, with correlations below 0.05 in absolute value and p -values above 0.5. The largest values of the regulation measures from the literature occur around the financial crisis, quarters in which the event

series takes the value zero.

Shock	Source	ρ	p -value	Sample Period
<i>Financial regulation</i>				
Financial regulation	Cascaldi-Garcia and Iacoviello (2026)	0.00	0.95	1984Q1–2025Q2
Financial deregulation	Cascaldi-Garcia and Iacoviello (2026)	−0.02	0.77	1984Q1–2025Q2
Bank regulation	Drechsel and Miura (2026)	−0.01	0.93	1998Q1–2023Q2
Financial regulation uncertainty	Baker et al. (2016)	−0.04	0.58	1985Q1–2025Q2
<i>Monetary policy</i>				
US monetary policy	Bauer and Swanson (2023)	0.15	0.08	1988Q2–2023Q4
US monetary policy	Jarociński and Karadi (2020)	0.04	0.63	1990Q2–2023Q4
US central bank info	Jarociński and Karadi (2020)	−0.02	0.79	1990Q2–2023Q4
EU monetary policy	Jarociński and Karadi (2020)	0.15	0.14	1999Q1–2023Q3
EU central bank info	Jarociński and Karadi (2020)	0.01	0.94	1999Q1–2023Q3
<i>Fiscal</i>				
Exogenous tax changes	Romer and Romer (2010)	0.00	0.98	1984Q1–2007Q4
<i>Uncertainty</i>				
US policy uncertainty	Baker et al. (2016)	0.07	0.38	1984Q1–2025Q2
Gold prices	Piffer and Podstawski (2018)	−0.08	0.33	1984Q1–2025Q1
Equity market volatility	Baker et al. (2026)	0.10	0.21	1985Q1–2025Q2
<i>Oil</i>				
Oil supply news	Känzig (2021)	−0.07	0.34	1984Q1–2025Q2
Oil demand	Baumeister and Hamilton (2019)	0.02	0.80	1984Q1–2025Q2
Oil demand (consumption)	Baumeister and Hamilton (2019)	−0.01	0.85	1984Q1–2025Q2
Oil demand (inventory)	Baumeister and Hamilton (2019)	−0.04	0.65	1984Q1–2025Q2
Oil supply	Baumeister and Hamilton (2019)	0.12	0.13	1984Q1–2025Q2
<i>Trade</i>				
Tariffs	den Besten et al. (2026)	−0.24	0.13	1984–2024

Table C.2: Correlation with other shocks

Notes: This table reports the correlation between the instrument z_t and identified shocks and regulation measures from the literature over the overlapping sample in the last column. Monthly and daily series are summed to the quarterly frequency, and the annual tariff comparison instead sums the instrument within the calendar year. The bank regulation news shock of Drechsel and Miura (2026) is signed so that positive values correspond to news of tighter regulation.

C.3 Alternative constructions of the instrument

I examine various alternative methods to construct the event series instrument. I outline the methodology for three alternative constructions of the instrument below.

Table C.3 lists the baseline event series together with every alternative version constructed in the paper, and reports the correlation of each version with the baseline series z_t . In addition to the three alternative constructions of the instrument described above, I also show versions of the instrument that vary the relevant regulation parameters, the units, the scaling, and the set of events.

Orthogonalized instrument. The first alternative constructs versions of the event series that are orthogonal to the measures of general financial regulation. The construction follows the treatment of monetary policy surprises in [Miranda-Agrippino and Ricco \(2021\)](#) and [Bauer and Swanson \(2023\)](#), who regress the surprises on information available before each announcement and use the residuals as the instrument. The event series is zero by construction in quarters without an announcement, so I estimate the auxiliary regression on the announcement quarters only. For each announcement quarter t_e , I regress z_{t_e} on a constant and the value of the regulation measure in the quarter, W_{t_e} . The orthogonalized series subtracts the component of each announcement that the measure explains,

$$z_{t_e}^\perp = z_{t_e} - \hat{\delta} (W_{t_e} - \bar{W}), \quad (40)$$

where $\hat{\delta}$ is the estimated slope and $\bar{W}$ is the average of the measure across the announcement quarters, and takes the value zero in all other quarters. Subtracting the explained component around the mean leaves the average size of the announcements unchanged. I do not estimate the regression on the full sample, as the residual would then take nonzero values in the quarters without announcements, equal to the negative of the fitted value, and would load on the crisis quarters in which the regulation measures peak.

I use three sets of measures for the regulation measure W_{t_e} . The first is the financial regulation and financial deregulation indices of [Cascaldi-Garcia and Iacoviello \(2026\)](#), which span the full sample. The second is the financial regulation uncertainty index of [Baker et al. \(2016\)](#). The third is the bank regulation news shock of [Drechsel and Miura \(2026\)](#), which is available from 1998, with the announcements before that year keeping their original values. The measures explain little of the variation across announcements, and the three orthogonalized series correlate between 0.94 and 0.99 with the baseline series.

Principal-component instrument. The second alternative method replaces the present value as the rule that collapses each demand path into a single number. I stack the event-level demand paths, scaled by the aggregate total assets of U.S. commercial banks in the quarter preceding each event, into a matrix with one row per event and one column per quarterly horizon, holding each path at its terminal value beyond the end of its phase-in. I then compute the first principal component of this matrix, and use each event's score on the first component as its measure of induced demand. I do this without demeaning, so that an event with no news keeps a score of zero. The first component accounts for roughly 90 percent of the variation across the paths. I then aggregate across events within each quarter, and rescale the series to match the volatility of the baseline instrument series. The resulting series, z_t^{pca} , has a correlation of over 0.99 with the baseline series. This provides supporting evidence that the event series instrument is robust to varying the methodology to collapse

the induced demand paths into a single number for each event.

Sign-only instrument. The third alternative discards the magnitudes altogether, following Boer and Lütkepohl (2021) and den Besten et al. (2026). Each event with nonzero news receives a value of +1 or −1 according to the direction of its induced safe asset demand, and the values are summed within each quarter to give the series z_t^{sign} . The identifying variation then comes only from the dates and directions of the announcements. This sign-only series has a correlation of 0.71 with the baseline series.

Version of the event series	Correlation with z_t
<i>Baseline</i>	
Present value, 38 exogenous events	1.000
<i>Alternative methods</i>	
Orthogonalized, financial regulation and deregulation indices	0.946
Orthogonalized, financial regulation uncertainty index	0.941
Orthogonalized, bank regulation news shock	0.986
Principal component	0.999
Sign only	0.709
<i>Parameters</i>	
Discount factor $\beta = 1.00$	0.999
Discount factor $\beta = 0.95$	0.973
Capital rebalancing share $\varphi = 0.10$	0.983
Capital rebalancing share $\varphi = 0.30$	0.988
Leverage response $\psi = 0.20$	0.994
Leverage response $\psi = 0.40$	0.995
<i>Units and scaling</i>	
Treasury securities only	0.866
Level 1 high-quality liquid assets only	0.850
Scaled by nominal GDP	0.996
Unscaled, billions of dollars	0.959
<i>Event subsets</i>	
Final rules only	0.390
Proposals only	0.367
Basel Committee announcements only	0.880
Excluding LCR events	0.765
Excluding NSFR events	0.875
Excluding leverage events	0.942
Excluding capital events	0.924
Excluding scope events	0.977
Events before 2020	0.958
Events after 1990	0.957

Table C.3: Versions of the event series

Notes: This table lists the baseline event series z_t and its alternative versions. The last column is the correlation of each version with the baseline series.

D Econometric framework

In this section, I explain the external instruments approach to derive the structural impact vector.

Recall the reduced-form VAR from Section 5:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \mathbf{B}_1 \mathbf{y}_{t-1} + \dots + \mathbf{B}_p \mathbf{y}_{t-p} + \boldsymbol{\Gamma} \mathbf{d}_t + \mathbf{u}_t, \quad (41)$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables whose first element is the safe asset share of bank assets, $\boldsymbol{\alpha}$ is an $n \times 1$ vector of constants, $\mathbf{B}_1, \dots, \mathbf{B}_p$ are $n \times n$ coefficient matrices (with p denoting the lag length), $\mathbf{d}_t$ is the vector of pandemic dummies with coefficient matrix $\boldsymbol{\Gamma}$, and $\mathbf{u}_t$ is the $n \times 1$ vector of reduced-form innovations with covariance matrix $\boldsymbol{\Sigma}$. The event series z_t serves as the instrument for the regulatory safe asset demand shock $\varepsilon_{1,t} = \varepsilon_t^{SA}$.

I make the following assumptions regarding the relationship between the reduced-form innovations, structural shocks, and the instrument:

$$\mathbf{u}_t = \mathbf{S} \boldsymbol{\varepsilon}_t, \quad (42)$$

$$\mathbb{E}[z_t \varepsilon_{1,t}] = \lambda \neq 0, \quad (43)$$

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] = \mathbf{0}, \quad (44)$$

corresponding to the invertibility assumption of Equation 12, the relevance assumption of Equation 14, and the exogeneity assumption of Equation 13, as discussed in the paper. Under these assumptions, $\mathbf{s}_1$ is identified up to sign and scale (Mertens and Ravn, 2013; Stock and Watson, 2018). Partitioning the structural impact matrix as $\mathbf{S} = \begin{pmatrix} \mathbf{s}_1 & \mathbf{S}_{2:n} \end{pmatrix}$, where $\mathbf{S}_{2:n}$ collects the remaining $n - 1$ columns,

$$\mathbb{E}[z_t \mathbf{u}_t] = \mathbb{E}[z_t \mathbf{S} \boldsymbol{\varepsilon}_t] = \mathbf{S} \mathbb{E}[z_t \boldsymbol{\varepsilon}_t] = \begin{pmatrix} \mathbf{s}_1 & \mathbf{S}_{2:n} \end{pmatrix} \begin{pmatrix} \mathbb{E}[z_t \varepsilon_{1,t}] \\ \mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] \end{pmatrix} = \begin{pmatrix} \mathbf{s}_1 & \mathbf{S}_{2:n} \end{pmatrix} \begin{pmatrix} \lambda \\ \mathbf{0} \end{pmatrix} = \mathbf{s}_1 \lambda. \quad (45)$$

The above relationship can be partitioned into the following:

$$\mathbb{E}[z_t \mathbf{u}_t] = \begin{pmatrix} \mathbb{E}[z_t u_{1,t}] \\ \mathbb{E}[z_t \mathbf{u}_{2:n,t}] \end{pmatrix} = \begin{pmatrix} s_{1,1} \lambda \\ \mathbf{s}_{2:n,1} \lambda \end{pmatrix}, \quad (46)$$

where $s_{1,1}$ is the first element of $\mathbf{s}_1$ and $\mathbf{s}_{2:n,1}$ collects the remaining $n - 1$ elements. Then,

the vectors can be rescaled to obtain

$$\begin{pmatrix} 1 \\ \mathbb{E}[z_t \mathbf{u}_{2:n,t}] / \mathbb{E}[z_t u_{1,t}] \end{pmatrix} = \begin{pmatrix} 1 \\ \mathbf{s}_{2:n,1} / s_{1,1} \end{pmatrix} = \begin{pmatrix} 1 \\ \tilde{\mathbf{s}}_{2:n,1} \end{pmatrix}, \quad (47)$$

where $\tilde{\mathbf{s}}_{2:n,1} \equiv \mathbf{s}_{2:n,1} / s_{1,1}$. Note that this requires $\mathbb{E}[z_t u_{1,t}] \neq 0$, which holds if and only if $\lambda \neq 0$ and $s_{1,1} \neq 0$.

Once $\mathbf{s}_1$ is identified up to scale, the scale of $\mathbf{s}_1$ can be normalized subject to

$$\mathbf{\Sigma} = \mathbf{S} \mathbf{\Omega} \mathbf{S}', \quad (48)$$

where $\mathbf{\Omega} = \text{diag}(\sigma_{\varepsilon_1}^2, \dots, \sigma_{\varepsilon_n}^2)$ is the covariance matrix of the structural shocks. In this paper, I set $\sigma_{\varepsilon_1}^2 = 1$, so that a unit positive value of ε_t^{SA} corresponds to a one-standard-deviation regulatory safe asset demand shock. Writing $\mathbf{v} \equiv (1, \tilde{\mathbf{s}}'_{2:n,1})'$ so that $\mathbf{s}_1 = s_{1,1} \mathbf{v}$, Equation 48 implies $\mathbf{s}'_1 \mathbf{\Sigma}^{-1} \mathbf{s}_1 = 1$, which yields $s_{1,1}^2 = (\mathbf{v}' \mathbf{\Sigma}^{-1} \mathbf{v})^{-1}$, resulting in the following structural impact vector:

$$\mathbf{s}_1 = \begin{pmatrix} s_{1,1} \\ \tilde{\mathbf{s}}_{2:n,1} s_{1,1} \end{pmatrix}. \quad (49)$$

This scales the structural impact vector $\mathbf{s}_1$ such that a unit positive value of $\varepsilon_{1,t}$ has an effect of magnitude $s_{1,1}$ on $y_{1,t}$, and I set the sign of $s_{1,1}$ such that a positive shock raises the safe asset share on impact.

To obtain the sample analogue of $\mathbf{s}_1$, denoted as $\hat{\mathbf{s}}_1$, one can run the regression of Equation 15 via equation-by-equation two-stage least squares using z_t as the instrument for $y_{1,t}$. The lag polynomial $\tilde{\mathbf{B}}(L)$ has the same number of lags as the reduced-form VAR. The point estimates of this regression are equivalent to running the regression of Equation 16 using z_t as the instrument for $\hat{u}_{1,t}$. However, the specification of Equation 15 yields the correct large-sample, strong-instrument standard errors (Stock and Watson, 2018). Using the estimated structural impact vector, one can impose the desired normalization to obtain a normalized estimate of the structural impact vector $\hat{\mathbf{s}}_1$.

Using the structural impact vector $\hat{\mathbf{s}}_1$ and the coefficient matrices $\hat{\mathbf{B}}_1, \dots, \hat{\mathbf{B}}_p$ from the reduced-form VAR estimates, one can estimate impulse response functions, the structural shock series of Equation 17, and other estimates of interest.

E Additional empirical results

In this section, I provide additional empirical results of the paper. In Section E.1, I conduct a number of exercises that examine whether the results from Section 6.1 are robust along a number of dimensions. In Section E.2, I provide additional results that complement the results on the transmission channels from Section 6.2.

E.1 Robustness of baseline results

I conduct a number of robustness checks with respect to the baseline results from Section 6.1.

Instrument construction method and event set. I examine whether the results are robust to the methodology of constructing the instrument and the event set used to construct the instrument. I estimate impulse responses using various versions of the instrument discussed in Sections 3 and C.3. Figure E.1 shows the results.

The estimated variants of the instrument are as follows. The PCA variant corresponds to the instrument constructed by taking the first principal component of the matrix of demand paths implied across all of the exogenous events. The methodology is described in detail in Section C.3. The $\beta = 0.95$ uses an alternative value of the discount rate when taking the present value changes of induced safe asset demand. The orthogonalized variants (denoted by 1, 2, and 3) correspond to the instruments that are constructed by subtracting the component of each announcement that is explained by measures of general financial regulation from the literature. I describe the methodology in Section C.3. The versions denoted 1, 2, 3 correspond to the instrument that is orthogonalized with respect to the financial regulation and deregulation measures from Cascaldi-Garcia and Iacoviello (2026), the financial regulation uncertainty measure from Baker et al. (2016), and the bank regulation measure from Drechsel and Miura (2026), respectively. The restricted event variants (denoted by 1 and 2) correspond to the instruments constructed with a limited set of events. Otherwise, the method used to construct the instrument is identical to the baseline analysis. The versions denoted 1 and 2 use events before 2020 and events after 1990, respectively.

The estimated impulse responses are largely consistent across variants of the instrument. Almost all of the estimates are inside the confidence bands of the baseline estimation. The impulse responses using many of the variants are nearly indistinguishable from the baseline estimates.

In addition to the instrument variants discussed above, I estimate the impulse responses using a sign-only variant. This corresponds to the version of the instrument that is constructed by assigning +1 or −1 for each of the 38 exogenous events. I report the signs of

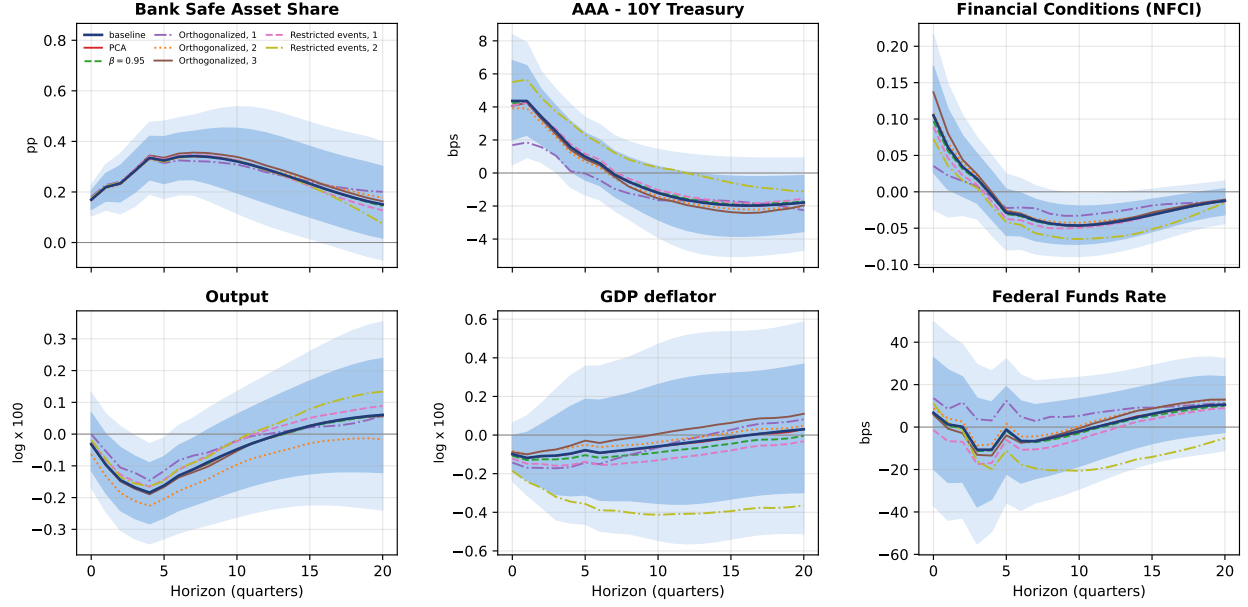


Figure E.1: Impulse responses to a regulatory safe asset demand shock

Notes: This figure shows the impulse responses to a regulatory safe asset demand shock estimated using the external instruments approach using alternative versions of the instrument. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively.

each event in Table A.1. This approach only requires that the timing and direction of the regulatory announcements are plausibly exogenous, and does not impose any assumptions on the exogeneity of the magnitudes. Figure E.2 shows the results. The estimated impulse responses are qualitatively consistent with the baseline estimates. The bank safe asset share has a persistent effect, while the funding advantage and financial conditions both increase at short horizons and show negative effects at longer horizons. The shock is contractionary with a similar magnitude at the trough of responses. The key difference between this version and the baseline estimates is that prices increase significantly. The fed funds rate also increases significantly at longer horizons, which is in contrast with the insignificant responses in the baseline version. However, the shape of the responses and the insignificant effects at shorter horizons are consistent with the baseline estimates.

LP-IV. To test robustness with respect to the identification strategy, I estimate the responses of the six baseline variables using the LP-IV method with the event series as an instrument. I estimate the impulse responses using the smooth local projection estimator from Barnichon and Brownlees (2019).

For each variable i and horizon h , I estimate

$$y_{i,t+h} = \alpha_h^i + \theta_h^i s_t + \gamma_h^{ij} \mathbf{w}_t + \xi_{i,t,h}, \quad (50)$$

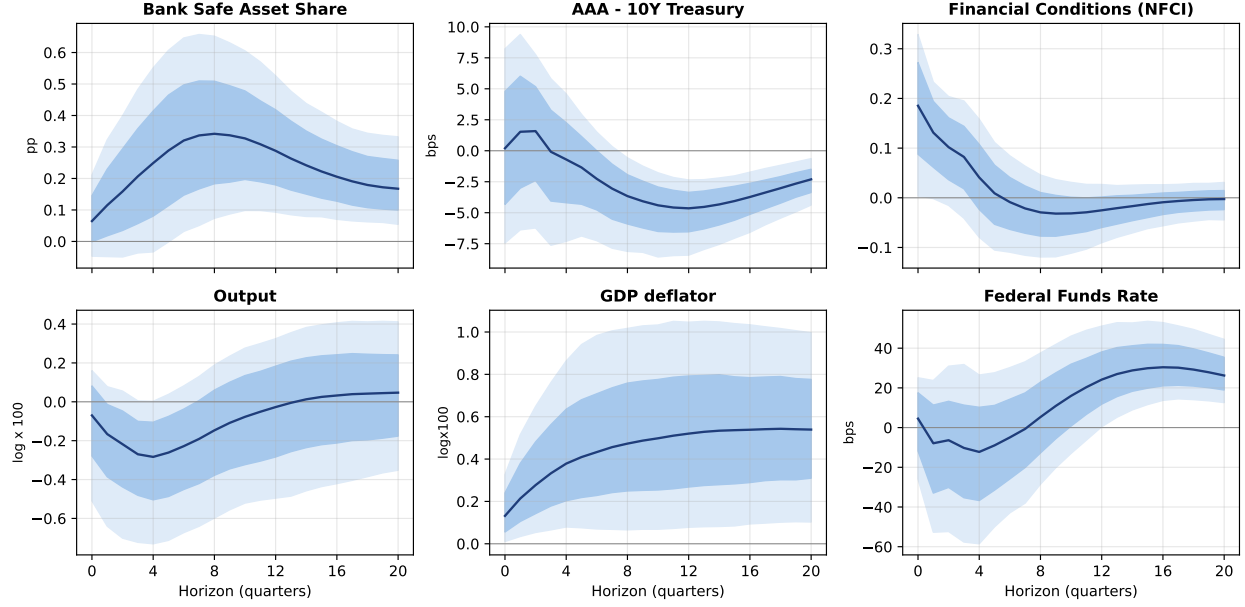


Figure E.2: Impulse responses to a regulatory safe asset demand shock

Notes: This figure shows the impulse responses to a regulatory safe asset demand shock estimated using the external instruments approach with the sign-only instrument. The shock is scaled so that the peak response of the bank safe asset share equals the peak response in Figure 4. The solid lines represent the bias-corrected point estimates (Kilian, 1998); the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, holding the scaling of the shock fixed across replications.

where s_t is the safe asset share of bank assets, instrumented with the event series, and $\mathbf{w}_t$ contains a linear trend, four lags of the six baseline variables, and dummies for the COVID quarters. The coefficient θ_h^i is the response of variable i at horizon h per unit impact response of the safe asset share. The smooth estimator restricts θ_h^i to a cubic B-spline in h with a penalty on its second differences. I set the penalty to six effective degrees of freedom for each variable. I also report the non-smoothed version of estimates. The sample runs from 1984Q1 to 2025Q2. Note that the sample is longer in the baseline analysis, as I estimated the reduced-form VAR with an extended sample, while using the same sample period for the instrument series. I conduct inference using a block wild bootstrap with 10,000 replications. Note that the impulse responses of the baseline analysis using SVAR-IV and the LP-IV do not have identical responses on impact, as they differ in the sample period and the specification (LP-IV uses linear trend).

Figure E.3 shows the results. I scale the impulse responses such that the magnitude of the peak safe asset share response is the same as Figure 4. The safe asset share rises on impact with a persistent effect that is statistically significant at all estimated horizons. The funding advantage increases in the first year, with a peak response of 2 basis points, followed by negative responses. The initial responses are smaller relative to the baseline analysis, while the negative responses at longer horizons are much bigger. Nonetheless, the estimates

are still consistent with the pattern of initial increases in the funding advantage, followed by decreases at longer horizons. Financial conditions also show muted insignificant responses on impact in comparison to the significant tightening estimated in the baseline analysis. The easing of financial conditions at longer horizons is statistically significant and consistent with the baseline analysis. Output declines temporarily with a hump-shaped response, with a trough of -0.2 percent. The contractionary effect is statistically significant from the second to the ninth quarter, matching the timing and the magnitude of the responses estimated in the baseline analysis.

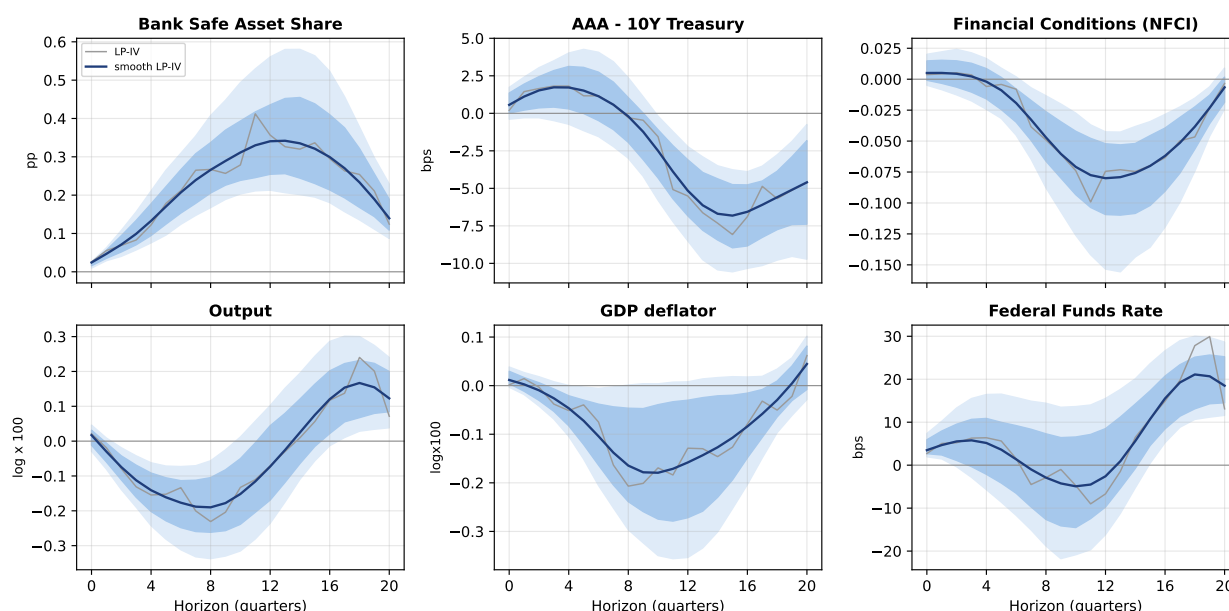


Figure E.3: Impulse responses to a regulatory safe asset demand shock (LP-IV)
Notes: This figure shows the impulse responses to a regulatory safe asset demand shock estimated using the LP-IV approach. The solid line is the smoothed estimate, and the thin gray line is the non-smoothed estimate. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively.

E.2 Responses of additional variables

In addition to the transmission channels discussed in Section 6.2, I examine the responses of a number of additional channels. I estimate impulse responses to additional variables using local projections. I use the same methodology and specification described in Section 5.2.

Financial conditions decomposition. Figure E.4 decomposes the NFCI response of Section 6.1 into the index's leverage, credit, and risk subindices. The initial tightening and subsequent easing appear in each subindex, with the leverage subindex having the largest and most persistent easing. This is consistent with the balance-sheet interpretation of the transmission.

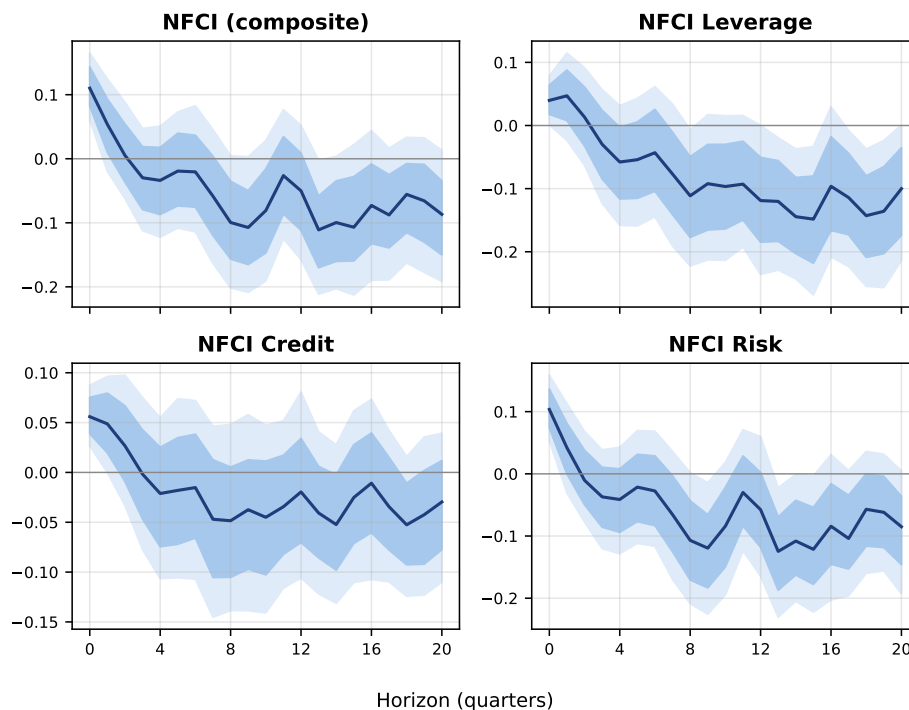


Figure E.4: Local projections: NFCI subindices

Notes: This figure shows local-projection responses of the NFCI and its leverage, credit, and risk subindices to the identified regulatory safe asset demand shock, standardized to unit variance. Four lags of the outcome; moving-block residual bootstrap. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively.

Exchange rates. Figure E.5 shows the responses of variables related to exchange rates, estimated using local projections. I examine the responses to the Real Broad Dollar Index and Nominal Dollar Index. Due to data availability, I construct each of the two series by combining two separate indices that are the most similar to each other in order to have a continuous series from 1973 to 2025. The real index combines the discontinued real broad

index (goods, 1973–2019) with the current real broad index (goods and services, 2006 onward). I use the current real broad index from 2006 onwards. The nominal index combines the discontinued major-currencies index to the current nominal broad index in the same way.

The dollar appreciates by about a quarter of a percent on impact and by around 0.6 percent two quarters after the shock, with statistically significant effects at the 90 percent level. The appreciation fades within a year, with statistically insignificant responses for longer horizons. The appreciation is the exchange-rate counterpart of the response to the funding advantage.

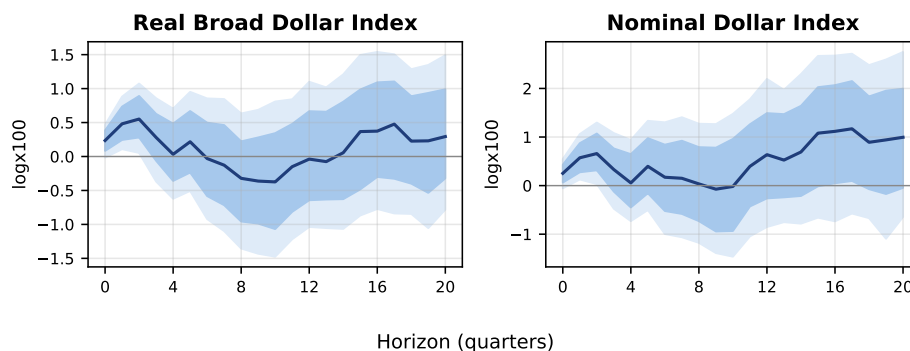


Figure E.5: Local projections: dollar indices

Notes: This figure shows local-projection responses of real and nominal trade-weighted dollar indexes to the identified regulatory safe asset demand shock, standardized to unit variance. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively. A positive response corresponds to an appreciation.

Credit decomposition. Figures E.6 and E.7 decompose the credit response of Section 6.2 by lender and by instrument, using the BIS credit series and the Z.1 flow-of-funds aggregates from FRED.

The estimates show that bank credit to the private nonfinancial sector falls significantly while nonbank credit does not. This provides supporting evidence that the shock is identifying changes in regulatory safe asset demand that specifically operate through banks. The banks respond the most because they are directly affected by the changes in regulations. Nonbank financial institutions also respond by decreasing credit, but at a lower magnitude. This is consistent with nonbank financial institutions experiencing the indirect effects of bank regulations, as they rely heavily on banks for funding. Examining the responses across corporate debt securities, corporate loans, and home mortgages, the corporate loans experience statistically significant declines, while corporate debt securities and home mortgages do not show significant responses.

The estimates examining the responses across types of loans show that commercial and industrial loans decline the most, decreasing by 2.3 percent at the trough of the responses.

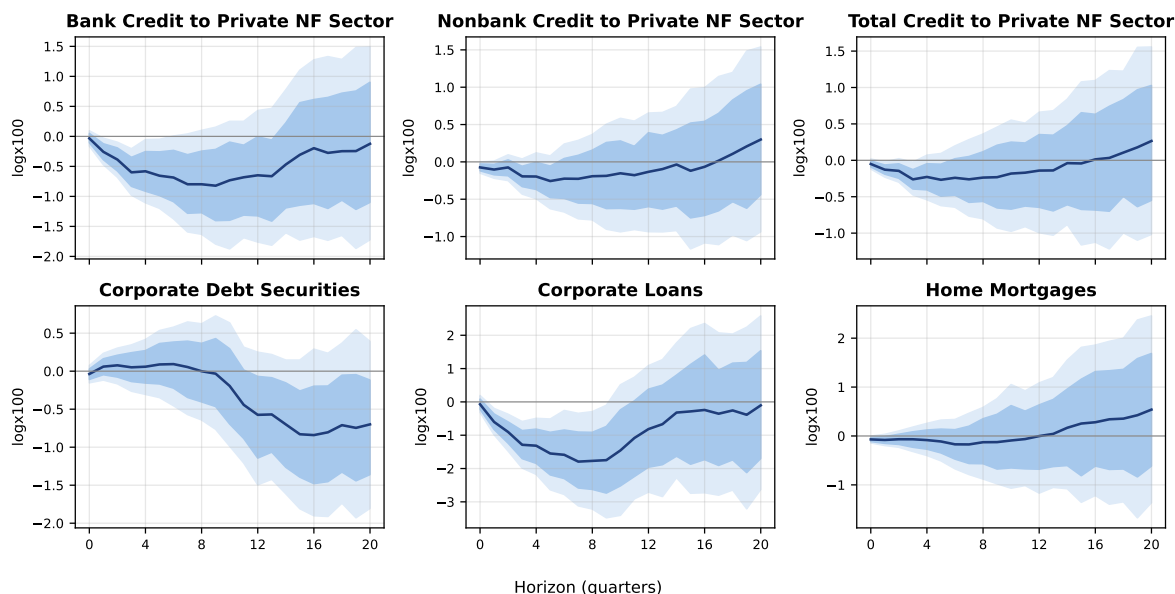


Figure E.6: Local projections: credit by lender and instrument

Notes: This figure shows local-projection responses of credit aggregates to the identified regulatory safe asset demand shock, standardized to unit variance. Bank and nonbank credit to the private nonfinancial sector are the BIS series from FRED, with nonbank credit the difference between total and bank credit. The corporate debt securities and loans are Z.1 aggregates for nonfinancial corporate business. Home mortgages are the Z.1 household aggregate. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively.

Consumer loans also experience statistically significant declines, although the effect is lower in magnitude relative to commercial and industrial loans. Real estate loans respond very little.

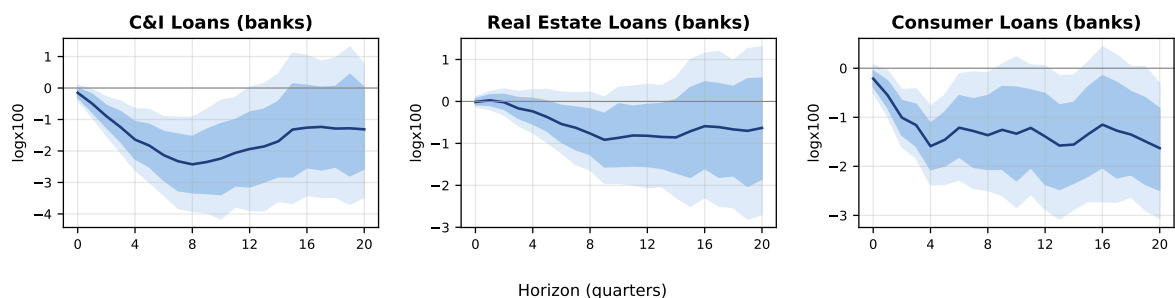


Figure E.7: Local projections: bank loan components

Notes: This figure shows local-projection responses of the H.8 bank loan components. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively.

Federal debt measures. Figure E.8 compares measures of the federal debt response. The baseline analysis in Section 6.2 uses the par value of gross federal debt over GDP. The market-value measure from the Dallas Fed rises slightly faster at short horizons, as the decline in

yields raises the price of outstanding debt. Debt held by private investors over GDP shows the similar responses in terms of shape, with slightly lower magnitudes, in comparison to the responses for gross debt.

I decompose the response of the debt-to-GDP ratio by examining the responses to the numerator and denominator separately. The estimates show that the increase in the debt-to-GDP ratio is driven mostly by the increase in debt levels. Both the par and market values of debt increase significantly, with a peak response of 1.8 percent for the par value of debt. In contrast, nominal GDP decreases by less than 0.5 percent at the trough of responses and subsequently recovers. Cumulating the primary-deficit response shown in Section 6.2 accounts for roughly half of the peak increase in the par value of debt, with the remainder attributable to the timing differences between the deficit flows and debt stock, as well as any fluctuations in net issuance that are not driven by the budget.

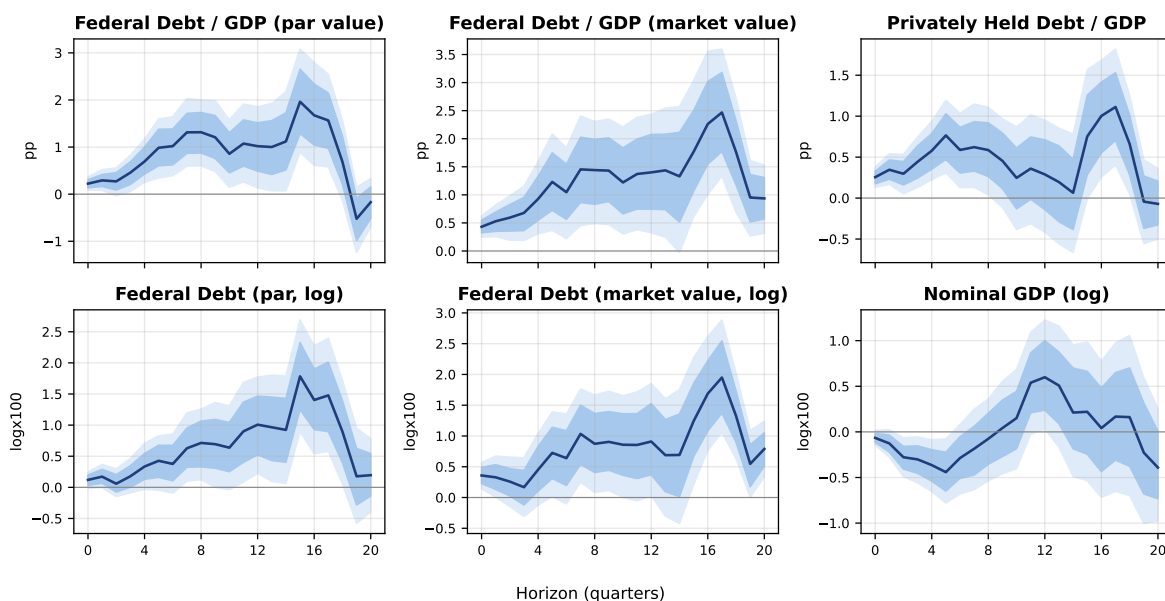


Figure E.8: Local projections: federal debt measures

Notes: This figure shows local-projection responses of federal debt measures to the identified regulatory safe asset demand shock, standardized to unit variance. The dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively.

F Model: additional details

This appendix provides additional details on the model presented in Section 7.

Timing conventions. The model uses the end-of-period stock convention, following [Gertler and Kiyotaki \(2010\)](#) and [Gertler and Karadi \(2011\)](#), where banks fund end-of-period asset positions with end-of-period deposits and net worth. S_t , K_t^b , D_t , and E_t are stocks outstanding at the end of quarter t . The balance-sheet identity and the regulatory constraint are defined in terms of the market value at time t . Production in quarter t uses the capital selected/installed in $t - 1$, so $Y_t = ZK_{t-1}^{\alpha_k}N_t^{1-\alpha_k}$.

The requirement binds on the current balance sheet at current prices, so valuation is affected by prices within the quarter. Bank net income realizes current returns on lagged positions, $\Pi_t = r_{t-1}^s S_{t-1} + (R_t^k - 1)q_{t-1}K_{t-1}^b - r_{t-1}^d D_{t-1}$, so equity is predetermined in its stock components. A capital loss in quarter t affects net income within the quarter, following the timing from [Gertler and Karadi \(2011\)](#). Dating the constraint on beginning-of-period stocks instead would just delay the impact response of the portfolio by one quarter and remove the within-quarter valuation channel. Otherwise, the responses at horizons beyond the announcement quarter would be unaffected by the difference in the timing conventions.

Equilibrium conditions. The precise equilibrium conditions of the model are as follows. Given a path for the regulatory weight $\{\kappa_t\}$ and initial conditions $(K_{-1}, S_{-1}, E_{-1}, W_{-1})$, the equilibrium is characterized by the set of paths for:

- Quantities $\{C_t, N_t, Y_t, I_t, K_t, S_t, D_t, B_t, E_t\}$;
- Prices $\{W_t, mc_t, q_t, \pi_t, \pi_t^w, i_t, r_t, r_t^s, r_t^d, s_t^d, s_t^s, s_t, s_t^k\}$; and
- Multiplier $\{\mu_t\}$

such that the following conditions hold:

- Household block: Euler equation on the policy rate [\(21\)](#) and the deposit spread schedule [\(34\)](#) with the deposit rate $r_t^d = r_t + s_t^d$, and the safe asset market requires the supply curve [\(35\)](#) with the safe asset rate $r_t^s = r_t - s_t^s$, so that the spread in the bank's conditions is $s_t = s_t^d + s_t^s$.
- Labor block: wage Phillips curve [\(23\)](#) and the identity linking the real wage to wage and price inflation,

$$W_t = W_{t-1} \frac{1 + \pi_t^w}{1 + \pi_t}.$$

- Production block: production function $Y_t = ZK_{t-1}^{\alpha_k}N_t^{1-\alpha_k}$, the price Phillips curve (24), and the factor-price conditions

$$W_t = (1 - \alpha_k) mc_t \frac{Y_t}{N_t}, \quad r_t^K = \alpha_k mc_t \frac{Y_t}{K_{t-1}},$$

where r_t^K is the rental rate of capital.

- Capital block: accumulation identity $K_t = (1 - \delta)K_{t-1} + I_t$, the price of capital $q_t = 1 + \phi_I(K_t/K_{t-1} - 1)$, and the realized gross return on capital claims

$$R_t^k = \frac{r_t^K + (1 - \delta) q_t}{q_{t-1}}.$$

- Bank block: first order conditions (29)–(30), the balance sheet constraint (26) with the bank holding the entire capital stock, $K_t^b = K_t$, the regulatory constraint (27) holding with equality, and the equity law of motion (28) with profits $\Pi_t = r_{t-1}^s S_{t-1} + (R_t^k - 1) q_{t-1} K_{t-1} - r_{t-1}^d D_{t-1}$.
- Policy block: Taylor rule (37), the Fisher equation $1 + r_t = (1 + i_t)/(1 + \mathbb{E}_t \pi_{t+1})$. The government budget (38) determines the lump-sum tax, and the stock outstanding equals the bank's holdings, $B_t^g = S_t$.
- Goods market clearing closes the system,

$$Y_t = C_t + I_t + \Psi_t,$$

where Ψ_t reflects the capital and portfolio adjustment costs.

Steady state. I characterize the steady state as follows.

First, the quarterly policy rate $r = 1/\beta - 1$. The safe asset rate is equal to r , as the scarcity premium is zero under the steady state. The policy rate and the safe asset rate, along with the targeted pair $(\bar{s}, \bar{\chi})$, pin down $\bar{s}^k$ and $r^d = r + \bar{s}$. The steady-state deposit spread $\bar{s}^d$ is equal to $\bar{s}$ (as the scarcity premium is zero under steady state). Since $\bar{R}^k = 1 + r^d + \bar{s}^k$, this pins down r^K and K/Y . The normalizations $Y = N = 1$ pin down Z and ψ_N .

The steady state bank balance sheet variables (S, D, E) are characterized using the targeted safe asset share and the leverage ratio D/E . In the regulatory block, the binding constraint fixes $\varrho = \Upsilon/D$, and the two FOCs (29)–(30) jointly determine $(\bar{\kappa}, \bar{\mu})$ from the targeted spreads. The safety preference of the household centers the hazard at the steady-state ratio, with $\Phi = 1/2$ at $\ell = \bar{\ell}$, so equation (32) maps $\varphi_D \gamma_0 = -s_0/[(1 + \bar{r})\bar{C}^\sigma]$ with

$s_0 = \bar{s} - \xi/2$ and $\varphi_D \eta = \xi/[(1 + \bar{r})\bar{C}^\sigma]$. The schedule's slope is $b = \xi/(4\sigma_s)$, where a persistent one-percentage-point rise in the safe asset share lowers the deposit spread by roughly 8 annual basis points. Because the estimated loss scale exceeds twice the steady-state spread, the implied s_0 is negative and the implied γ_0 is positive, which corresponds to a constant liquidity value of deposits. The counterfactuals never leave the range in which the marginal non-pecuniary value of deposits $\gamma(\ell)$ is negative, and the boundary of that range is exactly the capacity boundary of Section 7.4.1 in the Laffer curve exercise when the deposit spread reaches zero.

Finally, $\delta_e = \zeta \bar{\Pi}/E$ keeps D/E stationary. The slope of the supply of safe assets, θ_S , does not enter the steady state, since the premium is zero at the calibrated holdings.

Solution. The model is solved in sequence space (Auclert et al., 2021), with the unknown paths (C, N, π, K, S, E) , joined by the real wage under sticky wages, set against the corresponding targets (the Euler equation on the policy rate, the price and wage Phillips curves, goods clearing, valuation, the enforced requirement, equity accumulation). The deposit first-order condition is embedded in the spread schedule (34) and the supply of safe assets in the premium (36), so both hold by construction.

The announcement path uses the mixed version, where a fraction ω binds immediately and the remainder is phased-in linearly over eight quarters. This mixed version of the path is revealed as news at $t = 0$.

The counterfactual steady states of Section 7.4.1 are solved exactly by continuation in κ . Figure F.1 shows the counterfactual transition of Section 7.4.1 for additional variables (inflation and policy rate).

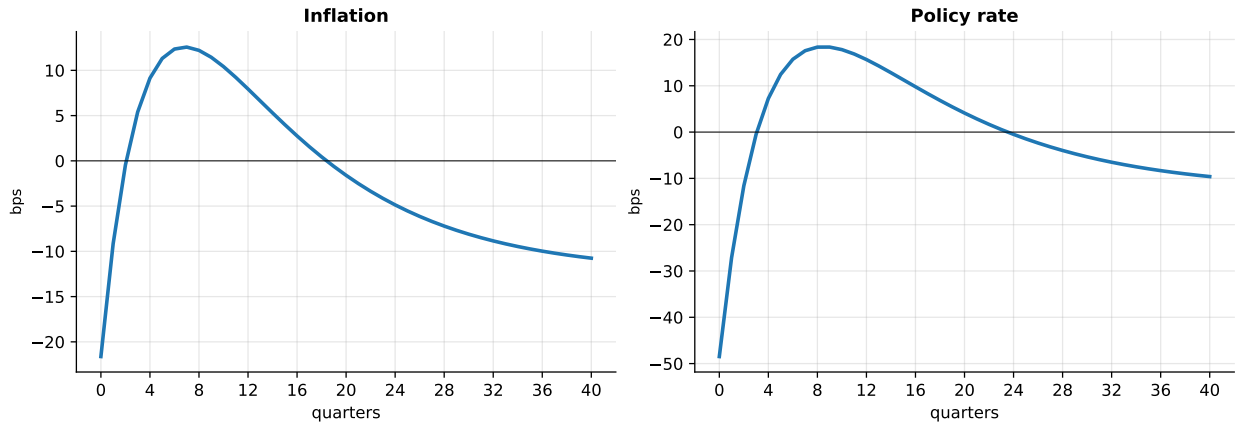


Figure F.1: Counterfactual transition: inflation and the policy rate

Notes: This figure shows the transition paths of inflation and the policy rate following the unanticipated permanent increase in the regulatory weight sized to induce \$250 billion of long-run safe asset accumulation. This figure complements Figure 10. Both panels are in annualized basis points.

Model estimation and sensitivity. I note some relevant details of the model estimation below.

The hazard dispersion σ_s is a pure normalization, since rescaling (ξ, σ_s) at a fixed slope $\xi/(4\sigma_s)$ leaves the minimized objective unchanged, so only the local slope of the spread schedule is identified. The equity retention rate is weakly identified, with the objective moving from 16.7 at $\zeta = 0.5$ to 17.8 at $\zeta = 0.3$ and 16.9 at $\zeta = 0.7$. As the objective changes very little across a wide range of the equity retention rate, I set ζ at 0.5, which is close to the minimum of the objective.

I set $\alpha = 0.75$, as it is close to the linear benchmark while remaining comfortably inside the range in which the model is well behaved. The requirement classes that the constraint aggregates, namely risk weights, liquidity coverage, and leverage exposure, are each linear in exposures. Therefore, there is empirical support for the α to be close to the linear end of the admissible range. The exactly linear limit itself does not provide an interior solution, which is the main reason for setting $\alpha = 0.75$. Re-estimating the dynamic parameters at $\alpha \in \{0.5, 0.6, 0.65, 0.7, 0.8, 0.85\}$ moves the objective between 16.1 and 17.0, against 16.7 at the fixed value. Across the estimated range the re-estimated models deliver the same qualitative counterfactual conclusions. For example, the calibrations using α ranging from 0.5 to 0.85 estimate that the calibrated model collects between 95 and nearly 100 percent of the maximum sustainable interest saving in the Laffer curve exercise.

I also find that the impulse response matching exercise is robust across the horizons used for estimation. I re-estimate the parameters using horizons zero through fourteen, following [Christiano et al. \(2015\)](#). This leaves all of the parameter estimates essentially unchanged. The portfolio transaction cost moves the most from 0.033 to 0.024.

Decomposing mechanisms. Figures [F.2](#) and [F.3](#) replicate figures from Section [7.3](#) that show the model fit with two variants that remove some of the model features. The first variant, labeled no wage rigidity, is the adjustment-cost model with flexible wages. The parameters are re-estimated without the wage rigidity. It matches the portfolio and the funding advantage nearly as well as the estimated model, and its deflation is deeper and closer to the estimated deflator response, but it delivers less than half the output decline. The second variant, labeled simple model, additionally removes the portfolio friction, imposing the requirement exactly on a frictionless portfolio with flexible wages. This version fails to match any of the variables well, as the entire economy adjusts much faster, with little to no effects on the funding advantage or output.

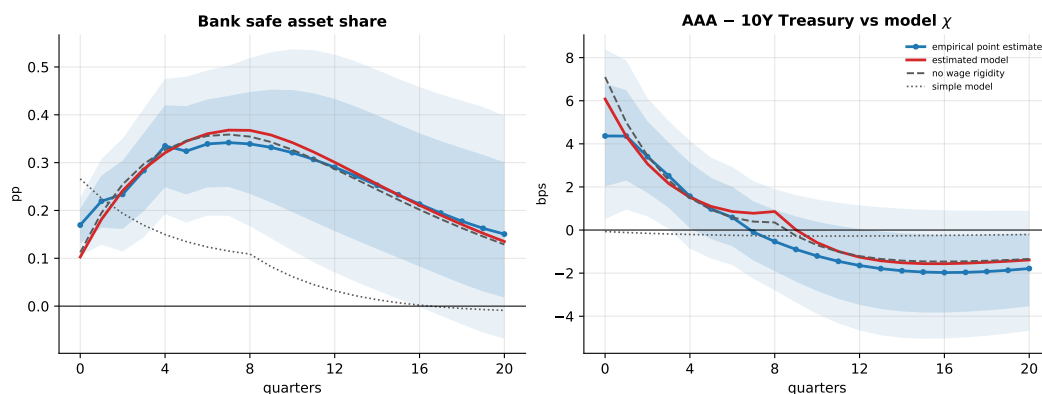


Figure F.2: Model variants: safe asset share and funding advantage

Notes: This figure overlays the estimated model and the two variants on the empirical point estimates of Figure 4. The variant labeled no wage rigidity is the adjustment-cost model with flexible wages, and the simple model has flexible wages and no portfolio adjustment costs.

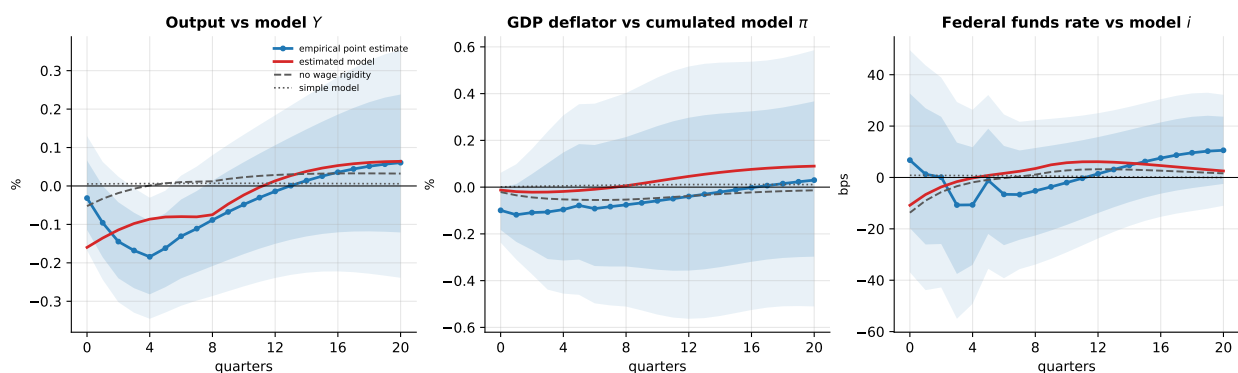


Figure F.3: Model variants: output, prices, and policy rate

Notes: This figure overlays the estimated model and the two variants on the empirical point estimates of Figure 4. The variant labeled no wage rigidity is the adjustment-cost model with flexible wages, and the simple model has flexible wages and no portfolio adjustment costs.

G Model: portfolio adjustment frictions

The estimated model of Section 7 contains a transaction cost on changes in the bank's safe asset holdings. This appendix describes the friction. The friction leaves every steady state unchanged by construction, so all results related to the long-run results are unaffected by this friction.

The bank pays a quadratic transaction cost on purchases beyond those that replace the securities maturing in the quarter. With gross purchases $F_t = S_t - (1 - \delta_S)S_{t-1}$ and a fraction δ_S of last quarter's portfolio maturing, the costly flow is $F_t - \delta_S S_{t-1} = S_t - S_{t-1}$, the net change in holdings,

$$\Psi_t^S = \frac{\phi_S}{2} \hat{f}_t^2 \bar{S}, \quad \hat{f}_t = \frac{S_t - S_{t-1}}{\bar{S}}, \quad (51)$$

a real resource cost subtracted from the bank's net income and from goods market clearing. This is the capital adjustment cost of Hayashi (1982) applied to a securities stock, with the same form as the cost that the model places on physical capital. This penalizes changes in the stock of holdings, so the runoff rate δ_S does not appear in the model.

The safe asset position is then a dynamic choice whose first-order condition includes the adjustment-cost terms:

$$s_t = \mu_t \left[\kappa_t (\Upsilon_t / S_t)^{1-\alpha} - \varrho \right] - \phi_S \hat{f}_t + \beta \phi_S \hat{f}_{t+1}. \quad (52)$$

The part of the equation in brackets is the net regulatory premium of the simple model's condition (29). The last two terms are today's marginal transaction cost and the discounted saving from buying less next quarter, discounted at β . Solving forward, abnormal purchases equal the discounted sum of future net regulatory premia. At $\phi_S = 0$ the condition collapses to condition (29). At any steady state holdings are constant, so $\hat{f}_t$ and the gap are zero, meaning that the steady states are unaffected by this friction.

This portfolio adjustment friction is similar to the holding costs that limit arbitrage in segmented-market models of the term structure and of asset purchases (Andrés et al., 2004; Chen et al., 2012; Gertler and Karadi, 2013). In such models, households pay a cost of holding long-term bonds away from a benchmark position. In this model, the cost falls on the bank and on changes in its holdings.

With adjustment costs, the bank cannot be exactly at the binding regulatory portfolio constraint in each period. Therefore, the constraint is priced instead of being imposed with equality. The multiplier becomes a steep increasing function of the violation,

$$\mu_t = \bar{\mu} \exp(\psi(\varrho D_t - \Upsilon_t) / \bar{D}), \quad (53)$$

where $\bar{\mu}$ is equal to the multiplier of the exactly imposed constraint. This is the soft-

constraint device from [Payne and Szőke \(2025\)](#), who approximate the multiplier on their constraint by a power of the ratio of required to actual backing with curvature ϖ in their paper. Their approximation and the formulation in my model coincide to first order with their $\varpi - 1$ corresponding to my $\psi\rho$. Similarly, [Gerali et al. \(2010\)](#) develop a banking model with a quadratic cost on deviations of the bank capital ratio from its regulatory target.

Parameters. I set the penalty steepness ψ to be 200. This implies that a violation of the regulatory portfolio constraint that is equal to a tenth of a percent of deposits raises the multiplier by roughly 20 percent. The cost slope $\phi_S = 0.033$ is estimated via impulse response matching described in [Section 7.2](#), with a standard error of 0.011. Under this estimated value, the marginal transaction cost at the peak rate of net purchases is a few basis points per dollar purchased. The steepness and the cost slope jointly govern the portfolio’s effective stiffness/stickiness, so I set the ψ value and then estimate ϕ_S to estimate the extent to which bank portfolios react.

Implications of the portfolio friction. [Figures F.2 and F.3](#) show the model fit for the baseline model, along with variants of the model (including a version without the portfolio frictions). The portfolio friction allows the model to reconcile the persistence of the safe asset share with the fast decay of the funding advantage. Without the friction, the safe asset share corresponds to the requirement as it binds, which would not generate the hump-shaped response we observe for the safe asset share of banks. The portfolio friction also allows the model to match the response of the funding advantage on impact.

H Model: normalization of the regulatory constraint

This appendix considers a normalization when varying the relative weight on safe assets in the regulatory portfolio constraint. The regulatory portfolio constraint in Equation 27 is a CES function with the relative weight on safe assets denoted by κ_t . A change in κ_t can be interpreted as a combination of two changes in the regulatory portfolio constraint. First, a change in κ_t changes the *relative* regulatory value of safe assets in comparison to the regulatory value of capital. Second, a change in κ_t changes the *overall* value of the constraint for a fixed portfolio. This is analogous to how a change in the share parameter of a CES production function changes output at fixed inputs.

This appendix describes a normalization that isolates the relative component. Using this normalization, I re-estimate the model under the normalized shock and compare the results. The normalized version matches the empirical responses, and current regulation is even closer to the peak of the Laffer curve under the normalized weight.

H.1 Normalization methodology

Consider the regulatory portfolio constraint:

$$\Upsilon_t = [\kappa_t S_t^\alpha + (1 - \kappa_t)(q_t K_t^b)^\alpha]^{1/\alpha}. \quad (54)$$

Differentiating the constraint with respect to κ_t at the steady-state portfolio gives

$$\frac{\partial \log \Upsilon}{\partial \kappa} = \frac{1}{\alpha} \frac{\bar{S}^\alpha - \bar{K}^\alpha}{\bar{\Upsilon}^\alpha}. \quad (55)$$

The expression is negative, as the bank holds fewer safe assets than capital claims in steady state. At the baseline calibration, the derivative is equal to -1.46 . An increase in κ of 0.01 lowers the regulatory value of the bank's existing portfolio by roughly 1.5 percent.

An increase in κ_t operates through two channels. First, it increases the regulatory value of safe assets *relative* to capital claims. Second, it lowers the *overall* regulatory value of the portfolio that the bank holds. The second channel is equivalent to an increase in ϱ . Both channels are features of the regulations considered in the empirical sections of the paper. For example, a liquidity coverage requirement or a higher risk-weight on loans favors safe assets and raises the required regulatory backing of deposits simultaneously.

I consider a normalization that isolates the effect of changes in the relative regulatory value of safe assets by following the normalization of Klump and de La Grandville (2000). The normalization writes the CES function around a baseline point so that a change in κ_t leaves the value of the function at the baseline inputs unchanged. The normalized form of

the portfolio constraint is the following:

$$\Upsilon_t = \bar{\Upsilon} \left[\pi_t (S_t / \bar{S})^\alpha + (1 - \pi_t) (q_t K_t^b / \bar{K})^\alpha \right]^{1/\alpha}, \quad (56)$$

where π_t is the normalized regulatory weight and its steady-state value $\bar{\pi} = \bar{\kappa} \bar{S}^\alpha / \bar{\Upsilon}^\alpha$ is the regulatory value share of safe assets at the baseline. At the baseline portfolio, $\Upsilon_t = \bar{\Upsilon}$ for every value of π_t , so a change in the normalized weight changes the relative regulatory values of the two assets without changing the regulatory value of the portfolio the bank holds. Equation 56 describes the same family of constraints as the baseline constraint multiplied by a factor that depends on the weight,

$$\Upsilon_t = A(\kappa_t) \left[\kappa_t S_t^\alpha + (1 - \kappa_t) (q_t K_t^b)^\alpha \right]^{1/\alpha}, \quad A(\kappa) = \left[\frac{\bar{\kappa} \bar{S}^\alpha + (1 - \bar{\kappa}) \bar{K}^\alpha}{\kappa \bar{S}^\alpha + (1 - \kappa) \bar{K}^\alpha} \right]^{1/\alpha}, \quad (57)$$

with $A(\bar{\kappa}) = 1$. Because the constraint $\varrho D_t \leq A(\kappa_t) \tilde{\Upsilon}_t$ is equivalent to $[\varrho / A(\kappa_t)] D_t \leq \tilde{\Upsilon}_t$, the normalized model is also the baseline model with a compensating path for the constraint scale, $\varrho_t = \bar{\varrho} / A(\kappa_t)$.

The normalized shock is a path for κ_t , along with the compensating path for ϱ_t , which keeps the regulatory value of the baseline portfolio unchanged. The level component of the baseline shock is the path for ϱ_t that the normalization removes. The steady state is the same under both forms, so every parameter calibrated using the steady state values keeps its value.

H.2 Re-estimation under the normalized shock

Table H.1 shows the estimates of the dynamic parameters of the model when the identified shock is mapped into the normalized shock instead of the baseline shock. The estimation of the parameters follows the same impulse response matching methodology discussed in Section 7.2.

Figures H.1 and H.2 show the model fit. The normalized model reproduces the main features of the empirical responses. The safe asset share has a hump-shaped response that peaks at 0.34 percentage points in the ninth quarter, the funding advantage rises by 7.5 basis points on impact and turns negative after five quarters, and the responses of prices and the policy rate are small. The output response is shallower, with a trough of 0.09 percent in comparison to 0.16 percent in the baseline model and 0.18 percent in the empirical estimates.

	Baseline model	Normalized shock
ξ	0.0420 (0.0029)	0.0020 (0.0067)
ϕ_I	0.0010 (0.9524)	2.4999 (3.9837)
ϕ_S	0.0327 (0.0114)	0.9761 (0.2877)
ρ_κ	0.9440 (0.0214)	0.8500 (0.0939)
ω	0.5511 (0.1002)	0.9908 (0.3603)
θ_w	0.7869 (0.0864)	0.6162 (0.5238)
Shock scale	0.0898 (0.0124)	2.6789 (1.2572)
Average deviation (standard errors per moment)	0.40	0.57
Share peak (pp)	0.37	0.34
Share peak quarter	7	9
Funding advantage on impact (bp)	6.1	7.5
Output trough (percent)	-0.16	-0.09

Table H.1: Estimates under the baseline shock and under the normalized shock

Notes: This table reports the estimates by impulse response matching of Section 7.2 (standard errors in parentheses) when the identified shock is mapped into the baseline shock and into the normalized shock.

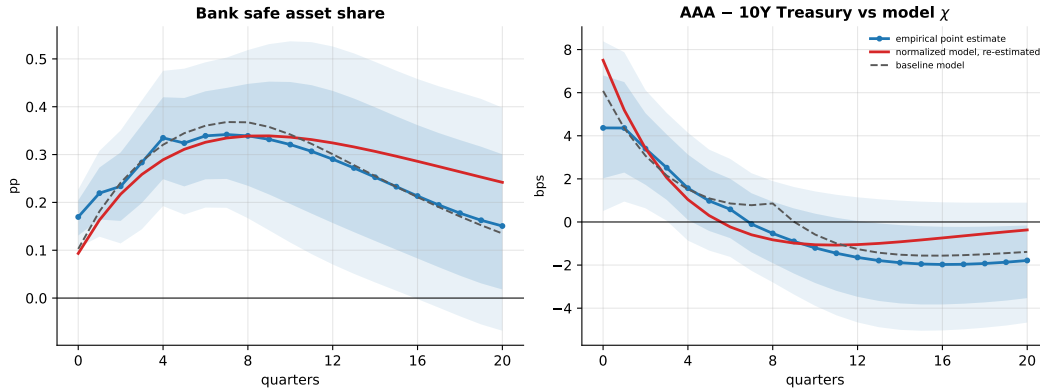


Figure H.1: Model fit under the normalized shock: the portfolio and the funding advantage

Notes: This figure overlays the model re-estimated under the normalized shock (Table H.1) and the baseline model on the empirical point estimates and bands of Figure 4.

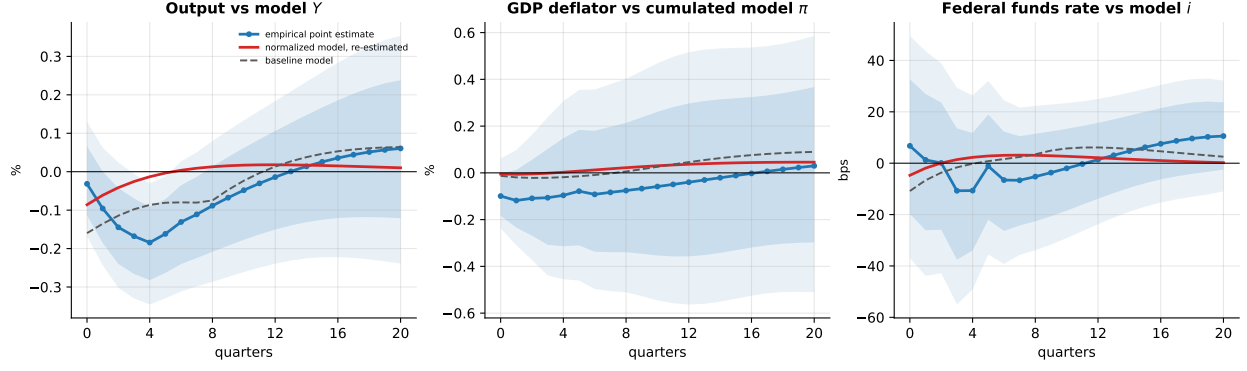


Figure H.2: Model fit under the normalized shock: output, prices, and the policy rate
Notes: This figure overlays the model re-estimated under the normalized shock (Table H.1) and the baseline model on the empirical point estimates and bands of Figure 4.

H.3 The Laffer curve under the normalized weight

The Laffer curve of Section 7.4.2 varies κ across steady states at the baseline constraint scale $\bar{\varrho}$, so each increase in the weight reflects both the effects on the relative regulatory value of safe assets and the overall regulatory value. Under the normalized weight, each value of κ is paired with the compensating change in the scale of the constraint, $\varrho = \bar{\varrho}/A(\kappa)$, so that the regulatory value of the baseline portfolio is the same at every point. This isolates the relative component of the changes in the regulatory portfolio constraint. Figure H.3 shows the regulatory Laffer curve with both paths.

The regulatory Laffer curves with the two variants show that the normalized version peaks at a lower level of κ . In the normalized version, an increase in κ is paired with a compensating change in the scale of the constraint that loosens the overall constraint. This is because for a fixed portfolio, an increase in κ results in a lower regulatory value, meaning that an increase in κ has an overall tightening effect without the normalization. Given that the normalization negates the tightening effect, the two counteracting effects of the regulatory Laffer curve (increase in safe asset holdings by banks vs. lower savings per dollar of safe assets) offset each other at a lower level of κ .

Coincidentally, interest savings under the normalized weight peak at the baseline calibration (within one grid step of $\bar{\kappa}$ with the calibration). Any further increase in κ would result in lower interest savings. The location of the peak is characterized by the elasticity of the funding advantage with respect to holdings. In the model, interest savings are the product of the funding advantage and the safe asset holdings, so the peak is defined by the level of κ where the marginal increase in safe asset holdings exactly offsets the marginal decrease in the funding advantage. In the normalized version, the level of κ in the baseline calibration corresponds to the offsetting level. In the original approach without the normalization, the effect of the increase in safe asset holdings dominates at the baseline level of κ , with the

peak of the Laffer curve being to the right of the baseline calibration.

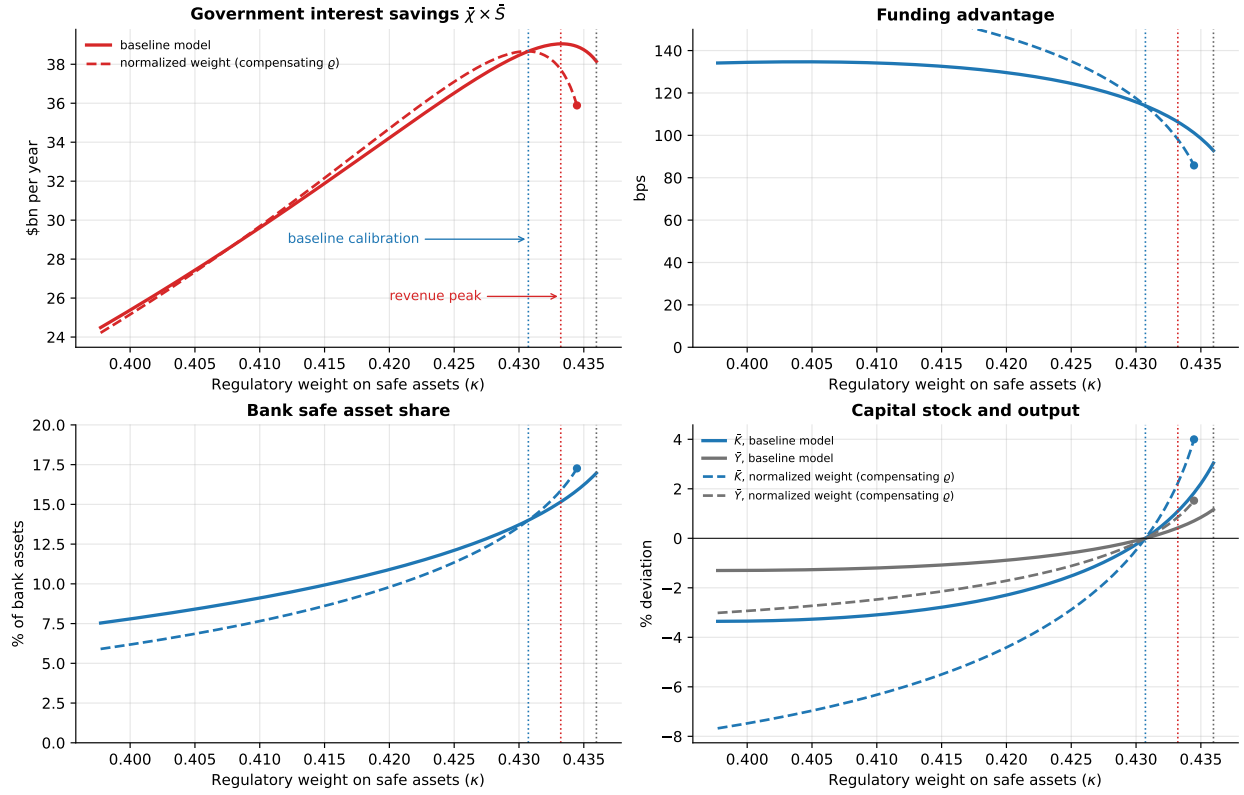


Figure H.3: The regulatory Laffer curve under the baseline and the normalized weight

Notes: This figure shows the steady-state values for varying levels of the regulatory weight on safe assets for the baseline model (solid lines, κ varied at $\bar{\varrho}$) and for the normalized weight (dashed lines, κ varied with the compensating $\varrho = \bar{\varrho}/A(\kappa)$), both at the baseline estimates and in dollars based on 2025 bank balance sheets. Dotted vertical lines show the baseline calibration, the revenue peak, and the capacity boundary of the baseline model, and the markers show the capacity boundary under the normalized weight.

I Model: extensions of the banking sector

This section examines two extensions of the banking sector that build on the baseline model from Section 7. In the baseline model, the representative bank chooses the banking sector's portfolio and takes the deposit spread schedule in Equation 34 as given. The representative bank does not internalize the effect of its balance sheet on its own funding cost. The first extension replaces the representative bank with a continuum of atomistic banks. This extension shows that the price-taking assumption of the baseline model is an equilibrium property of this decentralized version of the banking sector with a continuum of banks. Each bank takes the sector-wide ratio as given because its own portfolio has no effect on it, and the symmetric equilibrium of this economy coincides with the equilibrium of Section 7. The second extension keeps the representative bank and allows the representative bank to internalize the dynamics of its funding cost that arise from household preferences for liquidity and safe deposits. In other words, the bank takes into account that a safer portfolio lowers the rate it pays on its deposits. I describe the setting of the internalizing bank, and then discuss how the results of the model would differ under this setting.

I.1 Continuum of banks

Setup. The banking sector consists of a continuum of banks indexed by $i \in [0, 1]$ with unit mass. Bank i holds safe assets $S_{i,t}$ and capital claims $q_t K_{i,t}^b$, funded by deposits $D_{i,t}$ and inside equity $E_{i,t}$. Each bank solves the problem of the representative bank of Section 7. It maximizes expected profits as in Equation 25, subject to its own balance sheet constraint and its own regulatory portfolio constraint as in Equations 26 and 27. The equity of each bank accumulates from its own retained earnings as in Equation 28. Each bank pays the transaction cost of Appendix G on its own purchases. The only difference from the representative bank is that the bank funding cost is determined at the sector level. The household's non-pecuniary value of deposits in Equation 19 depends on the sector-wide ratio $\ell_t = S_t/D_t$, where $S_t = \int_0^1 S_{i,t} di$ and $D_t = \int_0^1 D_{i,t} di$ are the sector's safe asset holdings and deposits. The deposit spread in Equation 34 is a single spread paid by every bank. The scarcity premium in Equation 36 depends on the sector's holdings S_t in the same way. Because each bank has zero mass, its own portfolio leaves ℓ_t and S_t unchanged. The bank therefore takes s_t as given.

The first order conditions of bank i are

$$[S] \quad s_t = \mu_{i,t} \left[\kappa_t (\Upsilon_{i,t}/S_{i,t})^{1-\alpha} - \varrho \right], \quad (58)$$

$$[K] \quad \mathbb{E}_t R_{t+1}^k - (1 + r_t^d) = \mu_{i,t} \left[\varrho - (1 - \kappa_t) (\Upsilon_{i,t}/q_t K_{i,t}^b)^{1-\alpha} \right], \quad (59)$$

where $\Upsilon_{i,t}$ is the regulatory aggregator evaluated at the bank's own portfolio. $\mu_{i,t}$ is the multiplier on its constraint. These are conditions [S] and [K] of Section 7 for each bank, but with the term on the left side of condition [S] common to all banks.

Symmetric equilibrium. A symmetric equilibrium is an equilibrium in which every bank chooses the same positions, i.e., $S_{i,t} = S_t$, $K_{i,t}^b = K_t^b$, $D_{i,t} = D_t$, and $E_{i,t} = E_t$ for all i . Under a symmetric equilibrium, the bank-level conditions in Equations 58 and 59, the balance sheet and regulatory constraints, and the equity law of motion coincide with Equations 29, 30, 26, 27, and 28. The deposit spread and the premium satisfy Equations 34 and 36 at the common ratio and the sector's holdings. The symmetric equilibrium of the continuum economy is therefore equivalent to the equilibrium of Section 7 with respect to the model fit, transition dynamics, and the steady state properties.

Aggregation and price taking. The banking sector aggregates to the representative bank for any distribution of bank sizes in this model. This is due to the property that the bank's problem is linearly homogeneous. The CES aggregator in the regulatory constraint is homogeneous of degree one, the balance sheet and profits are linear, and the transaction costs are normalized by the bank's own steady-state stocks. Therefore, the optimal positions of a bank are proportional to its equity while its portfolio shares, its multiplier, and the spreads it faces are common across banks of any size. This is the aggregation property of the continuum of bankers in Gertler and Kiyotaki (2010) and Gertler and Karadi (2011), whose problem is linear in net worth so that the sector's lending is determined by its aggregate net worth. Van den Heuvel and Villavazo (2026), who also place deposits in the utility function and study liquidity requirements, write a continuum of perfectly competitive banks with constant returns to scale as a representative bank in the same way.

This decentralized version of the model shows that the price-taking assumption in the baseline model can be interpreted as a simplification of the setup discussed in this section. An individual bank cannot single-handedly influence the sector-wide ratio of safe assets to deposits. Therefore, the funding-cost benefit of a safer portfolio cannot be internalized by each atomistic bank. The structure is similar to that of the pecuniary externalities in Lorenzoni (2008) and Stein (2012), in which atomistic agents take as given a price that depends on their aggregate choices. In Stein (2012) in particular, a continuum of banks does not internalize the effect of its short-term debt issuance on fire-sale prices, in the same way that the banks here do not internalize the effect of their portfolios on the deposit spread.

I.2 Internalizing the effect of bank portfolios on funding costs

Setup. The second extension keeps the representative bank of Section 7 and allows the representative bank to internalize that its bank portfolio decisions can influence its own funding cost. A bank that adds a dollar of safe assets funded with deposits raises its safe-assets-to-deposits ratio $\ell_t = S_t/D_t$ by $(1 - \ell_t)/D_t$ and lowers the rate it pays on its entire deposit stock. A bank that internalizes this effect makes its decision based on whether the funding-cost saving outweighs the carry cost of the safe asset. Banks that take the pricing of their own liabilities into account appear in [Stein \(2012\)](#) and [Greenwood et al. \(2015\)](#), where banks weigh a money premium in their issuance choices. In [Drechsler et al. \(2017\)](#), banks price deposits against a household demand curve. [Bianchi and Bigio \(2022\)](#) and [Porcellacchia and Sheedy \(2024\)](#) generate funding costs that depend on bank liquidity from settlement and rollover frictions respectively, and banks in their settings internalize the dependence fully.

First order conditions. Let $M_t \equiv -\partial s_t^d / \partial \ell_t > 0$ denote the slope of the deposit spread schedule and let $\vartheta \in [0, 1]$ denote the fraction of the marginal funding-cost effect that the bank prices against its own ratio ℓ_t (with the remainder priced against the sector as in the continuum above). The bank's first order conditions are the following:

$$[S] \quad s_t - \vartheta M_t (1 - \ell_t) = \mu_t \left[\kappa_t (\Upsilon_t / S_t)^{1-\alpha} - \varrho \right], \quad (60)$$

$$[K] \quad s_t^k = \vartheta M_t \ell_t + \mu_t \left[\varrho - (1 - \kappa_t) (\Upsilon_t / q_t K_t^b)^{1-\alpha} \right]. \quad (61)$$

Condition [S] states that the funding-cost saving from an extra safe asset offsets part of its carry cost. Financing one more dollar of safe assets with deposits raises the ratio ℓ_t and lowers the rate the bank pays on its entire deposit stock, which saves $M_t(1 - \ell_t)$. The bank prices the fraction ϑ of this saving, so the regulatory premium on the right-hand side needs to compensate the bank only for the net carry cost on the left. Condition [K] states that lending becomes more expensive at the margin, because a dollar of capital claims funded with deposits lowers the ratio ℓ_t and raises the funding cost by $M_t \ell_t$. Summing the two conditions gives $\chi_t = \mu_t[\cdot] + \vartheta M_t$. With internalization, there can be a positive funding advantage even if the regulatory constraint is slack. In other words, the internalization adds a new motive for banks to hold safe assets, which can have price effects that show up in the funding advantage. At $\vartheta = 0$ the conditions collapse to Equations 29 and 30, and at $\vartheta = 1$ the bank prices the slope of the schedule in full. One interpretation of $\vartheta < 1$ is that a specific proportion of its funding is priced against the bank's own ratio (i.e., the uninsured margin), while the remainder of its funding is priced against the sector-wide ratio.

The regulatory portfolio constraint in the model binds with a positive multiplier only if the net carry cost in condition [S] remains positive, which restricts the values ϑ can take,

where:

$$\vartheta < \bar{\vartheta} = \frac{\bar{s}}{\bar{M}(1 - \bar{\ell})} \approx 0.04. \quad (62)$$

The steady-state carry $\bar{s}$ equals the deposit spread because the premium is zero at the steady state. A bank that prices even 4 percent of the marginal sector-wide saving on funding costs as its own would hold the observed portfolio voluntarily without any of the regulatory constraints. If a bank fully internalizes the effects, the multiplier on the regulatory portfolio constraint would be negative. The regulatory constraint would then be slack, which would be inconsistent with the empirical observations from this paper and the existing literature that the regulatory constraints are binding. The partial internalization is consistent with bank funding costs reflecting sector-wide safety that is not significantly influenced by any individual bank.

Differences from the baseline. Within the admissible range the internalizing bank differs from the baseline in three ways. First, a bank that values the funding-cost benefit of the safe assets it has accumulated unwinds them only as the benefit erodes, so internalization acts similarly to the portfolio transaction costs. This results in slower and more persistent responses of the safe asset share. Within the admissible range of internalization, this effect is modest relative to the transaction costs. Second, as discussed earlier, the sum of the two first order conditions shows that the internalization introduces a new motive for banks to hold safe assets. This implies that the funding advantage can be positive without the regulatory portfolio constraint binding. Such cases are not of interest in the context of this paper, but are nonetheless a feature of this version of the model. Third, internalization moves the private portfolio toward what regulation would force, which leaves regulation less room to force additional permanent accumulation. Therefore, the capacity of the permanent tightening in Section 7.4.1 shrinks as ϑ rises. Overall, the internalizing bank is inconsistent with binding regulation beyond a small degree of own-bank pricing. Within the limited admissible range of ϑ , the internalization has minimal effects on the model results. For this reason, the baseline model of this paper uses the price-taking representative bank described in Section 7, which can be rationalized by the continuum of banks discussed earlier in this section.

J Model: additional variants

This section considers two variants of the model that differ with respect to the market for safe assets relative to the baseline model from Section 7. I compare the two variants of the model to the baseline model.

In the baseline model, the banking sector holds the stock of safe assets outstanding and the supply available to it slopes upward, so that the safe asset rate falls relative to the policy rate by a scarcity premium when the bank accumulates safe assets. The first variant removes this scarcity premium. The government supplies safe assets elastically at the policy rate, the safe asset rate equals the policy rate at every date, and regulation moves the quantity of safe assets that the bank holds without any scarcity effects for the safe assets. The second variant generates the premium on the household side of the market. Households hold safe assets with a convenience value, the stock of safe assets outstanding is fixed, and the bank bids safe assets away from households, who require a larger premium for every extra percent of safe assets they reduce in holdings. Other than these changes, everything else in the model is unchanged. The steady state is identical across the three market structures since the scarcity premium (if it exists at all) is zero in the steady state. I estimate each variant using impulse response matching described in Section 7.2.

The three market structures are close to several strands of the literature. The baseline is a segmented market in the spirit of [Vayanos and Vila \(2021\)](#), in which the banking sector is the marginal holder of the safe asset and its regulatory demand is priced. The elastic supply is the treatment of government debt in the standard New Keynesian model, in which the household's Euler equation prices the safe asset at the policy rate, so that the funding advantage works through the deposit spread and the credit spread alone. The household-demand variant is the convenience demand for Treasuries of [Krishnamurthy and Vissing-Jorgensen \(2012\)](#), so that the bank's demand competes with the household's. This also relates to the safe asset scarcity discussed in [Caballero et al. \(2017\)](#), where a shortage of safe assets lowers the safe rate.

The household-demand model reproduces the baseline's estimates and responses. To first order, the two market structures have the same premium per unit of bank holdings and differ only in the curvature of the premium away from the steady state. The elastic-supply model is nearly indistinguishable from the baseline.

The three market structures. Let r_t denote the policy rate and r_t^s the safe asset rate. In every variant the Euler equation holds on the policy rate, the deposit schedule of Equation 34 prices deposits relative to it, $r_t^d = r_t + s_t^d$, the safe asset yields $r_t^s = r_t - s_t^s$, the bank's carry on safe assets is $s_t = s_t^d + s_t^s$, and the funding advantage is defined as $\chi_t = s_t^d + s_t^k + s_t^s$. The variants differ only in terms of the scarcity premium of safe assets.

- *Bank-held safe assets, sloped supply* (baseline model of the paper). Households cannot hold the safe asset. The banking sector holds the whole stock, $B_t^g = S_t$, and the supply available to it follows Equation 35, so that $s_t^s = \theta_S \log(S_t/\bar{S})$ with $\theta_S = 0.107$ percentage points per log unit of bank holdings. This is based on the calibration discussed in Section 7.2.
- *Elastic supply*. Households hold safe assets without a convenience value, so their first order condition for safe assets is the Euler equation on the safe asset rate. The government supplies the asset elastically at the policy rate to banks and households. The scarcity premium is therefore zero, $r_t^s = r_t$. The quantity of safe assets is fully determined by demand, and the slope θ_S is not part of the calibration (it is effectively zero since the scarcity premium is also zero).
- *Household demand*. Households hold the safe asset B_t with a convenience value $\nu(B_t)$ following Krishnamurthy and Vissing-Jorgensen (2012). The convenience value is part of the household utility function, similarly to how the deposits-in-utility shows up in the household utility function. Their first order condition for safe assets is

$$C_t^{-\sigma} - \nu'(B_t) = \beta (1 + r_t^s) \mathbb{E}_t C_{t+1}^{-\sigma}. \quad (63)$$

Safe assets earn the time value of consumption net of their marginal convenience value, and together with the Euler equation on the policy rate the condition prices the safe asset relative to the policy rate, $s_t^s = \nu'(B_t)(1 + r_t)C_t^\sigma$. The stock outstanding is fixed at $\bar{B}^g$ and the market clears between households and the bank, $S_t + B_t = \bar{B}^g$. The bank bids safe assets away from households and the premium is the household's marginal convenience value at its reduced holdings. I linearize the convenience value around the steady state and normalize its marginal value to zero at the steady-state stock, $\nu'(\bar{B}) = 0$, so that any constant convenience yield is part of the calibrated level of the safe asset rate. This ensures that only the slope of the demand matters,

$$s_t^s = \nu_1 \frac{\bar{B} - B_t}{\bar{B}} = \nu_1 \frac{S_t - \bar{S}}{\bar{B}}, \quad \nu_1 \equiv -\nu''(\bar{B}) \bar{B} (1 + \bar{r}) \bar{C}^\sigma > 0, \quad (64)$$

where ν_1 is the increase in the premium that households require to release one percent of their holdings. The calibration sets $\nu_1 = 0.75$ percentage points per log unit of the household stock, based on the response of the Aaa-Treasury spread to the log of debt to GDP estimated by Krishnamurthy and Vissing-Jorgensen (2012). I set $\bar{B}^g = 8\bar{S}$, the ratio of Treasury debt held by the public to bank safe asset holdings, so that $\bar{B} = 7\bar{S}$. This estimate is based on bank's holdings of safe assets relative to the aggregate quantity in the sample period. Per log unit of bank holdings the slope

is $\nu_1 \bar{S}/\bar{B} = 0.107$ percentage points, which is the value of θ_S in the baseline model. The household demand is in a sense a microfoundation of the safe asset supply curve in the baseline model, with the household sector serving as the rest of the market. The government budget of Equation 38 holds with the fixed stock of safe assets. Since taxes are lump sum, the distribution of holdings between the two sectors matters only through the premium.

In each variant the steady-state premium is zero, so the calibrated steady state of Section 7.2 and Panels A and B of Table 2 carry over.

Estimates and fit. Table J.1 reports the parameters estimated in each variant, along with the summary statistics of the fitted responses. The household-demand model reproduces the baseline’s estimates, because the linearized model that the estimation uses is the same across the two market structures. The elastic-supply model estimates a slightly flatter deposit schedule, with $\xi = 0.0381$ against 0.0420 in the baseline model. The transaction cost, the persistence of the shock, and the wage rigidity are within one standard error of the baseline estimates. The fit is roughly the same, with an average deviation of 0.38 standard errors per moment against 0.40 in the baseline.

	Bank-held, sloped supply (baseline)	Elastic supply	Household demand
Premium slope, pp per log unit of bank holdings	0.107	0	0.107
ξ	0.0420 (0.0029)	0.0381 (0.0028)	0.0420 (0.0029)
ϕ_I	0.0010 (0.9524)	0.0327 (1.0055)	0.0010 (0.9524)
ϕ_S	0.0327 (0.0114)	0.0319 (0.0111)	0.0327 (0.0114)
ρ_κ	0.9440 (0.0214)	0.9451 (0.0215)	0.9440 (0.0214)
ω	0.5511 (0.1002)	0.5547 (0.1016)	0.5511 (0.1002)
θ_w	0.7869 (0.0864)	0.7885 (0.0836)	0.7869 (0.0864)
Shock scale	0.0898 (0.0124)	0.0892 (0.0125)	0.0898 (0.0124)
Average deviation (standard errors per moment)	0.40	0.38	0.40
Share peak (pp)	0.37	0.37	0.37
Funding advantage on impact (bp)	6.1	6.1	6.1
Output trough (percent)	-0.16	-0.16	-0.16
Scarcity premium, peak (bp)	0.32	0.00	0.32

Table J.1: Estimates and fit by market structure

Notes: This table reports the parameters estimated for each market structure, with standard errors in parentheses, along with average deviation and summary statistics of the fitted responses.

Responses to the estimated shock. Figure J.1 shows the responses to the estimated regulatory shock for the three market structures. All three market structures result in very similar estimated responses. The responses are nearly identical for the safe asset share,

funding advantage, scarcity premium, and the credit spread. The elastic-supply version of the model differs slightly for the estimated responses for output and the capital stock. However, the differences are very small, with very similar responses in terms of shape and magnitude. Overall, the market structure for safe assets matters little for the responses to the estimated shock. This is mainly due to the fact that the scarcity premium is very small relative to the deposit and credit spreads that are affected by changes in the regulatory portfolio constraint on banks.

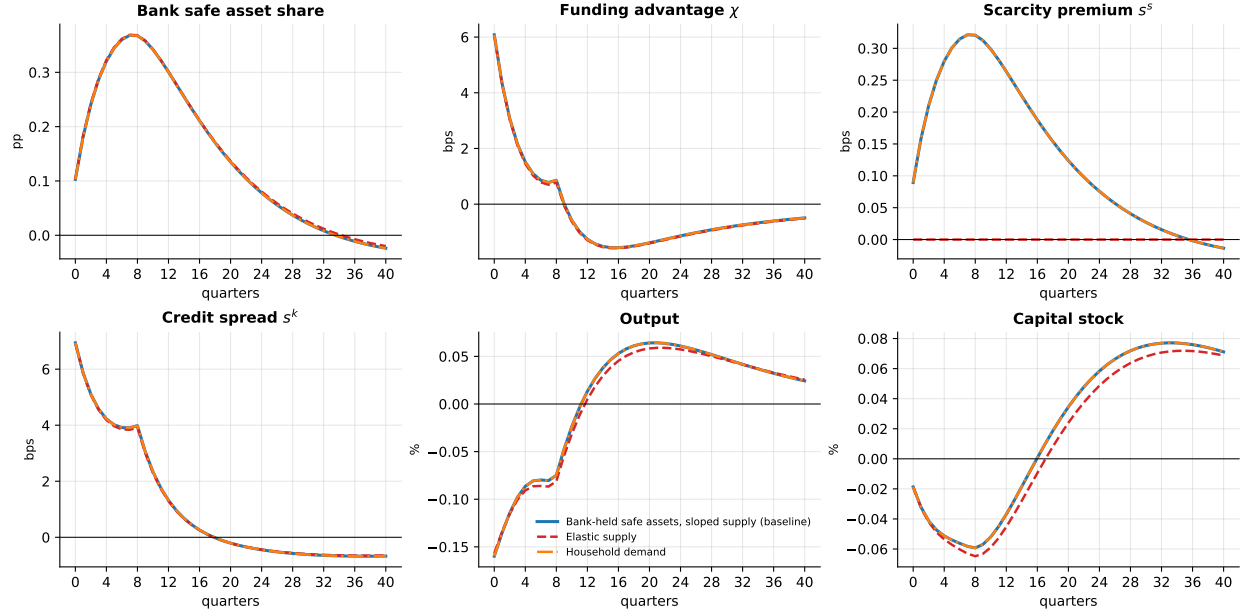


Figure J.1: Responses to the estimated shock by market structure

Notes: This figure shows the responses to the estimated regulatory weight shock in the baseline and in the two alternative market structures, each at its own estimated parameters.

K Model: counterfactual extensions

In this section, I examine variants of the counterfactual exercise discussing the permanent increase in the regulatory weight on safe assets in Section 7.4.1.

The baseline version in Section 7.4.1 examines a \$250 billion scenario. Under a \$500 billion scenario, the responses roughly double. The funding advantage increases by 51 basis points and output falls by 1.4 percent on impact under the unanticipated implementation. Under a \$1 trillion scenario, there is no attainable steady state in the calibrated model, since the implied accumulation exceeds the capacity boundary of Section 7.4.2.

The transitional dynamics depend on the implementation of the policy (unanticipated vs. phase-in), and the featured surprise implementation is the upper bound of responses, with the \$250 billion scenario's premium spiking at about 29 basis points on impact. On the calibrated timing of the identified shocks, with fraction $\omega = 0.55$ binding at $t = 0$, the response on impact is 15 basis points. A pure announced eight-quarter phase-in results in a peak response of just 5 basis points for the funding advantage with no immediate increase.

Figure K.1 compares the surprise permanent and surprise temporary implementations of Section 7.4.1. The temporary increase in the regulatory weight delivers a similar impact response of the funding advantage with a much smaller accumulation of safe assets, and it forgoes the long-run benefits that accrue based on the shift to safer bank portfolios with bank equity that fully recovers over time.

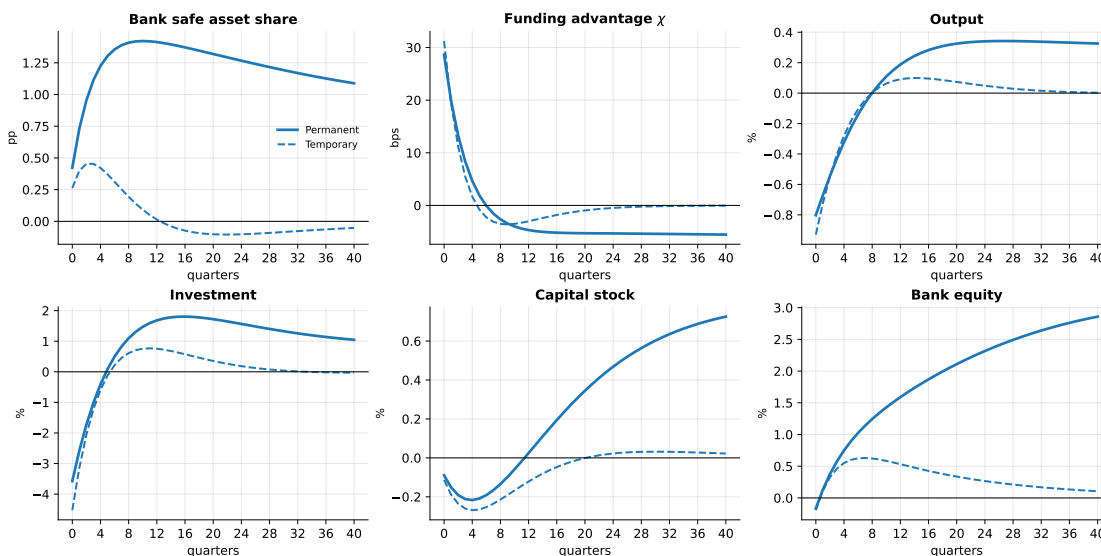


Figure K.1: Counterfactual transition: permanent and temporary increases

Notes: This figure compares the transition paths under the surprise permanent increase in the regulatory weight sized to induce \$250 billion of long-run safe asset accumulation and under a surprise temporary increase of the same impact size that decays with a half-life of one year.