The Rising Tide of Safe Assets and Large Bank Capital Requirements
Safe Asset Supply, the COVID Pandemic and GSIB Surcharges: 2016-2024

Sean Campbell[1] Financial Services Forum
Emma Tong Financial Services Forum

June, 2025

Abstract: Following the 2008 Financial Crisis, regulators introduced a new capital requirement – the GSIB surcharge - for the largest banks that regulators identified as "systemically important". We analyze the behavior of the GSIB score, the fundamental metric that determines the GSIB surcharge, between 2016 and 2024 for the eight U.S. banks subject to the requirement. Since its introduction, GSIB scores and surcharges have risen steadily. We show that the GSIB score is systematically related to the level of the nominal supply of safe assets – U.S. Treasuries and bank reserves – in the U.S. economy. We document that the observed increase in GSIB scores and surcharges since 2016 can be fully explained by the observed increase in the supply of safe assets. Relatedly, we find that roughly sixty percent of the observed increase in GSIB scores can be explained by the U.S. government's response to the COVID pandemic. Using official government projections of future Treasury supply and bank reserves through 2035, we forecast that GSIB scores and surcharges will continue to increase steadily absent any change to the GSIB surcharge regulation. The implications of these findings for systemic risk measurement and bank capital policy are discussed.

[1] Corresponding author: scampbell@fsforum.com

1. Introduction

Following the 2008 financial crisis, global regulators, under the auspices of the Basel Committee on Banking Supervision (BCBS), undertook an effort to establish a new capital charge that would be levied on the largest global banks that regulators deemed to present the most systemic risk to the financial system. The BCBS (BCBS, 2013) finalized its global framework for identifying such Global Systemically Important Banks (GSIBs) and the methodology for determining the size of the bank-specific surcharge in 2013. Since 2012, the Financial Stability Board has annually published a list of GSIB banks using this methodology. Over time, regulators have identified between 28 and 30 banks as GSIB banks based on this methodology. In the United States, eight bank holding companies have been identified as GSIBs each year since 2012.[2] In 2015, the Federal Reserve (Federal Reserve, 2015) published a final rule codifying in U.S. regulation, the methodology for identifying GSIB banks as well as the rule establishing the GSIB capital surcharge to which they are subject.[3]

The value of the GSIB surcharge applied by the Federal Reserve to U.S. banks is determined by a regulatory formula known as the GSIB score. The GSIB score is based on five distinct systemic risk indicators that regulators have deemed to be important indicators of "systemic risk". The individual indicators relate to regulator-defined measures of: 1) balance sheet size or simply "size", 2) complexity, 3) interconnectedness, 4) cross-

[2] The U.S. headquartered GSIBs are Bank of America, Bank of New York, Citigroup, Goldman Sachs, J.P. Morgan, Morgan Stanley, State Street, and Wells Fargo. The list of U.S. GSIBs has not changed over time.
[3] Other countries are responsible for promulgating GSIB surcharge capital regulations that apply to GSIBs headquartered in their jurisdictions. As will be discussed, the U.S. GSIB surcharge rule varies significantly from the Basel Committee standard and the regulation that is applied in non-U.S. jurisdictions.

jurisdictional activity, and 5) short-term wholesale funding or “STWF”. Each of these measures is constructed with reference to a complex formula that includes a wide range of data collected by regulators.[4] The resulting GSIB score is mapped into a GSIB capital surcharge using a step-wise function that increases by 0.5 percentage points for every 100-point increase in GSIB score.[5]

Since the U.S. GSIB Surcharge rule was finalized in 2015, the surcharge has had a significant influence on the capital requirements of U.S. GSIBs. As of the fourth quarter of 2024, the GSIB surcharge accounts for 2.6 percentage points – or roughly 25 percent- of the average overall minimum capital requirement of 11.1 percent for U.S. GSIBs. Moreover, GSIB surcharges have risen significantly since they were introduced in 2015. As shown in Figure 1, the average U.S. GSIB score for U.S. GSIBs has risen by roughly 80 points, from roughly 472 to 556, since 2016 and the resulting average capital surcharge has risen by 0.4 percentage points with some banks experiencing an increase as large as 1.0 percentage points.[6]

Empirical research has found sizeable impacts of the GSIB surcharge on credit supply and bank lending. Favara, Ivanov, and Rezende (2021), for example, demonstrate

---

[4] The full range of data that is collected to support the calculation of the GSIB score is reported by large banks subject to the reporting requirement on a quarterly basis using the FR-Y15 report. Historical data submitted by FR Y-15 filers can be found at the National Information Center’s website: https://www.ffiec.gov/npw/Institution/TopHoldings.

[5] The GSIB capital surcharge is the ultimate metric of interest for financial policy making as it determines a bank’s capital requirement. Under the U.S. rule, all U.S. GSIBs are subject to a surcharge of at least 1.0%. In this paper, we focus exclusively on the GSIB score because it is the sole determinant of a bank’s surcharge. Moreover, the surcharge is determined by a non-continuous mapping that obscures the value of the score.

[6] The data presented in Figure 1 reflects the average GSIB score as well as the average GSIB surcharge that corresponds to the average GSIB score at each point in time. The U.S. GSIB surcharge regulation introduces a complex time lag between the realization of the GSIB score and the realization of the GSIB surcharge. In this paper we abstract from this regulatory complexity and only consider the surcharge that corresponds with the score measured at each point in time.

that U.S. GSIB banks respond to higher GSIB surcharges by reducing corporate lending. Specifically, they estimate that a one percentage point increase in a bank's GSIB surcharge would reduce the bank's lending by four percent. Relatedly, Jian and Shen (2024) find that hedge funds that deal with bank-affiliated prime brokers with higher GSIB surcharges exhibit poorer financial performance that they relate to a lack of willingness of GSIB banks to provide financial services that could further increase their GSIB score and surcharge. More broadly, a range of economic research finds that increasing bank capital requirements increases borrowing costs, depresses output, and incentives growth in the shadow banking sector (Kashyap, Stein and Hanson (2010), King (2010), Baker and Wurgler (2013), Brooke et. al (2015), Cline (2015), D'Erasmo (2018)). Because the GSIB surcharge is a significant determinant of large bank capital requirements, an increase in GSIB surcharges leads to a direct increase in overall bank capital requirements.

Despite the significant impact that the GSIB surcharge has on large bank capital levels and economic activity, relatively little attention has been paid to the underlying behavior of the GSIB score, its components, and the resulting surcharge.[7] To the extent that GSIB surcharges influence capital levels and drive economic behavior – what exactly is driving GSIB surcharges? Given the novelty of the GSIB surcharge, and the clear evidence that it has an impact on economic outcomes, it is important to assess what drives GSIB scores and whether those drivers are consistent with consensus notions of systemic risk.

[7] Some recent work has considered the high-frequency behavior of GSIB scores and surcharges. A variety of papers including Migueis and Pierce (2025), Naylor, Corrias and Welz (2024), Behn, Magiante, Parisi and Wedow (2021), and Garcia, Lewrick, Secnick (2023), consider the evidence in favor of high-frequency, strategic balance sheet management by GSIBs to manage GSIB scores and surcharges. Rather than high-frequency behavior, this research focuses on longer run behavior and drivers of GSIB scores and surcharges.

In this paper, we analyze the behavior of the GSIB score and the five indicators that comprise the score using quarterly data from the fourth quarter of 2016 (2016:4) through the fourth quarter of 2024 (2024:4). We focus exclusively on the GSIB score implemented in the U.S. by the Federal Reserve Board because it is significantly different from the GSIB score endorsed by the BCBS and applied in all non-U.S. jurisdictions. Additionally, and importantly, we show that the U.S. deviation from the international (BCBS) standard has an important effect on the behavior of the U.S. GSIB score and surcharge.

Further, we relate the GSIB score to a fundamental aspect of the U.S. financial system – the supply of safe assets which we define to be the supply of U.S. Treasuries and bank reserves. The supply of safe assets is an important characteristic of the financial system that can be taken to be exogenous to the banking system. The Federal Reserve exogenously determines the overall level of bank reserves in the financial system while the U.S. government determines the overall supply of U.S. Treasury debt. Moreover, the supply of safe assets is a key aspect of the U.S. and global financial system that has direct implications for economic and financial activity (Ferreira and Shousha, 2021).

Our analysis shows that the indicators comprising the U.S. GSIB score as well as the U.S. GSIB score itself are systematically linked to the supply of safe assets. More specifically, we show that the GSIB score indicators are cointegrated with the level of bank reserves and outstanding U.S. Treasury debt. Further, we show that the five component GSIB score can be well approximated by a single dynamic factor that is estimated as the first factor in a standard principal component decomposition. Our analysis demonstrates that this factor is most strongly related to the balance sheet size of banks. We also show that this "size" factor is cointegrated with the supply of safe assets while the remaining identified factors are not cointegrated with the supply of safe assets.

These findings are important for two reasons. First, these findings show that while the GSIB score methodology is a complex, data-intensive, measurement methodology that considers five separate and distinct regulator-defined indicators of systemic risk – the resulting GSIB score is largely driven by a single factor that can be well approximated by a bank's balance sheet size. Second, these findings raise important questions about the underlying nature of the GSIB surcharge. To first approximation, GSIB scores and surcharges are an indication of a bank's nominal balance sheet size. Crucially, the U.S. GSIB score does not account for the size of the total banking or financial system. In particular, if every bank were to nominally increase its balance sheet size by, say, 20 percent, U.S. GSIBs would see their scores rise similarly even though their share of total banking activity would be unchanged. As a result, U.S. GSIB scores and surcharges are driven by the nominal size of the banking and financial system which raises a natural question as to whether any reasonable notion of "systemic risk" should scale with the nominal size of the banking system.

Second, we show that the observed growth in GSIB scores that has occurred since 2016 has been driven entirely by growth in the supply of safe assets. Figure 1 shows our counterfactual estimate of the change in the average GSIB surcharge that would have occurred had there been no growth in either bank reserves or outstanding U.S. Treasuries over the 2016-2024 period. As shown, absent the realized growth in reserves and Treasuries that has unfolded since 2020, there would have been no increase in average

GSIB scores (and surcharges) between 2016 and 2024. The quantitative magnitude of the effect portrayed in Figure 1 is striking. To the extent that other factors beyond the supply of safe assets determine the level of GSIB scores, none of those factors have any explanatory power for the observed increase in average GSIB scores since 2016.

Relatedly, we explore the extent to which GSIB scores were influenced by the extraordinary events surrounding the COVID pandemic. At the outset of the pandemic, the Federal Reserve massively increased the size of aggregate bank reserves and purchased roughly 40 percent of all U.S. Treasuries that were issued. In addition, post-COVID the rate of U.S. Treasury issuance has effectively doubled from roughly $850 billion per year to $1.6 trillion per year. Our analysis shows that roughly 60 percent of the growth in GSIB scores that has occurred since 2016 can be attributed to this unique event. The remaining growth in GSIB scores can be explained by background growth in the size of the supply of safe assets that would have occurred irrespective of the pandemic.

We conclude our analysis by considering a projection of future GSIB scores and surcharges based on official government projections for U.S. Treasury issuance and the level of bank reserves between 2025-2035. As shown in Figure 1, our estimates of the relationship between GSIB scores and the supply of safe assets implies that, absent any change to the U.S. GSIB surcharge regulation, average GSIB scores will rise by roughly an additional 100 points over the next decade and that the average GSIB surcharge will rise by roughly another 0.5 percentage points. Accordingly, the projected increase in the nominal size of the banking and financial system will lead to a mechanical rise in GSIB scores that will further raise capital requirements in the banking sector. This finding is important for two reasons. First, given the evidence on the economic impact of rising GSIB surcharges in particular, and the impact of rising capital requirements more broadly, this finding suggests further aggregate economic impacts from rising GSIB surcharges. Second, this finding raises a clear question as to the conceptual basis for a capital charge related to systemic risk that imparts a secular trend in capital requirements.

The remainder of this paper is organized as follows. In section 2, we discuss the GSIB score, the five systemic indicators, and the surcharge in greater detail. We also discuss important differences between the U.S. implementation of the GSIB surcharge and the surcharge that has been adopted by other major jurisdictions. In Section 3, we describe the data in more detail. In Section 4, we document the cointegrating relationship between the GSIB score indicators and the supply of safe assets. In Section 5, we introduce the factor model representation of the GSIB score and document how the estimated factors relate to each of the GSIB score indicators and the supply of safe assets. In Section 6, we decompose the rise in GSIB scores between 2016 and 2024 into the portion related to the increase in the supply of safe assets and all other factors. We conclude the section with a projection of future GSIB scores based on projected paths for future Treasury issuance and bank reserves. Section 7 discusses the relevance of the empirical findings for systemic risk measurement and regulatory policy. Section 8 concludes and considers directions for future research.

2. GSIB Score and Surcharge Institutional Background

Following the financial crisis, global bank regulators decided that capital requirements for the largest, global banks were too low and did not appropriately reflect the risk that their failure posed to the financial system. In response, the BCBS launched a two-prong effort to: 1) design a methodology for identifying which global banks posed sufficient "systemic risk" to warrant an additional capital surcharge and 2) a methodology to determine the size of the capital surcharge.[8]

The BCBS' process culminated in 2013 with a final framework establishing both the quantitative framework for identifying Global Systemically Important Banks (GSIBs) and the framework for determining the size of the surcharge that would apply to each GSIB. The GSIB identification framework depends on five specific quantitative indicators that have been deemed by the BCBS to be important indicia of "systemic risk": complexity, cross-jurisdictional activity, interconnectedness, size, and substitutability.[9] Each of the indicators is composed from a wide range of detailed financial data. In Table 1, we list each indicator, provide a brief definition of the indicator, and provide an example data input that is used to define each indicator.

The BCBS methodology measures complexity with reference to the value of OTC derivative exposures, level 3 assets, and trading and available-for-sale securities. Cross-jurisdictional activity is measured by the value of cross-jurisdictional claims and liabilities. Interconnectedness is measured with reference to the value of intra-financial system assets and liabilities, e.g. funds lent to or borrowed from other financial institutions, as well

[8] The GSIB capital surcharge is perhaps the best known and most significant bank regulation that is applied to GSIBs but it is not the only such regulation. Other regulations that are applied only to GSIBs would include so-called TLAC (long-term debt) requirements as well as certain counterparty exposure limits.

[9] Whether the indicators identified by regulators correspond to "systemic risk" is difficult to discern due to the lack of a common, well-accepted, and transparent measure of systemic risk. The term "systemic indicator" is used to align with standard parlance and not as an endorsement of the information content of the indicators for actual systemic risk.

as the value of a bank's outstanding debt and equity securities. Size is measured as the value of a bank's on-balance sheet assets and a regulatory measure of off-balance sheet exposures such as loan commitments and derivative exposures. Finally, substitutability is intended by regulators to measure the extent to which the failure of a bank would present problems for the financial system from the interruption of specific banking activities that are both important to the financial system and difficult for other banks to provide quickly due to technological, logistical, legal, or other constraints. The BCBS framework measures substitutability with reference to the level of assets under custody, the amount of payments activity, and the value of underwritten debt and equity transactions.[10]

A bank's GSIB score is calculated by summing the value of each indicator after first normalizing (i.e. dividing) each indicator by the aggregate value of the indicator across a large sample of global banks that is conducted annually. The most recent survey of banks, end-2023, used in the GSIB assessment methodology included over 100 banks from 20 countries.[11] Post-normalization, the five indicators are summed and any bank with a normalized score above 130 is labeled a GSIB and is subject to the additional capital surcharge. As of 2024, this process has identified 28 banks as GSIBs.

The normalization of each GSIB indicator is a critical aspect of the BCBS GSIB identification methodology. It represents an affirmative statement that the nominal size of a bank or the nominal amount of a given activity is not an indicator of systemic risk. As an

[10] The substitutability indicator is controversial. The BCBS framework limits the extent to which the substitutability category can influence the overall GSIB score by placing a limit on its maximum value. Further, and as will be discussed the U.S. implementation of the GSIB surcharge omits the substitutability category from the GSIB surcharge calculation.

[11] Data on the banks used in the end-2023 assessment can be found at: https://www.bis.org/bcbs/gsib/index.htm

example, if the world banking system grows by, say, 10 percent, due to underlying global economic growth and all banks see their "size" component increase by 10 percent in nominal terms, the BCBS size indicator will be unaffected for all banks. Moreover, most if not all the underlying indicator variables, variables such as securities outstanding, the value of underwritten transactions, and the value of trading securities, naturally scale with the overall size of the banking sector. Accordingly, normalizing each indicator by the aggregate value of that indicator across the global sample of banks ensures that GSIB scores are not inflated by nominal growth in the size of the banking and financial system. After defining the GSIB score for each bank, the GSIB score is mapped to a GSIB surcharge using a step-wise function that assigns a surcharge of one percent to a GSIB score between 130 and 229 and then generally rises by 0.5 percent for each 100-point increase in score.[12]

Every country that is a member of the BCBS implements national regulation through their own respective regulatory process. In general, there is an expectation that each member country of the BCBS will implement BCBS requirements in a manner consistent with the BCBS agreement though countries can and do deviate for reasons relating to national specificities that are not considered in the global agreements. In the U.S., the GSIB surcharge is under the sole jurisdiction of the Federal Reserve Board and the Federal Reserve finalized its implementation of the GSIB identification and capital surcharge methodology in 2015 (Federal Reserve, 2015). The Federal Reserve's implementation of

[12] More specifically, the BCBS surcharge schedule has 5 "buckets". The first four buckets exhibit a surcharge increase of 0.5 percent for each 100-point increase in score. The final "bucket" begins at a score of 530 and assigns a GSIB surcharge that is 1 percentage point higher, 3.5 percent, than the prior "bucket". A GSIB surcharge of 3.5 percent is the highest possible surcharge under the BCBS methodology.

the GSIB surcharge regulation exhibits two key departures from the BCBS methodology that is relevant for this analysis. These departures are depicted in Table 1.

First, unlike the BCBS approach, the U.S. implementation of the GSIB score for purposes of assigning the capital surcharge does not normalize the value of each GSIB indicator by the aggregate value of the indicator across the global banking system. Rather, the U.S. surcharge rule uses a set of "fixed coefficients" to scale each indicator before the indicators are summed to produce the overall GSIB score. The lack of any normalization of indicator scores implies that the U.S. GSIB score is subject to nominal growth or "inflation" in a manner not exhibited by the BCBS GSIB score. As an example, a 10 percent increase in the size of the global banking sector that is uniformly spread throughout the entire banking system will necessarily result in an increase in U.S. GSIB scores but no increase in the corresponding BCBS GSIB score. The Federal Reserve was fully aware of this issue in 2015 when the rule was finalized and contemplated a future adjustment to the U.S. GSIB score to account for nominal growth in GSIB scores unrelated to systemic risk.[13] To date, however, the Federal Reserve has not updated the GSIB Surcharge rule to deal with this outstanding issue.[14]

Second, for the purposes of calculating GSIB surcharges, the U.S. surcharge rule omits the substitutability indicator and includes an additional indicator, short-term

---

[13] More specifically, the final rule states that "[T]he Board acknowledges that over time, a bank holding company's method 2 score may be affected by economic growth that does not represent an increase in systemic risk. To ensure changes in economic growth do not unduly affect firms' systemic risk scores, the Board will periodically review the coefficients and make adjustments as appropriate."

[14] In June of 2023, the Federal Reserve issued a proposal that would make some adjustments intended to alleviate the nominal growth in the GSIB score. The proposal, however, has not been acted upon since it was released.

wholesale funding (STWF), that is not included in the BCBS framework. The STWF factor is defined as the amount of wholesale liabilities obtained by a bank with a maturity of one year or less divided by the value of the bank's risk-weighted assets. The indicator includes all sources of short-term wholesale liabilities – both secured and unsecured – and excludes retail short-term liabilities, i.e. deposits.

The exclusion of the substitutability indicator and the inclusion of the STWF indicator are controversial due to the clear global inconsistency that is created which undermines the underlying BCBS goal of a harmonized regulatory framework. Further, and importantly, views on the importance of short-term wholesale funding as an indicator of systemic risk have changed over the past fifteen years. Immediately following the crisis, regulators (Tarullo, 2013) often pointed to the problems created by using wholesale short-term funding (e.g. repo) to fund longer term illiquid and risky assets (e.g. sub-prime mortgage loans or securities).

In the ensuing decade, however, research (Andersen, Du, Schlusche, 2021) has shown that banks' use of short-term wholesale funding, (e.g. overnight repo funding provided by money funds), has shifted substantially and is now more commonly matched with short-term, liquid, and low-risk assets (e.g. bank reserves provided by the Federal Reserve) that pose no systemic risk. The matching of short-term liquid liabilities with short-term liquid assets greatly reduces the concern that asset liability mismatches in the use of short-term wholesale funding creates significant systemic risk in the banking sector.

It is important to note that while the U.S. GSIB score that is used to assign GSIB capital surcharges exhibits two important departures from the BCBS framework, the U.S does use the BCBS GSIB score to determine which banks are subject to the GSIB capital surcharge. In U.S. regulatory parlance, the BCBS GSIB score is deemed the Method 1 or "M1" score and the U.S. GSIB score is deemed the Method 2 or "M2" score. The Federal Reserve's GSIB capital surcharge rule uses the "M1" score to determine which U.S. banks are identified as GSIBs and then applies the "M2" score to determine the level of the GSIB surcharge. The U.S. GSIB capital surcharge – both in terms of the banks subject to the surcharge and the level of the surcharge – is updated annually.[15] Since the Federal Reserve's GSIB surcharge rule was finalized in 2015, the same set of eight U.S. headquartered bank holding companies have been identified as U.S. GSIBs.

Finally, U.S. GSIB surcharges are determined according to a step-wise mapping between Method 2 scores and surcharges. A GSIB with a Method 2 score of 130 is subject to a capital surcharge of 1 percentage point and the surcharge increases thereafter by 0.5 percentage points (50 basis points) for every additional 100 Method 2 score points. Figure 2 depicts the mapping between Method 2 scores and surcharges.[16]

3. Data

Before moving onto a detailed analysis of the U.S. GSIB score ("M2 score"), we provide a broad overview of the data. Our analysis focuses exclusively on M2 score data for U.S. GSIBs. We do not consider the M1 score because it plays no role in assigning the U.S

[15] The U.S. GSIB surcharge is updated annually based on fourth quarter reported values of the Method 2 or "M2" GSIB score. Large banks, however, are required to calculate and publicly report their Method 2 GSIB score each quarter.

[16] The difference between the M2 and M1 GSIB score results in a U.S. GSIB surcharge that is significantly higher for U.S. GSIBs than it is for their foreign peers. This aspect of the U.S. GSIB surcharge rule, however, is not a primary focus of this paper.

surcharge and the set of U.S. banks identified as GSIBs by the M1 score has been unchanged since 2015. The data on M2 scores is observed at a quarterly frequency from 2016:4 through 2024:4 (33 observations per bank). The data are retrieved from the FR Y-15 (Systemic Risk Report) and we measure the value of each of the five indicators. We do not analyze any of the sub-components or inputs that comprise the five separate indicators (e.g. the notional value of OTC derivatives which is an input into three of the five indicators). Accordingly, the data set is a balanced panel of five variables (five systemic risk indicators) across eight banks (eight U.S. GSIBs) between 2016 and 2024.

In Table 2, we show the average M2 score and its five individual components at three points in time: the beginning of our sample (2016:4), the period immediately prior to the onset of the COVID pandemic (2019:4), and the end of our sample (2024:4). We focus on the simple average M2 score across the eight U.S. GSIBs rather than an average that is weighted by total assets or some other metric to ensure that the average is not dominated by the behavior of only a few of the largest banks and to ensure that changes in the average are not driven by changes in the weights. Table 2 indicates that the average M2 score has risen by 84 points (556-472=84), or roughly 18 percent, over the sample period.[17] This increase aligns with the score increase that is depicted in Figure 1. Further, all the increase occurred post-COVID (post-2019:4) as the average M2 score dropped by one point between 2016:4 and 2019:4.

[17] It should be noted that the M2 GSIB score is constrained by an external limitation on the balance sheet of one U.S. GSIB. Since 2018, Wells Fargo has been subject to an explicit limit – an "asset cap" on its total consolidated assets. As a result of this limitation on growth, underlying trends that influence the value of the systemic indicators and M2 score are not operative for Wells Fargo. Accordingly, the increase in systemic indicators and M2 scores that we document likely understate the impact of these underlying trends.

Looking at the average of the individual score components shows a broad increase in the cross-jurisdictional, interconnectedness, size, and short-term wholesale funding (STWF) indicators that have each risen between roughly 15 and 30 score points over the sample period. In the case of the complexity indicator, the average score has fallen modestly (eight points) over the entire sample period though its value has risen somewhat (four points) in the post-COVID period. As in the case of the average M2 score, the observed increase in each of the five systemic indicators has been concentrated in the post-COVID period. Accordingly, both at the total M2 GSIB score level and at the level of each of the five indicators, the increase in average M2 scores is driven entirely by the post-COVID (2020:1-2024:4) period.

Figure 3 presents the time-series of the minimum, maximum, and average value of each systemic risk indicator as well as the M2 score over the sample period. Figure 4 presents the time-series of the minimum, maximum, and average share of the M2 score accounted for by each indicator.

Examining Figure 3 shows a good deal of dispersion between minimum and maximum values. Significant variation in overall scale across U.S. GSIBs is a primary contributor to variation in the level of the indicators. As an example, as of the fourth quarter of 2024 the largest U.S. GSIB has total assets of roughly $4.0 trillion while the smallest has a total asset base that is approximately one-tenth as large. In addition, each of the U.S. GSIBs maintains a focus on a particular business model that can be roughly characterized into three categories: commercial banking (Bank of America, Citigroup, JP Morgan, Wells Fargo), investment banking (Goldman Sachs, Morgan Stanley), and custody (Bank of New

York, State Street). And while most U.S. GSIBs engage in all or some of these three core banking functions, each GSIB maintains a particular business focus which does generate measurable differences in systemic indicators. As an example, custody banks generally have lower levels of OTC derivatives which significantly affect the complexity and interconnectedness indicators. At the same time, custody banks make greater use of short-term wholesale funding due to a smaller deposit franchise and more limited retail presence.

The plots in Figure 4 also reveal a significant degree of dispersion in the share that each indicator comprises of the overall score. Regulators attempted to calibrate the M2 GSIB score so that each indicator would account for roughly 20% of the overall score (Federal Reserve, 2015). Figure 4, however, shows that the short-term wholesale funding (STWF) indicator comprises a considerably larger share. On average, the STWF score accounts for over 30% of the M2 score and this has been the case over the entire sample period. At the same time, the maximum share of the STWF indicator has consistently accounted for more than 60 percent of the M2 score while the minimum STWF share amounts to roughly 10 percent of the M2 score which is broadly consistent with the minimum share of the other four indicators. As previously discussed, the complexity indicator's share has dropped modestly over the sample period while the average share of the other indicators has remained relatively stable over the sample period.

In addition to the data on M2 scores and the five indicators, we also consider two measures of the size and scale of the U.S. financial system – the size of bank reserves issued by the Federal Reserve and the amount of outstanding U.S. Treasury securities.

These two series are obtained from the Federal Reserve Economic Database (FRED) and are depicted in Figure 5.[18] Between 2016 and 2019 the level of bank reserves declined from roughly $2.2 trillion to $1.6 trillion as the Federal Reserve was in the process of normalizing the size of its balance sheet after its expansion during the 2008 financial crisis. Beginning in 2020:1, however, the Federal Reserve abruptly reversed course and massively expanded its balance sheet in response to the COVID pandemic. By 2021:4 bank reserves reached a maximum of roughly $4.2 trillion before dropping to roughly $3 trillion as the Federal Reserve sought to raise interest rates and remove monetary accommodation. Since 2022 bank reserves have been relatively stable at a level of roughly $3 trillion.

The behavior of outstanding U.S. Treasuries also shows the pronounced impact of the COVID pandemic. In just a single quarter, between 2020:2 and 2020:3, total outstanding U.S. Treasuries increased by roughly $3.3 trillion. Prior to 2020:2, outstanding U.S. Treasuries grew at roughly $850 billion per year. The significant increase in Treasuries outstanding reflects the heightened issuance that was required to fulfill the requirements of COVID-era fiscal policy such as direct payments to households, funding for extended unemployment benefits, and various other COVID programs. Following the initial burst of COVID-driven issuance in 2020:2 U.S. Treasury issuance accelerated, running at roughly $1.6 trillion per year or roughly double the pre-COVID rate.

Finally, in Table 3 we report the degree of persistence in the average M2 Score, the average of each of the five indicators, as well as the bank reserve and U.S. Treasury series

[18] In the case of bank reserves we use total reserves of depository institutions (TOTRESNS) and in the case of U.S. Treasuries we use federal debt held by the public (FYGFDPUN) which represents net issuance.

as measured by the first five autocorrelations of each series. In what follows, we will analyze the relationship between the systemic indicators, U.S. Treasuries, and bank reserves. Accordingly, it is important to assess the degree of persistence in these variables to assess the possibility for spurious correlations in the data. As shown in Table 3, all variables, except the complexity indicator, show a high degree of persistence. Values of the first-order autocorrelation coefficient are between 0.8 and 0.9 for every series except the complexity indicator. In the case of the complexity indicator, the degree of first-order serial correlation is relatively low at 0.09 as is the level of autocorrelation at every displacement except the fourth lag which corresponds to a period of one-year.[19]

4. The Relationship Between GSIB Scores, GSIB Score Components, and the Supply of Safe Assets

In this section, we consider the relationship between each systemic indicator and the level of bank reserves and outstanding U.S. Treasury debt. In general, there are two reasons to expect that the systemic risk indicators are systematically related to the level of bank reserves and outstanding Treasury debt. First, both bank reserves and U.S. Treasuries appear directly on bank balance sheets that then directly enter multiple systemic indicators. In the case of bank reserves, bank reserves directly enter the size indicator. In the case of U.S. Treasuries, U.S. Treasuries directly enter the size indicator and the complexity indicator (through U.S. Treasuries held in trading or Available-For-Sale accounts).

[19] The value of the fourth-order autocorrelation is 0.55 which is statistically significant.

In addition, and importantly, the level of safe assets in the economy are likely to have an indirect but significant influence on the level of the five systemic indicators beyond their direct impact. In particular, the level of safe assets in the economy is an important proxy for the overall size and scale of the financial system. The overall size and scale of the financial system is likely to spur additional economic and financial activity that flows through the banking sector. As an example, notional OTC derivatives are a key component of several systemic indicators (size, interconnectedness, complexity). As the level of U.S. Treasuries increases in the economy, various holders of Treasuries will bear greater interest rate risk and demand derivative hedges from dealer banks that increase the notional outstanding of OTC derivatives among large banks. Relatedly, a large increase in bank reserves may spur lending that creates additional asset exposures for banks that are captured in the various systemic indicators. Indeed, the large increase in bank reserves that accompanied the COVID pandemic was intended by the Federal Reserve to supply a large amount of liquidity to the banking system so that banks could more easily provide credit to the economy.[20] Accordingly, increases in the supply of safe and liquid assets is likely to have both direct and indirect effects on bank balance sheets that will influence the systemic indicators and ultimately M2 scores.

We consider the relationship between each systemic indicator and the level of bank reserves and outstanding U.S. Treasuries with the following simple empirical framework,

---

[20] As an example, in describing its decision to purchase $700 billion in Treasury and Agency securities in March of 2020, the Federal Reserve stated that it was taking this action to “use its full range of authorities to provide powerful support for the flow of credit to American families and businesses.” https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm

$$Indicator_{ijt} = \alpha_{ij} + \beta \times Reserves_t + \gamma \times UST_t + \varepsilon_{ijt}. \quad (1)$$

Given the high degree of autocorrelation in each of the systemic indicator series as well as bank reserves and outstanding Treasuries that is documented in Table 3, there is a valid concern that standard OLS inference applied to equation (1) may be highly misleading due to a spurious regression problem (Granger and Newbold, 1978). Time series variables displaying a high degree of persistence may appear to be systematically related according to standard OLS diagnostics (e.g. t-statistics) even if no such population-level relationship exists. To address this possibility, we conduct Engle-Granger (Engle & Granger, 1987) cointegration tests that directly address the spurious regression concern. Because the data are in a panel format, we consider panel cointegration tests (Pedroni, 2004) that are adapted to a panel data setting.

In Table 4 we report the p-value associated with the Pedroni ADF cointegration test. In addition, we also report the result of the panel ADF unit root test for each series given that the presence of a unit root is a precondition for cointegration. We consider the case for cointegration between each systemic indicator and the level of bank reserves and outstanding U.S. Treasuries as well as between the M2 score itself and the level of bank reserves and U.S. Treasuries.

The data generally do not reject the unit root hypothesis for each of the included series which is not surprising considering the level of autocorrelations observed in Table 3. The cointegration tests all reject the null hypothesis of no cointegration below the 10 percent level of significance and most of the tests reject the null of no cointegration at the five percent significance level or less. In the case of the M2 score, which aggregates and summarizes all the data in the systemic indicators, the p-value of the test is one percent indicating a strong rejection of the null of no cointegration. Accordingly, this analysis points to a systematic relationship in the levels of the systemic indicators and the level of safe assets in the U.S. economy that is not simply an artifact of the statistical vagaries of the data. As previously described, there is strong economic intuition to expect a systematic relationship between the indicators and the supply of safe assets given both the direct and indirect effect that the supply of safe assets has on the level of financial and banking activity.

In Table 5, we report the result from estimating equation (1) above via OLS. Below the estimated parameters, we present the F-test of the joint hypothesis that neither the level of bank reserves nor outstanding U.S. Treasuries is systematically related to the indicator. Below the F-test we report the R2 from equation (1) as well as the "within" R2 that excludes the variation accounted for by variation in fixed effects across banks and measures the amount of time-series variation in each indicator exclusively accounted for by time-series variation in the supply of safe assets.

Among the five systemic indicators, the complexity indicator shows the weakest evidence in favor of a systematic relationship to the supply of safe assets. Each of the estimated coefficients is insignificant and the F-test is also insignificant at all conventional significance levels. This result is also consistent with the cointegration results presented in

Table 4, in which the complexity indicator was not found to exhibit cointegration with the level of bank reserves or U.S. Treasuries at or below the five percent significance level.

Each of the remaining indicators show clear support for a significant relationship between the indicator and the supply of safe assets. In each case, the resulting F-test is significant at all conventional significance levels. The overall R2 is generally in excess of 95 percent with “within” R2 values ranging from a low of 17 percent (STWF) to a high of 56 percent (Size). Looking at the individual point estimates on reserves and U.S. Treasuries shows a considerable degree of consistency in point estimates across the indicators.

The estimated impact of bank reserves on each indicator is positive in all but one case (interconnectedness) where it is insignificant and the magnitude and statistical significance of the point estimate is similar across all indicators that show joint statistical significance. Likewise, in the case of outstanding U.S. Treasuries, all point estimates, save the insignificant complexity indicator are positive, are of roughly similar magnitude, and are statistically significant in the case of all four indicators showing joint significance except for the STWF indicator.

Overall, the results in Table 5 agree with the broad evidence in favor of cointegration presented in Table 4. The systemic indicators, save the complexity indicator, exhibit a statistically significant relationship with the level of safe asset supply in the Unites States. As previously discussed, this relationship is not difficult to understand considering the nominal nature of each indicator. In the case of the size indicator, for example, an increase in the nominal level of bank reserves naturally leads to an increase in bank assets as reserves are mechanically absorbed by the banking sector.[21]

Similarly, a rise in the global level of outstanding U.S. Treasuries results in an increase in banking sector assets as banks generally absorb a portion of the increase in U.S. Treasury supply. In the case of banks' absorption of U.S. Treasury supply there are at least two factors at play. First, most U.S. GSIBs act as primary dealers in the U.S. Treasury market.[22] According to the Federal Reserve Bank of New York, "primary dealers are expected to make markets for the New York Fed on behalf of its official accountholders as needed, and to bid on a pro-rata basis in all Treasury auctions at reasonably competitive prices." Accordingly, as U.S. Treasury supply increases, primary dealers have some obligation to increase their participation in, and ultimately holdings of, U.S. Treasury securities. Second, post-crisis liquidity requirements essentially mandate that large banks hold a significant amount of low-risk, safe assets against their various liability sources. Recent research has documented how these requirements have led to a large expansion in the holdings of U.S. Treasuries on the balance sheet of U.S. GSIBs (Stulz, Taboada, van Dijk, 2023). In addition, as the U.S. government flooded the economy with liquidity during the COVID pandemic, household and businesses extended their banking relationships thereby creating more bank liabilities via various forms of deposits and other types of bank funding that then

---

[21] Of course, the Federal Reserve exogenously determines the aggregate supply of reserves but not the level of reserves maintained by an individual bank. While it may be possible, in theory, for a bank to reduce its share of sector-wide reserves, in practice such a change would require significant and abrupt changes to a bank's own business model as well as its relation to the rest of the financial sector.

[22] According to the Federal Reserve Bank of New York, six of eight U.S. GSIBs act as primary dealers in the U.S. Treasury market.

mechanically demanded higher levels of U.S. Treasury holdings through the mechanical operation of regulatory liquidity requirements.[23]

The link between the remaining systemic indicators and the supply of safe assets can similarly be understood in two ways. First, in the case of some indicators there is simply a mechanical relationship between the supply of safe assets and the indicator. As an example, trading securities and AFS securities - both of which are comprised of some portion of U.S. Treasury securities – directly enters the complexity indicator.

Second, there is a broader and likely more important sense in which a nominal increase in government securities and government provisioned liquidity results in a nominal increase in banking activity. As an example, a significant increase in government provisioned liquidity generally increases the cash holdings of money market mutual funds as households sought to park the additional liquidity provided by COVID-driven fiscal policy.[24] But money funds typically place this cash with large banks via "overnight repo" in which the bank takes cash from the fund, pledges U.S. Treasury collateral to the fund, and places the cash on deposit in the form of a reserve asset at the Federal Reserve. This transaction mechanically increases the magnitude of the bank's short-term wholesale funding (STWF) indicator, even though the transaction is financing a nearly risk-free, liquid asset (Andersen A., Du W., Schlusche B., 2021).

---

[23] Abdelrahman and Oliviera (2024) document an increase in excess savings of roughly $2.1 trillion during 2020 and 2021 as a direct result of COVID-era fiscal policy that funded by elevated U.S. Treasury issuance. This excess savings was largely plowed back into the banking system through various bank liabilities such as deposits and CD's.

[24] According to the Federal Reserve's Financial Accounts of the United States, between the fourth quarter of 2019 and the fourth quarter of 2024 the aggregate value of financial assets held by money market mutual funds doubled from $3.6 trillion to $7.2 trillion.

Relatedly, as the government increases the supply of U.S. Treasury securities, so too does it increase the amount of interest rate risk in the economy. Large banks constitute a large majority of the worldwide derivative dealing capacity that is used by various financial end-users (banks, insurance, companies, non-financial corporates) to hedge that risk. Moreover, gross notional amounts of derivative activity enter four separate systemic indicators. Accordingly, a general rise in the nominal supply of safe assets essentially creates a nominal increase in the demand for financial services provided by banks.

The results of the model described by equation (1) and reported in Table 5 can be used to estimate the value of the average M2 GSIB score over the sample period by evaluating the estimated model for each systemic indicator and each U.S. GSIB at each point in time between 2016:4 and 2024:4. The result of this exercise is presented in Figure 6. The data in Figure 6 show a close degree of agreement between the actual average M2 GSIB surcharge and the model's fitted value. Indeed, the fitted value tracks the trend in the average M2 GSIB score quite closely and also replicates the sharp increase at the onset of the COVID pandemic in 2020 as well as the modest deceleration in the trend that occurred after 2022. The results displayed in Figure 6 show that effectively the entire increase in the average M2 GSIB score over the sample period can be attributed to the increase in the supply of safe assets. To the extent that other factors affect the level of the average M2 GSIB score, none of those factors have any significant explanatory power for the increase in the average M2 GSIB score since 2016.

The analysis presented in Tables 4 and 5 and Figure 6 demonstrates a clear empirical link between the supply of safe assets and the level of systemic indicators that determine the M2 GSIB score. The estimated relationship between the systemic indicators and the supply of safe assets is robust to concerns of a spurious relationship considering the cointegration results reported in Table 4. Further, the estimated relationship is significant across all systemic indicators with the exception of the complexity indicator. The clear and robust relationship between the systemic indicators and the supply of safe assets suggests the presence of a common factor structure underlying the systemic indicators which we explore in the next section.

5. A Common Factor Representation of the Systemic Indicators

The analysis that we have presented considers each systemic indicator in isolation as though it were completely separate and distinct from each of the other systemic indicators. Considering the evidence that each indicator is driven by a common component related to the supply of safe assets and the scale of the financial system, it is useful to consider the extent to which the indicators themselves may be driven by a small set of common factors. Such a factor representation, if present, can yield important insights into the nature of the common drivers of the systemic indicators. To explore this possibility, we consider the following unobserved factor model for the systemic indicators,

$$Indicator_{ijt} = \alpha_{ij} + \lambda_{1ij} \times F_{1,t} + \lambda_{2ij} \times F_{2,t} + \cdots + \lambda_{kij} \times F_{k,t} + \varepsilon_{ijt} . \tag{2}$$

This model relates each of the 40 indicators (8 U.S. GSIBs and 5 indicators each) to a comparatively smaller number of factors. We estimate the above factor model representation using a standard principal components decomposition and we consider a maximum of five factors. The common factor representation and principal components decomposition is a standard modeling approach in contexts where a relatively large number of macroeconomic and financial variables exhibit significant co-movement that is generated by a small number of fundamental economic drivers (Stock and Watson, 2002).

In Table 6 we report the proportion of variance accounted for by each of the five estimated factors. As shown in the table, the first factor accounts for more than sixty percent (63.1) of the observed variability in the systemic indicators. The second through fifth factors account for roughly between twelve and four percent of the observed variability in the systemic indicators. Taken together, the five-factor representation accounts for over 90 percent (90.3) of the variability in the systemic indicators across the eight U.S. GSIBs.

These results provide clear indication of a latent, common factor structure in the systemic indicator data. A simple three factor representation accounts for over eighty percent (81.7) of the variability in the forty systemic indicators observed over the sample period.

In Figure 7 we show time-series plots of each of the five factors. The first factor shows evidence of a clear trend over the sample period which accords with the overall increase in the M2 score that is documented in Figure 1. The factor loadings (unreported) show that for most indicators, the factor loading on the first factor is positive and is the largest among the five factors, indicating clear evidence of a trend in both the M2 score and the underlying indicators. The second factor does not display any clear trend but does display interesting behavior that is concentrated during the COVID period. More specifically, this factor shows a pronounced decline in 2020 and 2021 that is then reversed in the later, post-COVID, years. The third factor displays no trend but interesting cyclical behavior with a period of roughly two years. The fourth and fifth factors are substantially less variable than the first three factors and do not display any significant or interesting dynamics akin to that exhibited by the first three factors.

While the factor representation presented in Figure 7 is a useful means of characterizing the systemic indicator data, it is also useful to analyze how the identified factors relate to the systemic indicators. To assess the relationship between each of the factors and each of the five systemic indicators we perform a univariate regression of each indicator onto each factor. We then report the average R2 – averaged across the eight U.S. GSIBs for a given indicator - for each pairing of factor and systemic indicator. The average R2 provides a useful measure of association between the identified factor and systemic indicator. The results are reported in Table 7 with factors ordered along the rows and indicators ordered along the columns. In each row of the table, we highlight the maximal R2 value in bold which shows which systemic indicator is most highly correlated with each factor.

Looking at the results in Table 7 shows that in the case of the first factor, there is a high degree of association between all systemic indicators and the first factor – R2s range from 0.87 to 0.98. The R2 is maximized in the case of the size indicator. Moreover, the size indicator is not associated with the maximal R2 for any of the other four factors. Accordingly, one can loosely consider the first factor as being a measure of bank “size”. The second and third factors are both most closely associated with the short-term wholesale funding (STWF) factor. The fourth factor is most closely associated with the cross-jurisdictional indicator while the fifth factor is most closely associated with the complexity indicator.

Finally, we relate the identified factors to the supply of safe assets as was done in the previous section. Specifically, we consider the case for cointegration between each factor and the level of outstanding U.S. Treasuries and bank reserves in the context of the following model,

$$Factor_{it} = \zeta_i + \delta \times Reserves_t + \rho \times UST_t + \varepsilon_{it}. \tag{3}$$

The results of the Engle-Granger tests for each of the five estimated factors are reported in Table 8 and follow the form of the results previously reported in Table 4. The results reported in Table 8 show clear evidence of cointegration between the first factor, reserves, and outstanding U.S. Treasuries with a p-value of 0.01. A regression of the first factor onto the level of outstanding U.S. Treasuries and reserves results in an R2 of 96%. The remaining tests show significantly less compelling evidence in favor of cointegration between the other factors, bank reserves and U.S. Treasuries. In the case of the other four factors, the p-value of the Engle-Granger test is measurably larger than any conventional significance value.

These results provide important context for the previous results showing cointegration between the systemic indicators, bank reserves, and U.S. Treasuries. The results outlined in Table 8 indicate that the source of the identified cointegration in the systemic indicators is the result of a strong link between bank reserves, the level of outstanding U.S. Treasuries, and the first or “size” factor. This relationship further suggests that the size factor itself is related to the scale of the financial system and the economy. As the supply of safe assets, the financial system, and the economy grow, so too do the systemic risk indicators because, unlike the systemic indicators adopted by the BCBS, the U.S. M2 score is not invariant to a scaling of the overall financial system.

These findings that document an important link between M2 scores, the underlying systemic indicators, and the scale of the overall financial system has important policy implications. As previously discussed, scale growth in the financial system that is unrelated to risk will impart an upward drift in M2 scores and ultimately, capital surcharges. Moreover, decisions to further grow the supply of safe assets will mechanically increase M2 scores and surcharges even if growth in the supply of safe assets is intended to limit or reduce systemic risks. In the next section, we quantitatively explore the extent to which growth in the supply of safe assets has driven observed increases in M2 GSIB scores since 2016. In addition, we consider the future trajectory for GSIB scores given long-range projections for the supply of safe assets.

6. The Quantitative Impact of Safe Asset Supply on GSIB Scores: Past, Present and Future

The previous analysis has documented a clear, statistically significant relationship between the level of bank reserves, the level of outstanding U.S. Treasuries, and the systemic indicators that comprise the M2 GSIB score. In this section we explore the economic significance of this relationship by documenting the quantitative extent to which changes in the supply of safe assets over the past several years has resulted in increased GSIB scores, and ultimately surcharges.

We consider a counterfactual analysis in which the supply of safe assets deviates from the path that was observed over the 2016-2024 period. These counterfactual paths are depicted in Figure 8.

In the case of bank reserves we simply assume that bank reserves remained unchanged from their level in 2020:1. Accordingly, the COVID-era expansion in the Fed's balance sheet does not take place in the counterfactual analysis. In the case of outstanding U.S. Treasuries, we consider two different counterfactual paths. In the first path, as in the case of bank reserves, we simply assume that U.S. Treasuries outstanding remain at their 2020:1 level. Taken together, these two paths assume no growth in the supply of safe assets and is helpful to assess how much M2 GSIB score growth is driven by growth in the supply of safe assets. Of course, it is not realistic to assume that the U.S. government would cease to issue Treasury securities as borrowing is a regular part of U.S. fiscal policy. Accordingly, we consider a second counterfactual path for U.S. Treasury growth in which growth occurs at the pre-COVID rate of roughly $850 billion per year.

Figure 9 shows the results of the counterfactual analysis. Each counterfactual path is generated by assuming a given counterfactual path for reserves and U.S. Treasuries and then using the model estimated in equation (1) to calculate the counterfactual time-series path for each systemic indicator and each U.S. GSIB. The resulting counterfactual paths for systemic indicators are then aggregated to form a counterfactual M2 GSIB score path for each U.S. GSIB. The resulting counterfactual M2 GSIB score paths are then averaged across U.S. GSIBs to construct the counterfactual average M2 GSIB score path.[25]

The top-left panel of the figure shows the counterfactual average M2 GSIB score that would have resulted under the counterfactual path for reserves and outstanding Treasuries that exhibit zero growth. This panel shows that the counterfactual average M2 GSIB score would have remained essentially flat over the entire sample period, so that growth in the supply of safe assets accounts for essentially all observed growth in the average M2 GSIB score since 2016. As discussed in the context of Figure 6, to the extent that other factors beyond the supply of safe assets and the scale of the financial system play a role in determining M2 GSIB scores, none of these factors have had an appreciable impact on average M2 GSIB scores since 2016.

The top-right panel of the Figure 9 shows the counterfactual path for the average M2 GSIB score from halting the growth in bank reserves but allowing U.S. Treasuries outstanding to grow unabated as they did over the 2016-2024 period. According to this analysis, the average M2 GSIB score would have increased from roughly 470 to 540 between 2016 and 2024 based on observed Treasury growth alone.

The bottom-left panel of Figure 9 shows the corresponding analysis in the case the Treasury growth was halted and bank reserves increased at the rate observed over the 2016-2024 period. Under this counterfactual scenario, average M2 GSIB scores would have increased from roughly 470 to 510 by the end of 2021 before declining to roughly 500

[25] In the case of the complexity systemic indicator, equation (1) finds no evidence of a systematic relationship between the indicator, reserves, and U.S. Treasuries. As a result, we simply use the realized value of the complexity indicator rather than the models' fitted value.

as the Federal Reserve reduced its balance sheet somewhat following the COVID pandemic.

Finally, the bottom-right panel of Figure 9 shows how average GSIB scores would have evolved if U.S. Treasury issuance had slowed to its pre-COVID pace of $850 billion per year while bank reserves were halted at their 2020:1 level. This counterfactual analysis shows that returning to a pre-COVID rate of debt issuance and a pre-COVID level of bank reserves would have greatly slowed the rate of increase in average M2 GSIB scores. Under this scenario, GSIB scores would have risen from roughly 470 to 500 over the sample period which is roughly 40 percent of the observed increase over the 2016-2024 period.

Taken together, these counterfactual analyses demonstrate significant economic as well as statistical significance of the documented relationship between safe assets and GSIB scores. Essentially, all observed growth in average M2 GSIB scores over the sample period can be attributed to growth in the supply of safe assets. Moreover, the extreme growth in government borrowing and liquidity provision that accompanied the COVID pandemic accounts for roughly 60 percent of the observed increase in average GSIB scores.

The counterfactual analysis presented in Figure 9 is useful for analyzing how past changes to GSIB scores have been driven by safe asset supply. Perhaps more importantly, one can project how average GSIB scores will evolve in the future given projections for bank reserves and Treasury issuance. A forward-looking assessment of future GSIB scores (and surcharges) is important to assess how bank capital policy will impact the banking sector and economy in the coming years. To project future levels of outstanding Treasuries we use the Congressional Budget Office's (CBO) public projection (CBO, 2025) of outstanding U.S. Treasuries and to project future levels of bank reserves we use the Federal Reserve Bank of New York's (FRBNY) projection of future bank reserves (FRBNY, 2023).

In Figure 10 we show the projection paths for both bank reserves and outstanding U.S. Treasuries. In the case of bank reserves, the FRBNY projection shows reserves dropping to a level of roughly $2.8 trillion through 2026 before rising again throughout the remainder of the projection period to a level of roughly $3.7 trillion.[26] In the case of outstanding U.S. Treasuries, we provide two projections paths. In one case, we simply adopt the CBO (CBO, 2025) projection which shows outstanding debt rising from roughly $30 to $52 trillion. We also consider a less dramatic projection in which outstanding Treasuries increase at a rate consistent with pre-COVID issuance. Under this scenario, outstanding U.S. Treasuries increase from roughly $30 to just under $40 trillion.

The projection results are displayed in Figure 11.[27] Under both projections, average M2 GSIB scores rise substantially through the end of 2035. Under the CBO projection, GSIB scores will increase by roughly an additional 120 points which is similar in magnitude to the increase that was observed over the 2016-2024 period. Under the more moderate projection, average M2 GSIB scores would rise by about 50 points or roughly half as much as under the CBO projection. The projected rise in GSIB scores is fully explained by the nominal nature of the M2 GSIB score. Continued growth in the U.S. economy, the financial

[26] The FRBNY projection ends in 2033:4. We extend the FRBNY projection through 2035 by assuming a flat level of reserves from 2033:4 through 2035:4.
[27] When computing projections for M2 GSIB scores we use the same procedure that was used in the case of the counterfactual projections. In the case of the complexity indicator, we project the current (2024:4) value into the future, given the insignificant results for the complexity indicator in equation (1).

system, and the supply of safe, liquid assets will have a direct, and mechanical effect on GSIB scores that will, if left unabated, result in further increases in capital requirements for U.S. GSIBs.

7. Policy Discussion and Implications for Systemic Risk Measurement

The analysis that has been presented clearly documents several significant features of the M2 score that have clear implications for bank regulatory policy and systemic risk measurement.

First, the M2 score is clearly driven by an aggregate trend that results from the fact that the U.S. M2 GSIB score is not invariant to the size and scale of the economy and the financial system while the BCBS M1 score, which is the adopted standard in non-U.S. jurisdictions, is invariant to the scale of the economy. The stark difference created by the lack of scale invariance in the M2 GSIB score can easily be seen by comparing the average M2 GSIB score with the average M1 BCBS score for U.S. GSIBs. In Figure 12 we present a time series plot of the M1 and M2 GSIB score from 2016-2023 and we index the 2016 score to 100 for both the M1 and M2 score to create an index.[28] The divergence between the BCBS M1 score and the US M2 score is clearly evident. While U.S. M2 scores expanded greatly after 2019 as the U.S. government, and governments around the world, added liquidity and government debt to the financial system, BCBS M1 score remained stable and even declined slightly for U.S. GSIBs. In particular, central banks around the world expanded their balance sheets while governments around the globe increased the supply

[28] Figure12 includes data from 2016-2023 and does not extend to 2024 because the M1 GSIB score for 2024 will not be available until the end of 2025.

of safe assets in response to the COVID pandemic. While the U.S. M2 score rose mechanically and significantly during this period, the normalization process employed by the BCBS M1 score forestalled any aggregate increase.

The lack of scale invariance and the starkly divergent behavior between the U.S. and BCBS GSIB scores raises important questions about the fundamental nature of systemic risk measurement for regulatory purposes. At one level, it is incongruous for a single, global regulatory initiative that is intended to measure a fundamental risk characteristic of banks across the globe – systemic risk – to result in such widely diverging metrics being applied. The results in Figure 12 make clear that a large bank operating in one jurisdiction will be subjected to a radically different regulatory regime than it would be if it were operating in another jurisdiction. The stark and widening rift in treatment across different jurisdictions raises obvious concerns around competitive equity while undermining the entire motivation for a global regulatory framework.

In addition to the obvious concerns raised by Figure 12, the trend growth in M2 scores that is systematically linked to the level of safe asset supply raises further questions. The empirical results show a strong and clear link between the growth in M2 GSIB scores and the growth in bank reserves and the outstanding Treasury supply. On its face, it is unclear how a development that increases the supply of safe and liquid assets in the financial system could increase the systemic risk of banks. Standard intuition would, at least arguably, run in the opposite direction: increasing the supply of low-risk, liquid assets in the banking system would generally be expected to reduce rather than raise systemic risks. Even if one contends that there are reasons why systemic risks could rise in such circumstances, it remains to explain why it is appropriate to reflect that position in one jurisdiction's regulatory regime and not others.

The trend growth in M2 scores raises another important concern regarding the regulatory capital requirements of U.S. GSIBs. The empirical results strongly indicate a common trend in bank reserves, outstanding U.S. Treasuries, and M2 GSIB scores. And as the projections presented in Figure 11 makes clear, M2 GSIB scores, and ultimately, GSIB surcharges for U.S. GSIBs will continue to rise indefinitely. Left unabated, these results indicate that M2 GSIB scores and surcharges will continue to rise indefinitely and will account for an ever-increasing share of bank regulatory capital requirements.

Beyond the important issue of the systematic link between GSIB scores and the level of safe asset supply, these findings raise important questions about the measurement of systemic risk for regulatory purposes. More specifically, the factor model results show that roughly 65 percent of the variability in the systemic indicators is driven by bank size alone. At the same time, the GSIB score reporting framework is extremely complex, involving hundreds, if not thousands, of specific data items. The net benefit of this elaborate reporting regime should be evaluated considering the results reported here. Even if one contends that the additional information contained in the GSIB score has meaningful information content for systemic risk measurement, that assertion must contend with the fact that the entire increase in GSIB scores since 2016 is driven entirely by the size factor that is driven by nominal economic growth.

Of course, one may reasonably contend that the primary value of the GSIB score is to identify important cross-sectional variation in bank-level systemic risk rather than any aggregate trend. Even accepting that premise, however, these results still raise questions about whether the data underlying the GSIB score accurately measures “systemic risk”. Unlike other types of risk such as default risk or asset price risk there is no universal, agreed upon data that measures “systemic risk” that can be reliably used to benchmark the efficacy of the existing measurement program. Essentially, while regulators have identified a large number of complex variables (i.e., right-hand side variables) that they believe defines “systemic risk” there is no clear measure of systemic risk (i.e., left-hand side variable) with which to assess the information content of the hypothesized risk drivers. Accordingly, there is a clear and significant onus on regulators to re-evaluate and re-assess the efficacy of the GSIB measurement program on an ongoing basis.

8. Conclusion

The Federal Reserve finalized its framework for systemic risk measurement in the context of the GSIB capital surcharge in 2015. Since that time, while some research has examined the impact of the GSIB capital surcharge on lending and other financial activity, no research has systematically analyzed the long-run time-series behavior of the U.S. Method 2 GSIB score that underlies the surcharge. In this paper we have systematically analyzed the behavior of U.S. GSIB scores over the 2016-2024 period. Our analysis has identified a clear and systematic link between the level of safe asset supply and the average GSIB score. The significant increase in safe asset supply that has occurred since the COVID pandemic has resulted in a significant increase in GSIB scores, accounting for the entire observed increase in GSIB scores since 2016. Our analysis also strongly suggests that, left unabated, further projected growth in the supply of safe assets will result in further increases in GSIB scores and capital surcharges for U.S. GSIBs. In addition, we document that most of the variability in GSIB scores is driven by fluctuations in bank size and this dependence on bank size accounts for the strong link between safe asset supply and GSIB scores.

These findings suggest some additional directions for future research. First, in the spirit of Favara, Ivanov and Rezende (2021), these findings raise important questions about how efforts to stimulate the economy through liquidity provision and related efforts may be frustrated by rising capital requirements on large banks. Examining how large bank credit intermediation responds to increased GSIB scores resulting from an increase in bank reserves may shed light on the actual efficacy of efforts to stimulate the flow of credit in the economy. Second, these findings raise important questions about the efficacy and relative costs and benefits of systemic risk measurement for regulatory purposes. Further research into this issue may yield important insights that could improve the ability of the regulatory framework to control important risks while also ensuring that credit is not unduly restricted in the economy.

<u>References</u>

Abdelrahman H., Oliveira L.E. (2024), “Pandemic Savings Are Gone: What’s Next for U.S. Consumers?”, San Francisco Federal Reserve Blog, May 3, 2024.

Andersen A., Du W., Schlusche B. (2021), “Arbitrage Capital of Global Banks.”, NBER Working paper #28658.

Basel Committee on Banking Supervision (2013), “Global Systemically Important Banks: Updated Assessment Methodology and the Higher Loss Absorbency Requirement”.

Baker M., Wurgler J. (2015), “Do Strict Capital Requirements Raise the Cost of Capital? Bank Regulation, Capital Structure, and the Low-Risk Anomaly.”, *American Economic Review*, 105(5): 315-320.

Behn M., Mangiante G., Parisi L., and Wedow M. (2021), “Behind the Scenes of the Beauty Contest – Window Dressing and the GSIB Framework.”, *International Journal of Central Banking*, 18, 5, 301-42.

Brooke M., Bush O., Edwards R., Ellis J., Francis B., Harimohan R., Neiss K., and Siegert C. (2015), “Measuring the Macroeconomic Costs and Benefits of Higher UK Bank Capital Requirements.”, Financial Stability Paper No. 35, Bank of England.

Cline W. (2015), “Testing the Modigliani Miller Theorem of Bank Capital Structure Irrelevance for Banks.”, Working Paper 15-8, Peterson Institute for International Economics.

Congressional Budget Office (2025), “The Budget Outlook: 2025-2035.”, https://www.cbo.gov/publication/60870.

D’Erasmo P. (2018), “Are Higher Capital Requirements Worth It?”, Economic Insights, Federal Reserve Bank of Philadelphia Research Department.

Engle, R. F., C. W. J. Granger. (19887) “Co-Integration and Error Correction: Representation, Estimation, and Testing.”, *Econometrica* 55, no. 2, 251–76.

Ferreira T., Shousha S. (2021), “Supply of Sovereign Safe Assets and Global Interest Rates, International Financial Discussion Papers.”, No. 1315.

Favara G., Ivanov I., Rezende M. (2021), “GSIB Surcharges and Bank Lending: Evidence from U.S. Corporate Loan Data.”, *Journal of Financial Economics*, 142, 3, 1426-1443.

Federal Reserve Bank of New York (2023), “Open Market Operations During 2023.”, https://www.newyorkfed.org/medialibrary/media/markets/omo/omo2023-pdf.pdf.

Federal Reserve Board. (2015), “Regulatory Capital Rules: Implementation of Risk-Based Capital Surcharges for Global Systemically Important Bank Holding Companies.”, Federal Register, 12 CFR Parts 208 and 217, 49082-49116.

Garcia L., Lewrick U., and Secnik T. (2023), “Window Dressing and the Designation of Global Systemically Important Banks.”, *Journal of Financial Services Research*, 64, 142(3)1426-1443.”

Jiang Y., Shen Y. (2024), “Balance Sheet Constraints of Prime Brokers on Hedge Fund Performance: Evidence form GSIB Surcharge.”, HKUST Business School Research Paper No. 2024-175.

Kashyap A., Stein J., and Hanson S. (2010), “An Analysis of the Impact of ‘Substantially Heightened’ Capital Requirements on Large Financial Institutions.”, mimeo, Harvard University.

King M. (2010), “Mapping Capital and Liquidity Requirements into Bank Lending Spreads.”, BIS Working Paper #324, Bank for International Settlements, Monetary and Economic Department.

Migueis, M., Pierce S. (2025), “Effect of the GSIB Surcharge on the Systemic Risk Posed by the Activities of GSIBs.”, Finance and Economics Discussion Series #2025-029, Federal Reserve Board.

Pedroni, P. (2004) “Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis.” *Econometric Theory* 20, no. 3, 597–625.

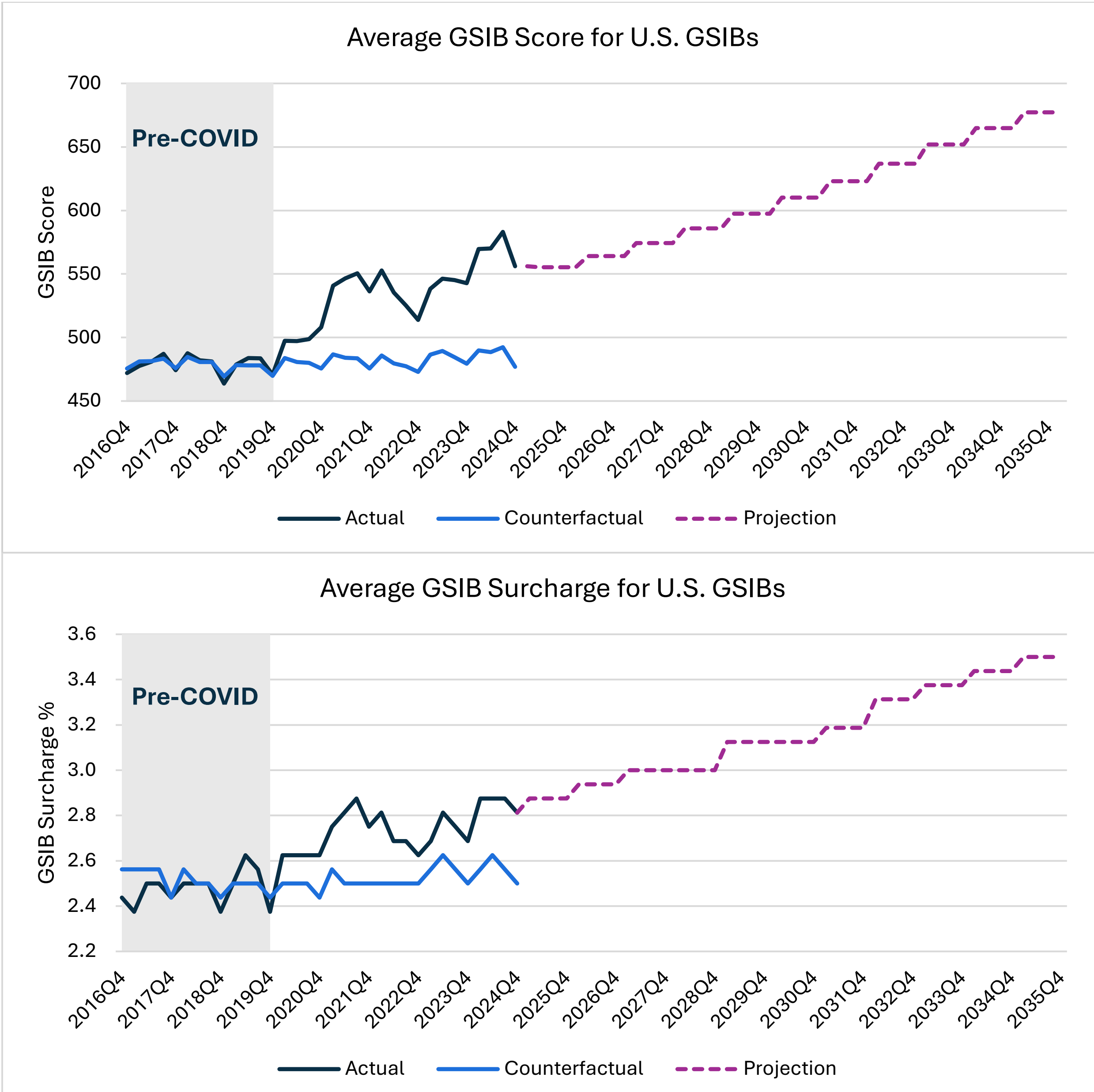
Naylor M., Corrias R., and Welz P. (2024), “Banks’ Window Dressing of the G-SIB Framework: Causal Evidence from a Quantitative Impact Study.”, Working Paper 42, Basel Committee on Banking Supervision.

Stock J.H., Watson M.W. (2002), “Macroeconomic Forecasting Using Diffusion Indexes.”, *Journal of Business and Economic Statistics*, April, 145-162.

Stulz R., Taboada A., van Dijk, Mathias A. (2023), “Why Are Banks Holdings of Liquid Assets so High?”, NBER Working Paper #30340.

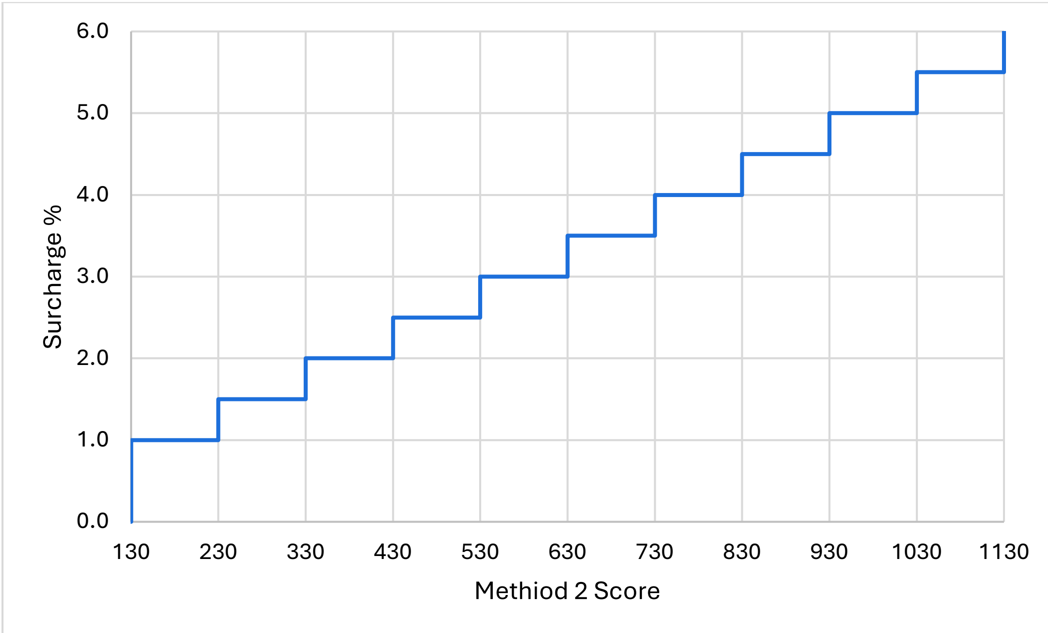
Tarullo D. K. (2013), “Macroprudential Regulation”, speech at the Yale Law School Conference on Challenges in Global Financial Services, New Haven, Connecticut, September 20, 2013.

Figure 1
GSIB Score and Surcharge: 2016-2035



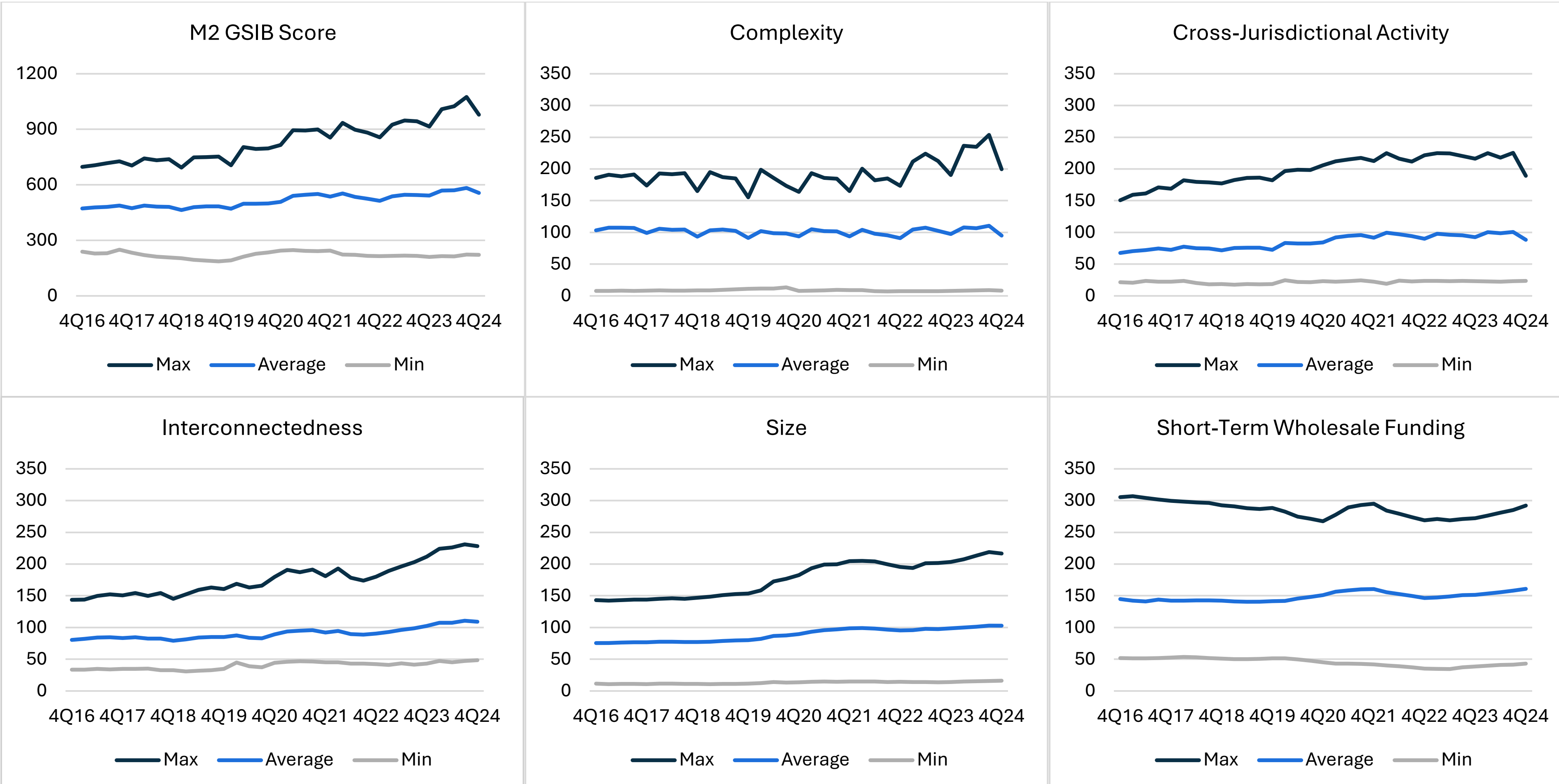
Notes: The top panel displays the U.S. Method 2 GSIB Score averaged across the eight U.S. GSIBs. The bottom panel displays the average GSIB surcharge across the eight U.S. GSIBs that corresponds to the Method 2 GSIB Score at each point in time. Notably, the surcharge presented in the lower panel does not correspond with the actual GSIB surcharge of each U.S. GSIB due to a timing lag between the realization of the Method 2 score and the resulting surcharge that is required by the Federal Reserve's GSIB surcharge rule. The projected score and surcharge are based on official government (FRBNY, CBO) projections of bank reserves and outstanding U.S. Treasuries.

Figure 2
Relationship Between Method 2 GSIB Score and Surcharge



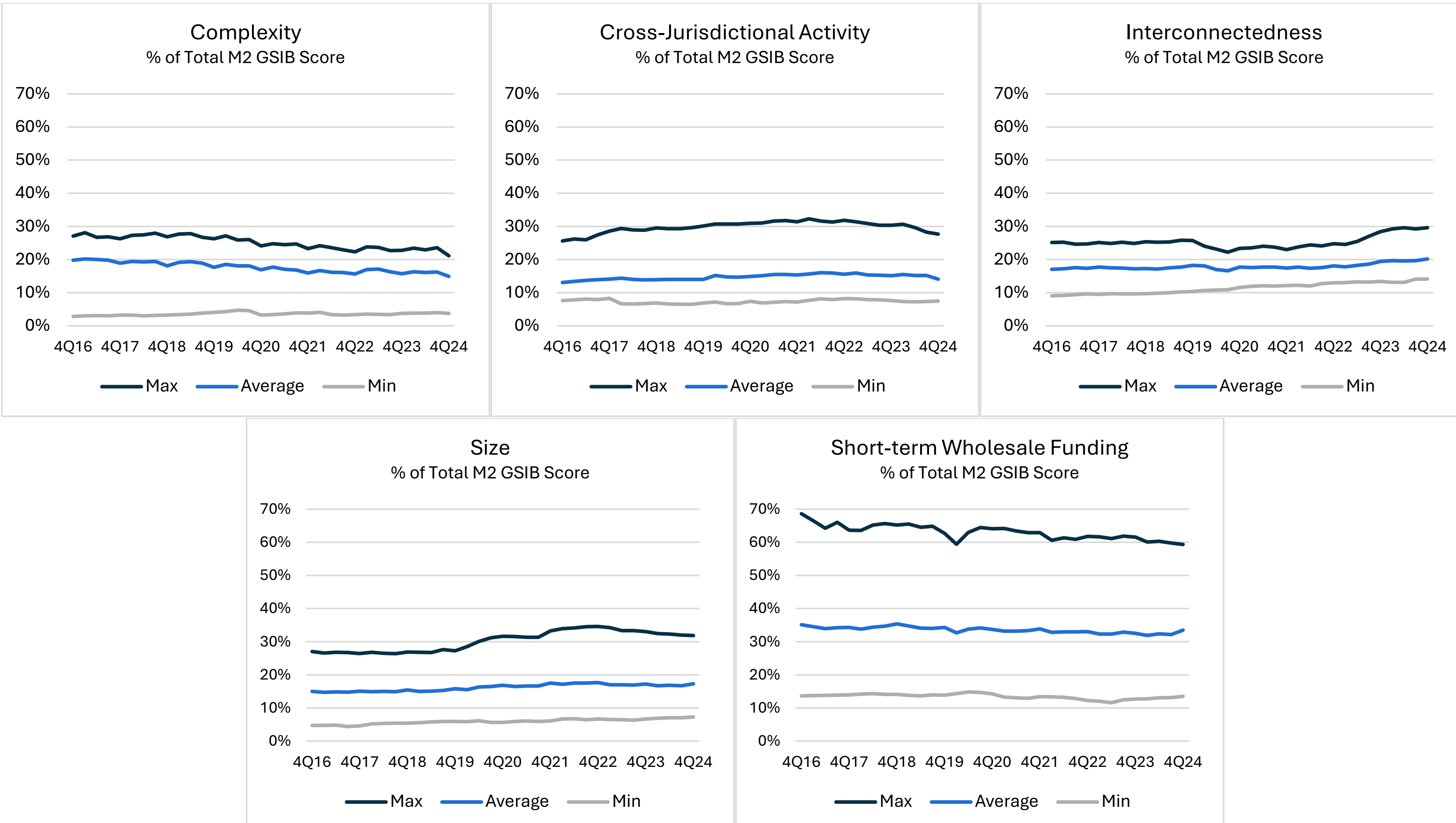
Notes: The figure shows Method 2 GSIB Score and its relative surcharge. Banks who have a Method 2 score below 130 will not be subject to a surcharge, and above 1130 will be subject to an additional 0.5 percentage point on top of 5.5 percentage point for every 100 basis points increase in score.

Figure 3
GSIB Score Indicators, 2016-2024



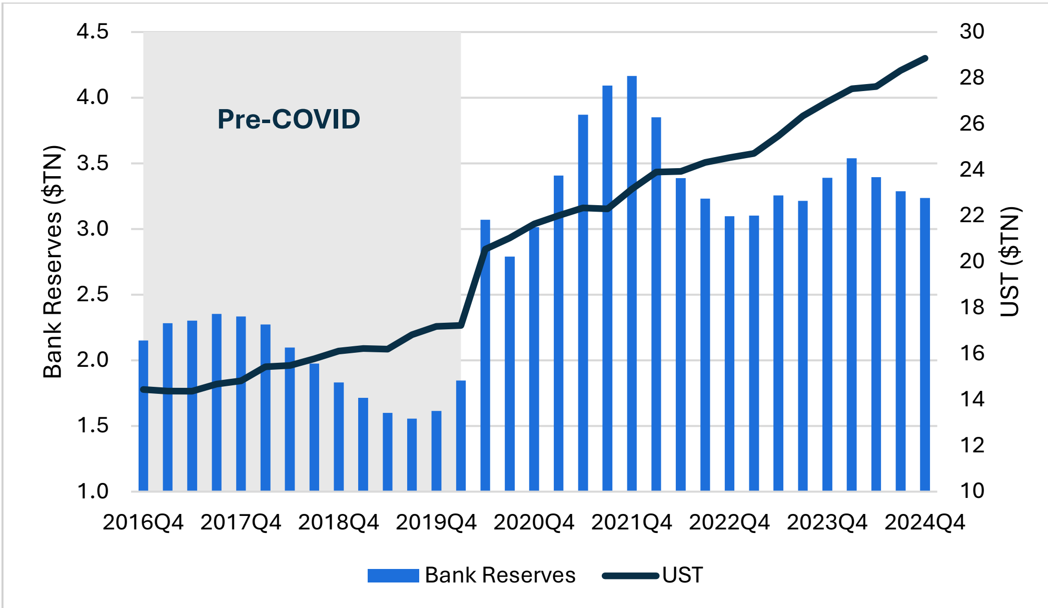
Notes: For the Method 2 GSIB Score and each systemic indicator, each panel displays a time-series of: 1) the maximum value of the indicator (score), 2) the average value of the indicator (score), 3) the minimum value of the indicator (score).

Figure 4
Share of Indicators in GSIB Score, 2016-2024



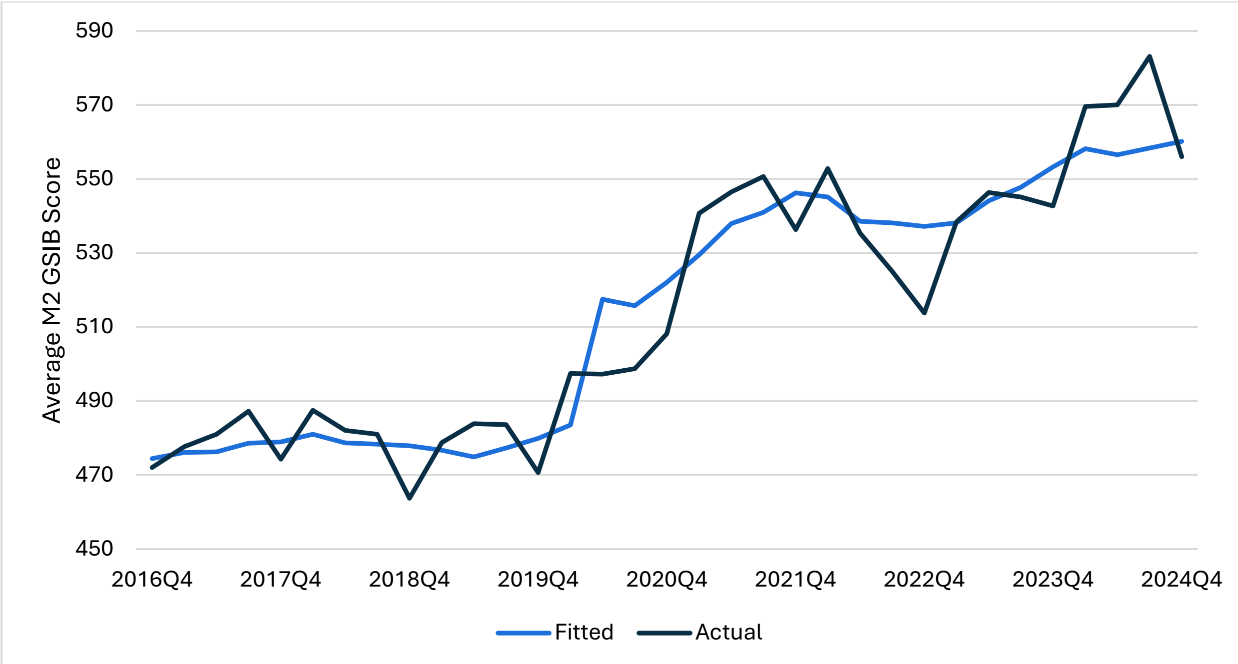
Notes: For each systemic indicator, each panel displays a time-series of: 1) the maximum share of the indicator in the Method 2 Score, 2) the average share of the indicator in the Method 2 Score, 3) the minimum value of the indicator in the Method 2 Score.

Figure 5
Bank Reserves and Outstanding U.S. Treasuries: 2016-2024



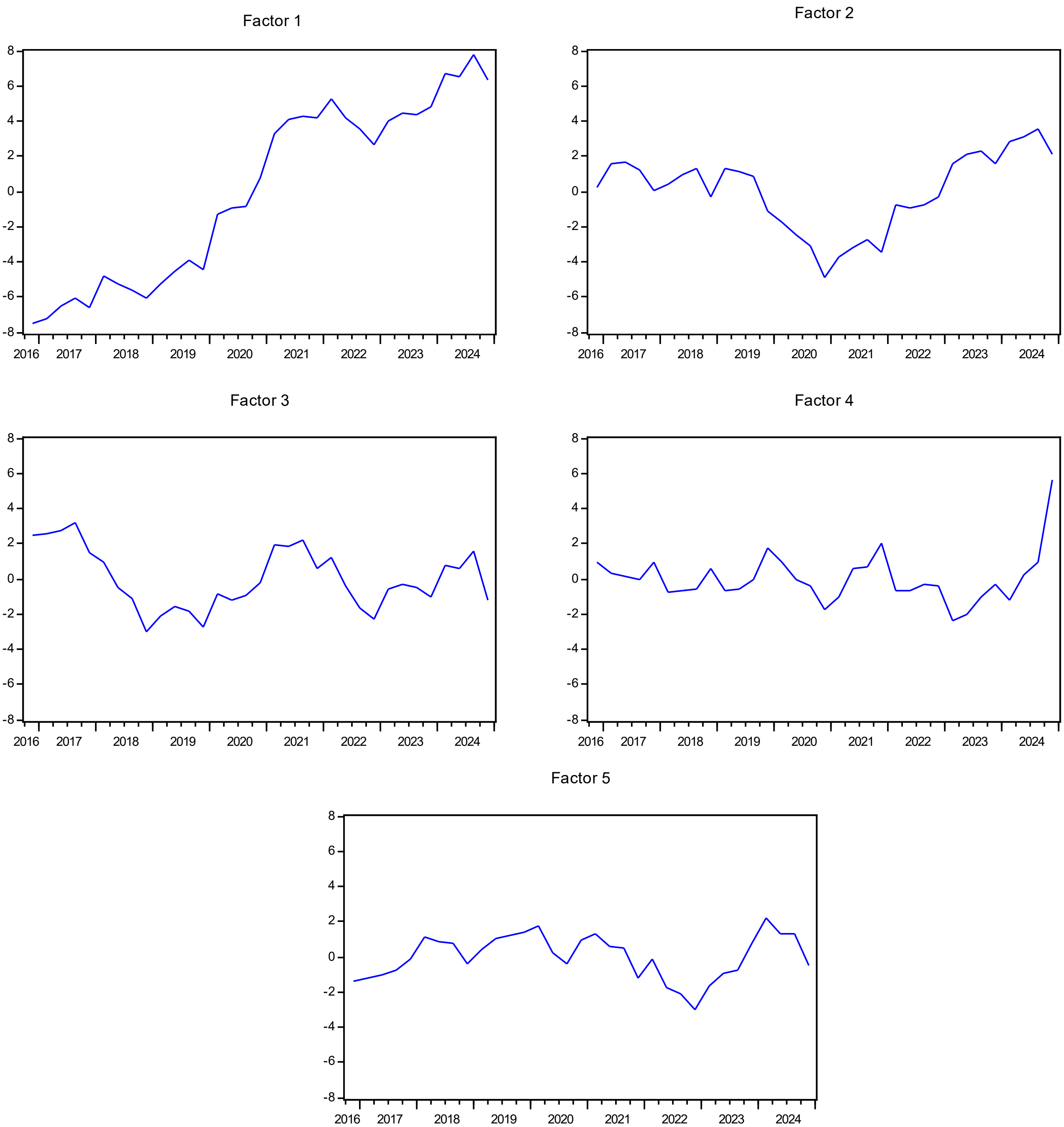
Notes: The chart displays the time-series of bank reserves (bars) and outstanding U.S. Treasuries (solid line) from 2016:4 to 2024:4.

Figure 6
Actual and Fitted Average M2 GSIB Score



Notes: The chart displays the time-series of the average M2 GSIB score for U.S. GSIBs (black line) as well as the estimated average M2 GSIB score that results from the model: $Indicator_{ijt} = \alpha_{ij} + \beta \times Reserves_t + \gamma \times UST_t + \varepsilon_{ijt}$.

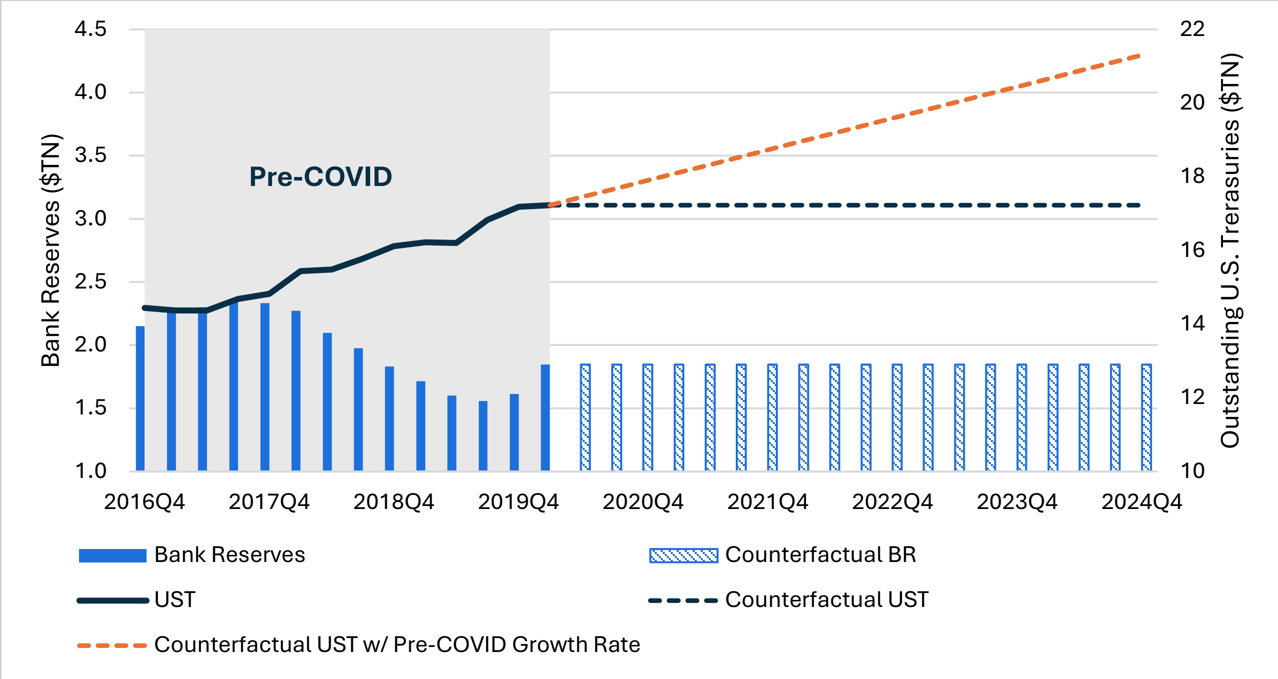
Figure 7
Estimated Factors: 2016-2024



Notes: Each panel shows a time series plot of the estimated factor from a five factor principal components decomposition of the five systemic indicators (complexity, cross-jurisdictional activity, interconnectedness, size, short-term wholesale funding (STWF)), for each of the eight U.S. GSIBs.

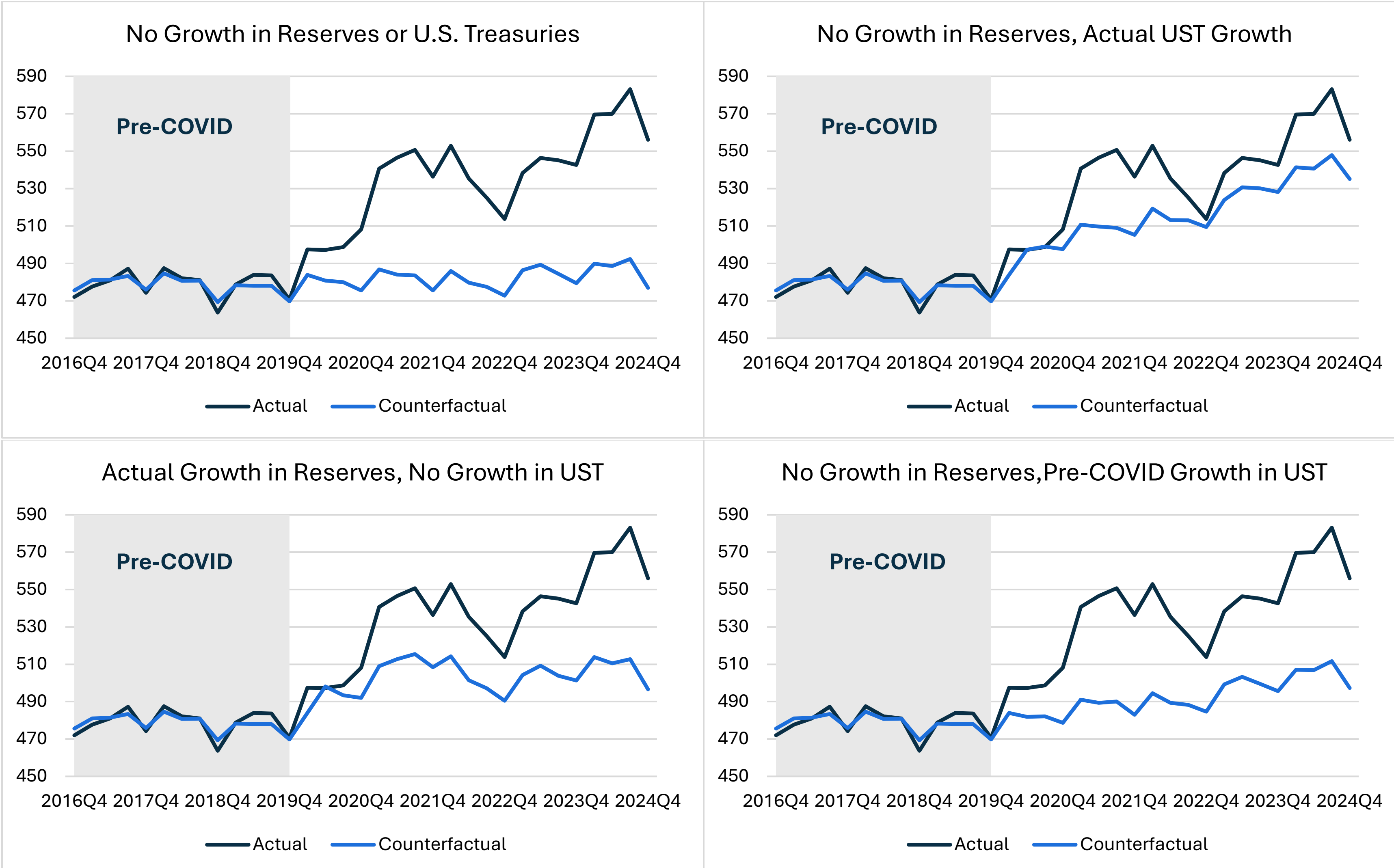
Figure 8

Counterfactual Bank Reserves and Outstanding U.S. Treasuries: 2020-2024



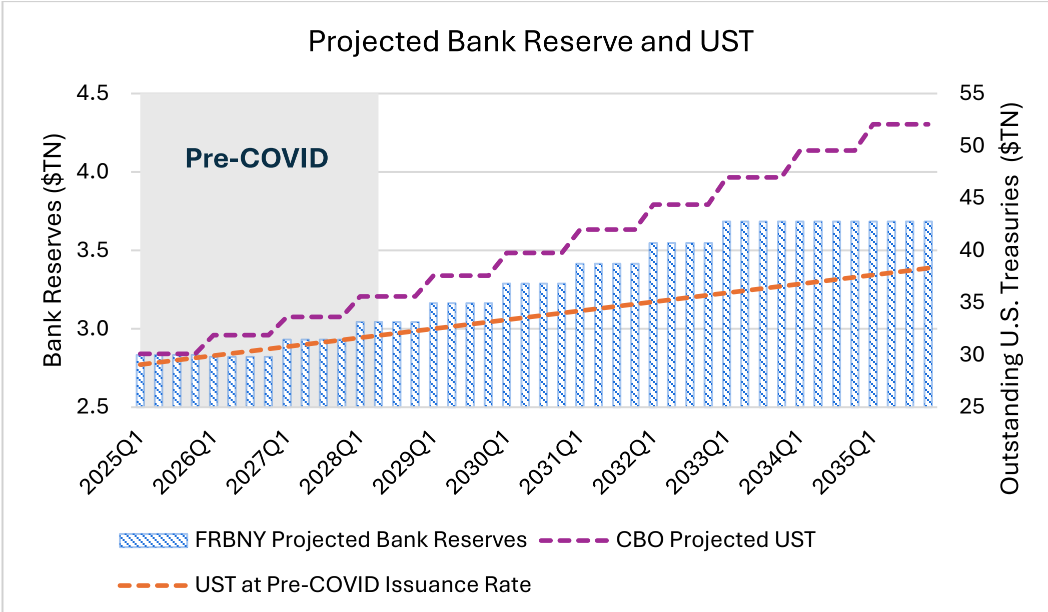
Notes: The chart displays counterfactual time-series paths for the level of bank reserves and outstanding U.S. Treasuries. In the case of outstanding U.S. Treasuries, we consider two counterfactual paths: 1) a path in which outstanding Treasuries are held constant at their 2019:4 level and 2) a path in which outstanding U.S. Treasuries grow at the pre-COVID rate of $850 billion per year.

Figure 9
Actual and Counterfactual Method 2 GSIB Scores



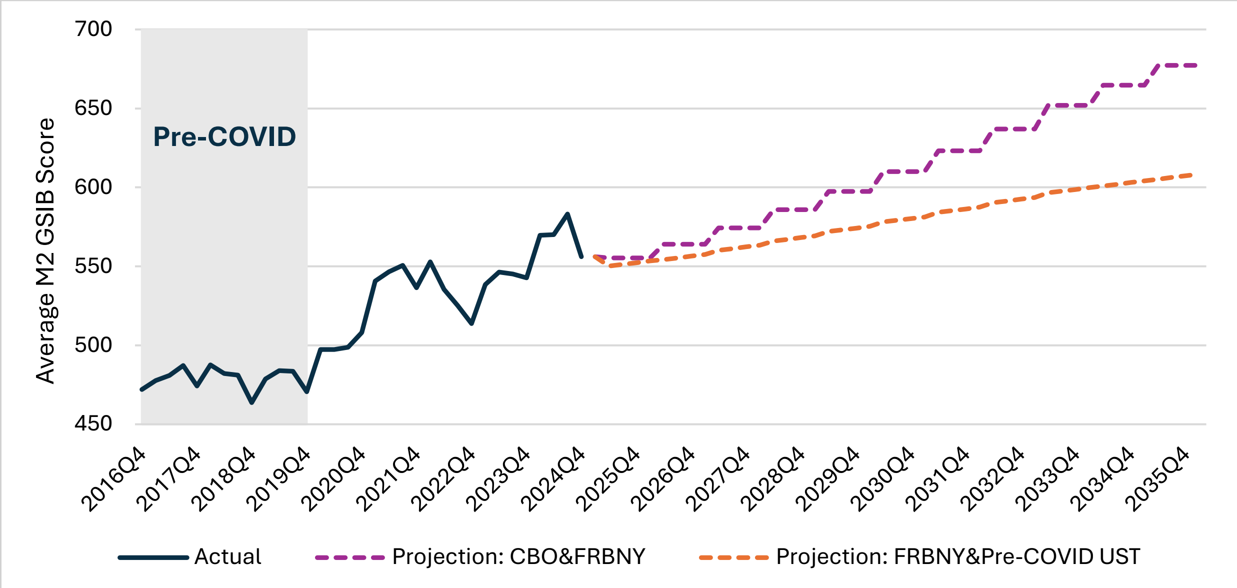
Notes: The figure above shows four counterfactual scenarios: upper-left panel shows the actual average GSIB score and counterfactual GSIB score if bank reserves and outstanding U.S. Treasuries experienced no growth post-COVID; the upper-right panel shows the actual average GSIB score and counterfactual GSIB score if bank reserves were held constant at their 2020Q1 level but outstanding U.S. Treasuries exhibit the actual growth observed from 2020:1-2024:4; the bottom-left panel shows the actual average GSIB score and counterfactual GSIB score if outstanding U.S. Treasuries were held constant to 2020:1 level but bank reserves exhibit the actual growth observed from 2020:1-2024:4; the bottom-right panel shows the actual average GSIB score and counterfactual GSIB score if bank reserves were held constant at their 2020:1 level but outstanding U.S. Treasuries grow at their pre-COVID rate of $850 billion per year.

Figure 10
Projected Bank Reserves and Outstanding U.S. Treasuries: 2025-2035



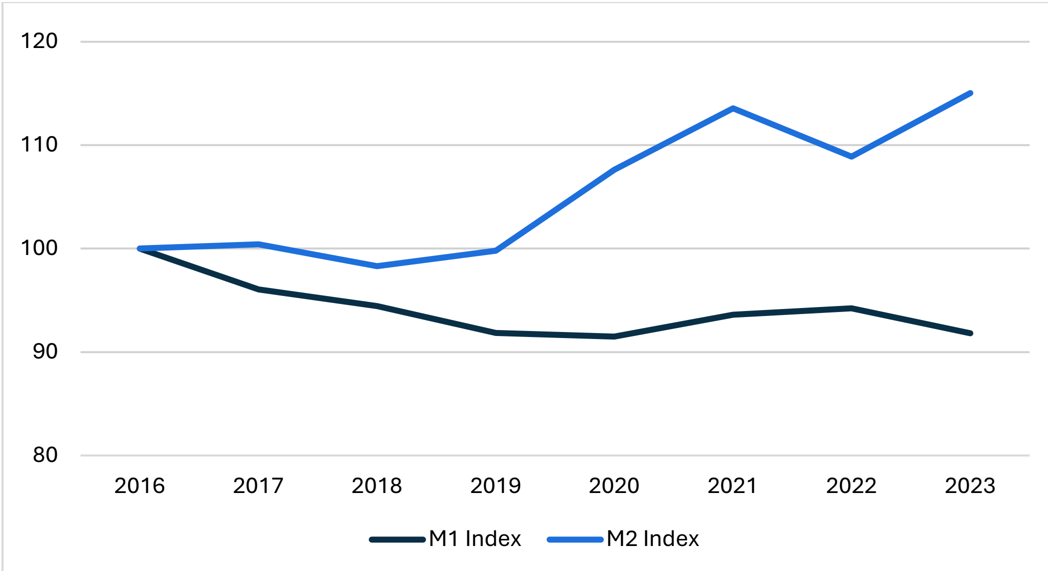
Notes: The chart displays projections for both banak reserves and outstanding U.S. Treasuries from 2025:1 through 2035:4. Projections for bank reserves are taken from Federal Reserve Bank of New York projections. Two projections of outstanding U.S. Treasuries are considered: 1) the Congressional Budget Office's projections, 2) a projection that assumes a pre-COVID rate of U.S. Treasury issuance of $850 billion per year.

Figure 11
Actual, Counterfactual, and Projected GSIB Scores



Notes: The chart displays the actual Method 2 GSIB Score through 2024:Q4 as well as projected scores from 23024:4 through 2025:4. Two projections are considered: 1) a projection that assumes bank reserves grow at the rate projected by the Federal Reserve Bank of New York (FRBNY) and outstanding U.S. Treasuries grow at the rate projected by the Congressional Budget Office (CBO), 2) a projection that assumes bank reserves grow at the rate projected by the Federal Reserve Bank of New York (FRBNY) and outstanding U.S. Treasuries grow at the pre-COVID rate of issuance of $850 billion per year.

Figure 12
M1 GSIB Score and M2 GSIB Score Comparison: 2016-2023



Notes: The chart compares the Method 2 or “M2” GSIB score utilized in the U.S. with the Method 1 or “M1” score endorsed by the Basel Committee on Banking Supervision (BCBS) and utilized in non-U.S. jurisdictions. The average M2 and M1 score for U.S. GSIBs is normalized to 100 in 2016:4 and the resulting M2 and M1 index is plotted in each year between 2016:4 and 2023:4. The M1 score for 2024 is not yet available because the denominators that are used to normalize the 2024 indicators in the M1 score will not be published until the end of 2025.

Table 1
BCBS vs. US GSIB Identification and GSIB Surcharge Calculation

Systemic Indicator	Brief Definition	Example Data Input	GSIB Identification		Surcharge Calculation	
			BCBS (M1)	*USA (M1)*	*BCBS (M1)*	*USA (M2)*
Complexity	Measure of the complexity of a bank's business activity	OTC derivative notional	Yes	Yes	Yes	Yes
Cross-Jurisdictional	Measure of the amount of activity conducted in jurisdictions other than the bank's home country	loan to foreign counterparty	Yes	Yes	Yes	Yes
Interconnectedness	Measure of exposure to and exposure created to other financial institutions	debt securities outstanding	Yes	Yes	Yes	Yes
Size	Total balance sheet size adjusted for off-balance sheet items	total assets	Yes	Yes	Yes	Yes
Short-Term Wholesale Funding	Use of wholesale funding with a maturity of one-year or less	repo w/ maturity <=365 Days	No	No	No	Yes
Substitutability	Measure of business activities that are difficult for other financial institutions to replace in the event of a bank's failure	Assets under custody	Yes	Yes	Yes	No
Indicator normalized by aggregate global indicator?			Yes	Yes	Yes	No

Notes: The table reports the name of each systemic indicator, a brief definition, and an example data input that is used to calculate the systemic indicator. The table reports whether the systemic indicator is used to identify which banks are identified as a GSIB in both the case of the BCBS and US standard. Finally, the table reports whether the indicator is used to determine the amount of the surcharge in the BCBS and US standard.

Table 2
GSIB Score and Indicators Growth

	2016Q4	2019Q4		2024Q4	
	Level	Level	Δ %	Level	Δ %
Complexity	103	91	-11.6	95	-8.0
Cross-Jurisdictional Activity	68	72	7.1	88	30.3
Interconnectedness	81	85	5.6	109	35.1
Size	76	80	6.0	103	36.0
Short-Term Wholesale Funding	145	141	-2.3	161	11.2
Method 2 GSIB Score	472	471	-0.3	556	17.8

Notes: The table presents the average systemic indicator across U.S. GSIBs at three points in time: 2016:4, 2019:4, 2024:4. Both 2019:4 and 2024:4 percentage changes (Δ%) are calculated using 2016:4 score as baseline. The indicator components do not add to the M2 GSIB score due to rounding.

Table 3

Correlogram of Systemic Risk Indicators, U.S. Treasuries, and Bank Reserves

Displacement	GSIB	Comp.	Cross.	Intercon.	Size	STWF	BR	UST
1-Qtr.	0.87	0.09	0.87	0.86	0.93	0.90	0.91	0.92
2-Qtr.	0.75	-0.03	0.78	0.70	0.85	0.74	0.80	0.84
3-Qtr.	0.64	-0.12	0.70	0.56	0.77	0.56	0.66	0.75
4-Qtr.	0.57	0.55	0.67	0.42	0.68	0.36	0.52	0.66
5-Qtr.	0.43	-0.10	0.54	0.32	0.59	0.19	0.37	0.57

Notes: The autocorrelation in each variable identified by the column header is presented for the first five lags (quarters). The variables considered in the table include the Method 2 GSIB Score, the five systemic indicators (Complexity, Cross-Jurisdictional, Interconnectedness, Size, Short-Term Wholesale Funding (STWF)), the outstanding amount of U.S Treasury securities, and the level of bank reserves. Based on the sample size, the 95% confidence interval for an autocorrelation of 0.0 is (-0.34,0.34).

Table 4
Cointegration Tests
Systemic Indicators, Bank Reserves, and U.S. Treasuries

	Unit Root	Cointegration
M2 Score	0.64	0.01
Complexity	0.49	0.09
Cross-Jurisdictional	0.32	0.00
Interconnectedness	0.98	0.01
Size	0.99	0.06
Short-Term Wholesale Funding	0.77	0.03
Bank Reserves	0.69	NA
Outstanding U.S. Treasuries	0.98	NA

Notes: The table presents the p-value associated with panel ADF tests for the presence of a unit root in each series and the p-value of panel cointegration tests. In the case of the unit root tests, the null hypothesis is that the series contains a unit root. In the case of the cointegration tests, the null hypothesis is that the systemic indicator, bank reserves, and outstanding U.S. Treasuries are not cointegrated. The unit root tests for bank reserves and outstanding unit root tests are univariate rather than panel tests.

Table 5
Fixed Effect Model: Systemic Indicators, Bank Reserves, and U.S. Treasuries

	Complexity	Cross-Juris.	Intercon.	Size	STWF
constant	82.28	-18.64	51.06	57.61	21.22
	(16.87)	(-4.39)	(12.12)	(18.19)	(4.68)
BR	4.96e-4	4.72e-3	-5.47e-4	3.63e-3	6.37e-03
	(0.33)	(3.24)	(-0.49)	(3.31)	(4.17)
UST	-1.64e-07	1.44e-06	1.69e-06	1.57e-06	3.05e-07
	(-0.55)	(5.05)	(7.11)	(7.39)	(0.95)
F test	0.17	85.80	65.92	138.59	39.11
	(0.85)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.96	0.97	0.95	0.98	0.96
R^2 within	1.90e-03	0.42	0.40	0.56	0.17

Notes: The table presents the results of estimating the model, $Indicator_{ijt} = \alpha_{ij} + \beta \times Reserves_t + \gamma \times UST_t + \varepsilon_{ijt}$. The bank-specific intercepts are omitted for clarity. Robust standard errors are reported in parentheses under the parameter estimates. In the lower panel of the table, we report the F-test (p-value) of joint significance of bank reserves and U.S. Treasuries. We also report the R2 of the regression as well as the "within" R2 that measures the amount of indicator variability that is accounted for by variation in bank reserves and U.S. Treasuries.

Table 6
Factor Model Variance Analysis

Factor	Variance (%)	Cumulative (%)
1	63.1	63.1
2	11.5	74.6
3	7.1	81.7
4	4.8	86.5
5	3.8	90.3

Notes: The table presents the proportion of variance accounted for by each of the five factors that have been estimated by principal components.

Table 7
Correlation Between Systemic Indicators and Factors

	Complexity	Cross-Juris.	Intercon.	Size	STWF
Factor 1	0.87	0.91	0.94	**0.98**	0.96
Factor 2	0.47	0.43	0.33	0.18	**0.70**
Factor 3	0.37	0.22	0.26	0.17	**0.47**
Factor 4	0.31	**0.44**	0.13	0.12	0.20
Factor 5	**0.24**	0.07	0.20	0.01	0.12

Notes: The table presents the average R2 between each factor and systemic indicator. The reported average R2 is taken with respect to the eight U.S. GSIBs. As an example, in the case of Factor 1, Complexity pairing, the result of 0.87 represents the average R2 from regressing each U.S. GSIB's complexity indicator onto Factor 1. In the table, the indicator exhibiting the highest average R2 with each factor is highlighted in **bold**.

Table 8
Cointegration Tests
Factors, Bank Reserves, and U.S. Treasuries

	Unit Root	Cointegration
Factor 1	0.78	0.01
Factor 2	0.09	0.80
Factor 3	0.00	0.30
Factor 4	0.39	0.28
Factor 5	0.15	0.50
Bank Reserves	0.69	NA
Outstanding U.S. Treasuries	0.98	NA

Notes: The table presents the p-value associated with the ADF test for the presence of a unit root in each series and the p-value of the Engle-Granger cointegration test. In the case of the unit root tests, the null hypothesis is that the series contains a unit root. In the case of the cointegration tests, the null hypothesis is that the factor, bank reserves, and outstanding U.S. Treasuries are not cointegrated.