Banking Stability: The Impact of Financial Sector Heterogeneity on Systemic Risk in Financial Crises and Economic Recessions

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Abstract

Financial institutions heterogeneity, a high degree of dissimilarity across multiple dimensions, including business focuses, correlated asset holdings, capital structures, and funding sources, reduces systemic risk. We empirically test this hypothesis using a bank holding company (BHC) level heterogeneity index based on granular balance-sheet, income statements, cash flow statements, and off-balance-sheet information for the U.S. bank holding companies over a sample period spanning the second quarter of 2000 to the fourth quarter of 2021. We find that the BHC-level heterogeneity negatively correlates with BHC-level systemic risk, SRISK, measured both at the global and local level. We also construct a sector-heterogeneity index and demonstrate that a reduction of heterogeneity occurred in the U.S. financial sector prior to both the Great Recession (2007-2009) and the COVID-19 Recession, especially for the largest bank holding companies (BHCs). As such, a declining level of financial sector heterogeneity can be an early warning signal of economic recessions.

Keywords: Financial institutions, Bank holding companies, COVID-19, Great Recession, FDIC, Financial markets, Financial crises, Economic Recessions, Heterogeneity; Systemic risk, Dodd Frank

JEL Classifications: D62, E02, G21, G28, G32, G33, G38

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1. *Introduction*

About a decade and a half after the collapse of Lehman Brothers (September 2008), systemic risk – the risk that many market participants in the financial sector are simultaneously struck by significant losses, which then spread through the economic system - is still not well understood [Benoit, Colliard, Hurlin, and Pérignon, 2017; Elliott and Golub, 2022]. The complexity of financial networks and the intricacies of interconnectedness brought about by implicit and explicit contracts and financial infrastructure (including payment, securities settlement, remittance, credit reporting, and central counterparty systems) obscure our understanding of systemic risk. The global financial crisis, often called the Great Recession, that commenced in 2007 has set off new explorations into correlated asset holdings in financial institutions, and the negative externalities that a build-up in the systemic risk (through contagion effects) can have not only on the financial system but also on the real economy. In the extreme, if there are only homogeneous banks in the financial sector and all banks are exposed to the same tail risk simultaneously due to similar or correlated business focuses, capital structures, asset holdings, lending portfolios, and funding sources, the financial system as a whole can be easily undercapitalized. A systemic crisis in the financial sector may then spill over to non-financial sectors due to, for example, a fall in credit supply from the financial industry.

This paper focuses on cross-sectional heterogeneity at the bank holding company (BHC) level as a novel resilience factor to systemic risk. We also study the U.S. financial sector's aggregate heterogeneity index and systemic risk. In a systemic crisis, healthy financial institutions can be swept along and fail together with distressed banks unless the government intervenes, possibly at very high costs to the real economy. It goes without saying how important it is to correctly understand the channels that enhance systemic risk. We can then minimize the probability of a downfall of the financial system.

We study the degree of heterogeneity of financial institutions by examining bank holding companies (BHCs) in the U.S. and find that BHC-level heterogeneity negatively correlates with systemic risk. The BHCs are the top-tier financial holding corporations that directly control one or more depository institutions, such as commercial banks. A BHC often owns other financial institutions, such as hedge funds and insurance companies. Moreover, the public FR Y-9 filings to the Federal Reserve Bank (FRB) of Chicago offer an interesting laboratory to study the multi-dimensional heterogeneity of financial institutions. The FR Y-9 filings offer granular financial information on BHCs (and include a balance sheet, an income statement, a cash flow statement, and detailed supporting schedules, including a schedule of off-balance-sheet items for each BHC). In particular, there are two steps to construct our BHC-level heterogeneity index. First, we use book information's pairwise Euclidean distance (PED) to calculate the dissimilarity between two BHCs. Second, we use all PEDs of each BHC to the rest of the BHCs in our sample as an input measure for the heterogeneity index at the BHC level. Our heterogeneity index is based on BHCs' granular financial information (365 features) for each quarter from 2000Q2 to 2021Q4 (87 quarters). We use equal weights for each standardized accounting feature as our benchmark case. BHC-level distance is then calculated using the size-weighted average of the PEDs of a BHC to the rest of the BHCs in the U.S.

In the empirical tests, we relate our heterogeneity measure to the widely-used systemic risk measure at a BHC level, i.e., the so-called SRISK measure [Acharya, Pedersen, Philippon, and Richardson, 2017; Brownlees and Engle, 2017]. The measure can estimate the severity of capital losses of a financial institution in a prolonged recession such as the Great Recession. The firm-level SRISK measure considers a firm's market information and book information. More specifically, the SRISK incorporates the asset prices and funding liquidity risk by using publicly available information such as stock prices and quasi-leverage of a firm. The approach is consistent with the stress tests that the banking regulators have performed in the U.S. and Europe on systemically important financial institutions (SIFIs) since 2008.

An increase in our BHC-level heterogeneity measure decreases the BHC-level SRISK. In our baseline case, a 1% (or one standard deviation) increase in the value-weighted BHC-level heterogeneity decreases the systemic risk of the average BHC by approximately 0.2936%[i] (or $ 59.3 million)[ii] after controlling for BHC characteristics and year-quarter fixed effects. In order to address the right-skewness in the distribution in the systemic risk measures and thus reduce biases of our estimations, we apply

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[i] The elasticity coefficient is reported in column (5) of Table 3.

[ii] In Table 2, one standard deviation of heterogeneity (value-weighted Euclidean distance or VWD – see below for a definition) equals 3.35, and the mean of the VWD is 20.39. Thus, one standard deviation increase in VWD translates in an increase of 4.82% (3.35/20.39×29.36%) in the average SRISK (of $1.23 billion), which equals $59.3 million ($4.82\% \times \$1.23\ billion$).

an inverse hyperbolic transformation [Bellemare and Wichman, 2020; Norton, 2022]. Bank heterogeneity can mitigate systemic risk because correlated asset holdings can expose financial institutions to a similar degree of tail risk and induce contemporaneous failure (an aggregate expected capital shortfall) in the financial sector [Albuquerque, Cabral, and Guedes, 2019; Allen, Babus, and Carletti, 2012; Duarte and Eisenbach, 2021]. In this paper, we show that the gradual decrease in financial institutions' heterogeneity is an essential factor that should be considered by the supervisory authorities responsible for financial stability. Our measure of BHC-level heterogeneity is economically meaningful and easy to implement.

We capture the heterogeneity in the financial sector by a quarterly index composed by aggregating our BHC-level heterogeneity measures. We document that our size-weighted heterogeneity index shows a higher level of heterogeneity for the financial sector than the equally-weighted index, consistent with the literature on bank interconnectedness [Chen, 2022] and herding behavior [Jin Cai, 2022]. This signifies that there are a few large banks that are interconnected with many small banks, which tend to mimic peers' investment, funding, and lending portfolios and exploit implicit and explicit government guarantees. In case of financial distress, the government may stimulate large banks to acquire a number of interconnected failing small banks or bail out many small (similar) banks directly.

This paper contributes to the literature on systemic risk and, more specifically, to the strand of literature proposing systemic risk measurement based on balance-sheet information. While over the past decade, the literature has focused on contagion as a consequence of direct interconnectedness among financial institutions, the research on heterogeneity or homogeneity in the financial sector is only a recent phenomenon [Abduraimova and Nahai-Williamson, 2021; Chu, Deng, and Xia, 2020; Duarte and Eisenbach, 2021; Fricke, 2016; Fricke and Roukny, 2020]. In line with Duarte and Eisenbach [2021], we find that the effect of heterogeneity on systemic risk can be significant and varies over time. We further contribute to the literature by measuring the effect of heterogeneity on systemic risk by relaxing the assumption that banks are homogeneous (and are similar in terms of asset size, which is one of the most systemic-important factors). Moreover, our heterogeneity measure is based on a granular balance sheet and off-balance sheet information.

We focus on a 'going concern externality', the negative spillover caused by an aggregate expected shortfall or systemic shock in the financial sector which can occur with or without bank runs, and hence do not assume the failure of an individual bank [Hufeld, Koijen, and Thimann, 2017]. Acharya et al. [2017] and Brownlees and Engle [2017] calculate the systemic expected shortfall of a firm in terms of its likelihood to be undercapitalized conditional on a globally distressed financial system and call the respective systemic expected shortfall "SRISK". Specifically, we focus on how BHC-level heterogeneity can decrease the government's ex-post-required capital injection ("SRISK") to sustain a well-functioning financial system after a systemic shock. Our results have implications for how macro-prudential regulation can be improved by incorporating BHC-level heterogeneity into an ex-ante systemic risk tax, a CEO incentives' cap, stress tests, or recapitalization of financial firms during systemic crises. We also contribute to the literature that studies financial institutions' indirect connections that are created by the investment, funding, and lending portfolios and by a wide range of other market-based business activities such as proprietary trading, broker-dealer services, and securitization, and – more broadly – a supply of various financial market services, from advisory to hedging. Finally, this paper also contributes to new insights into the systemic risk during the latest COVID-19 recession [Duan, El Ghoul, Guedhami, Li, and Li, 2021; Elnahass, Trinh, and Li, 2021; Trinh, Cao, and Elnahass, 2022].

Our paper also helps to explain the amplification mechanisms of systemic risk [Benoit et al., 2017], i.e., how a small shock can lead to significant impacts. A higher heterogeneity at a BHC level can increase the sector resilience and decrease a BHC's contribution to systemic risk. A typical example would be a downside shock to real estate values [Reinhart and Rogoff, 2009a, 2009b; Sufi and Taylor, 2021]; financial institutions could be distressed at the same point in time when the downside risks of their homogeneous investment holdings, e.g., mortgage-backed securities (MBS), manifest themselves simultaneously. When financial institutions cannot obtain more liquidity by selling MBS, their financial intermediation is paralyzed, and the aggregate capital supply in the financial markets falls significantly. The negative externalities extend to the real economy [Bongaerts, Mazzola, and Wagner, 2021; Mian, Sufi, and Trebbi, 2015; Shleifer and Vishny, 1992].

This research may be helpful for macroprudential policymakers, financial institutions, and retail investors as it considers systemic risk from a novel channel (heterogeneity) that amplifies the systemic risk during economic downturns. This paper proceeds as follows. Section 2 defines heterogeneity and systemic risk. Section 3 documents our datasets and empirical measurements (systemic risk, heterogeneity measures, and control variables). In Section 3, we discuss the relation between heterogeneity and systemic risk. We conclude in Section 4 with some policy implications and develop a plan for further research in Section 5.

2. Heterogeneity and systemic risk

At the basis of the decreasing heterogeneity of the financial institutions (and the potential increase in systemic risk) lie three reasons: (i) the pursuit of optimal diversification, (ii) rational herding behavior motivated by government guarantees, and (iii) relative performance evaluation (RPE) of bank managers. The first reason for the financial system to become more homogeneous is optimal diversification of financial institutions' investment and funding portfolios without consideration for negative externalities to the whole system, which makes a joint failure of the financial system more likely [Chu et al., 2020; Girardi, Hanley, Nikolova, Pelizzon, and Sherman, 2021; Haldane and May, 2011; Wagner, 2010, 2011]. A second reason why homogeneity leads to higher systemic risk is rational herding behavior by financial institutions: mimicking their peers' investment or funding decisions leads to holding highly correlated assets or similar risks. Consequently, banks take advantage of expected government bailouts and "too-many-to-fail" guarantees [Altinoglu and Stiglitz, 2022; Farhi and Tirole, 2012; Grieser, Hadlock, LeSage, and Zekhnini, 2022; Silva, 2019]. Even though rational herding behavior may be beneficial in risk-sharing among financial institutions, the likelihood of joint failure increases. This can induce negative externalities to the real economy.

Meanwhile, there is a recent literature on a novel source of systemic risk regarding incentive pay for bank managers. This incentive loop could lead to a more homogenous financial sector and increase systemic risk. A financial institution with a relative performance evaluation (RPE) contract for the top managers may invest more in rival firms' correlated asset holdings. Since their variable compensation is benchmarked to the performance of rival firms, the firm manager can lower her pay volatility [Albuquerque et al., 2019; Arifa, Donovanb, Gopalanc, and Morrise, 2021; Armstrong, Nicoletti, and Zhou, 2021; Cziraki, 2018; Koudijs, Salisbury, and Sran, 2021].

A few empirical papers on financial institutions' homogeneity and contribution to systemic risk need to be highlighted. Gandhi and Purnanandam [2022] find that U.S. commercial banks become more homogeneous in terms of risk exposures after the implementation of the first stress test under the Dodd-Frank Act in 2013. Their theoretical model and empirical findings raise consistent concerns about the increasing homogeneity in the banking system. They do not find such an increase for non-bank financial firms or non-financial firms. However, the empirical findings focus on bank stock returns without further investigation of systemic risk measures. We contribute to this literature by offering a novel heterogeneity measure and further research on empirical systemic risk measures. We will empirically show that the heterogeneity decreases in the banking sector and answer the question as to whether heterogeneity mitigates systemic risk. Duarte and Eisenbach [2021] briefly discuss the effect of heterogeneity on their systemic risk measure – aggregate vulnerability (AV) – within a theoretical framework. Still, they do not measure heterogeneity directly or separate the effect from the bank size.

Jian Cai, Eidam, Saunders, and Steffen [2018] studied indirect interconnectedness using syndicated loan portfolios and confirmed that bank-level risk diversification does not consider the whole financial system's negative externalities. In addition, without referring to systemic risk empirically, León (2020) finds cross-sectional homogeneity in the Colombia banking sector based on granular balance sheet information without a time series dimension or investigating the negative externalities. In contrast to the above papers testing the systemic risk empirically, our heterogeneity measurement is based on much more granular and refined data with a time dimension. We contribute to the empirical literature by offering a better BHC-level heterogeneity measure based on granular balance and off-balance sheet accounts (rather than syndicated loan portfolios). We show that the U.S. financial sector has become less heterogeneous over the past decade. Our BHC-level heterogeneity measure negatively associates with BHC-level systemic risk.

3. *Data and measurements*

3.1 Bank holding companies (BHCs)

We focus on BHCs because they are the most comprehensive type of financial institution and the most significant contributors to the total assets of the financial sector. The BHCs are the top-tier holding corporations directly controlling one or more banks. In addition to commercial banks, BHCs often control other financial subsidiaries such as insurance companies, securities broker-dealers, and investment banks. A significant parent BHC in the U.S. is usually a universal financial institution with several domestic bank subsidiaries and non-banking and foreign subsidiaries. The BHC can eventually engage in a broad range of financial services, including lending, deposit-taking, insurance, securities dealing and underwriting, real estate, private equity, leasing and trust services, and asset management. Therefore, studies on BHCs also offer insights into the broader shadow banking system [Gelman, Goldstein, and MacKinlay, 2022; Irani, Iyer, Meisenzahl, and Peydro, 2021]. Finally, BHCs are the focus of government supervision. BHCs are required to file FR Y-9C reports, which we obtain from the Bank Regulatory database on the Wharton Research Data Services platform. These public reports contain detailed public financial information, e.g., capital structure, deposit collection, derivative contracts, and employee benefits. Large banks with total assets over $1 billion starting in the 2015Q1 (with total assets over

$500 million between 2006Q1 and 2014Q4 and over $150 million before 2006Q1) are obliged to supply FR Y-9C forms.

The financial sector in our paper is represented by 74 prominent U.S. BHCs that include systemically important financial institutions (SIFIs), such as JP Morgan Chase &Co, Bank of America, and Citigroup. This sample is not only representative but is also quite comprehensive. In 2020, The total assets of BHCs ($ 19 trillion) stand for about 15.4% of the total assets of U.S. financial institutions ($ 123.1 trillion[iii]) (that include banks, insurance, capital markets, consumer finance, diversified financial services, mortgage REITs, and thrift & mortgage finance). Meanwhile, this sample of BHCs stands for around 92.7% of the consolidated total assets of all commercial banks ($ 20.5 trillion) in 2020[iv].

Since 1986, a total of 3,057 individual items of balance sheet and off-balance sheet information have been available quarterly for each BHC. However, not all these items are numerical as they also consist of textual notes. Some items are not always available across the whole sample period (e.g., the item BHCAP859 - common equity tier 1 capital is only available since 2014Q1), which is why we drop these variables for the calculating of our heterogeneity measurements. In order to avoid double accounting for the granular features, we also exclude summary accounts such as total assets and total liabilities from our measures. Instead, we only include the individual accounts without the summarizing accounts. The data covers three recessions (2001, 2008, and the COVID-19 recession in 2020) and three financial crises (the bursting of the dot-com bubble in 2000, the large financial crisis 2007/8 leading in the Great Recession, and the crisis of 2011). Eventually, we constructed a database with 365 items, available quarterly from 2000Q2 to 2021Q4. The variables, comprising total assets, combined thrift assets, mortgage servicing assets and goodwill, income statement variables such as the sale of common stock, salaries and employee benefits and other interest expenses are harvested from the FR-Y9 reports. The report also includes off-balance sheet items such as foreign exchange swaps, foreign exchange futures contract and equity

[iii] Data source: https://www.statista.com/statistics/421697/financial-institutions-assets-usa/

[iv] Data source: https://www.federalreserve.gov/releases/h8/20220128/

derivative futures contracts. A more detailed description of the FR-Y9 reports of BHCs is presented in Appendix 1, and a detailed list of balance and off-balance sheet items can be found in the Online Appendix[v].

3.2 Measurements of systemic risk

In terms of managing systemic risk, regulators such as the Financial Stability Oversight Council (FSOC)[vi] should ensure that potential distress of the financial sector does not stop financial institutions from performing their intermediation functions needed by the real economy. This is not an easy task since systemic risk measurement is still an interdisciplinary challenge that combines insights from banking, microeconomics, macroeconomics, econometrics, and network theory. We denote the "system" as the U.S. financial sector and define "systemic risk" as the risk of undercapitalization of the entire U.S. financial sector, most likely triggered by the bankruptcy of one or more large and interconnected institutions [Berger, Curti, Mihov, and Sedunov, 2022; Montagna, Torri, and Covi, 2020]. A financial firm is systemically risky if the firm's distress could lead to a negative externality (high social costs) to the real economy [Benoit et al., 2017; Elliott and Golub, 2022].

As mentioned in the introduction, two strands of literature mainly study systemic risk. The first strand focuses on contagion without a presumption of an aggregate expected shortfall or a systemic shock in financial networks. The central economic insight is that the distress of a BHC at a critical node within the financial network, possibly due to maturity mismatching, could make the whole system collapse [Allen et al., 2012; Allen and Gale, 2000; Chen, 1999; Gorton and Metrick, 2012]. This strand of literature is the so-called 'runs externality' literature since they do not assume an aggregate expected shortfall or systemic shock but focuses on

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[v] For a detailed list of items, please refer to our online appendix: https://www.dropbox.com/sh/ldu00q0mqewnogz/AACV4jXqDcmBbzR-RZgFMsUka?dl=0

[vi] FSOC was created in the U.S. following the Dodd-Frank Wall Street Reform after the 2007-2009 financial crisis. FOSC has the responsibilities to monitor and address the overall risks to financial stability.

bank runs triggered by an individual bank failure [Diamond and Dybvig, 1983; Diamond and Rajan, 2001, 2005, 2011; Farboodi, 2021].[vii]

The second strand of literature focuses on the 'going concern externality'. It emphasizes an aggregate expected shortfall or systemic shock, which can occur with or without bank runs in the financial sector. This literature mainly attempts to measure the firm-level contribution to systemic risk conditional on a systemic event based on market prices or macroeconomic indicators. De Jonghe [2010] measures a bank's systemic importance through its tail beta, i.e., the probability of a sharp decline of its stock price conditional on a crash in a banking index. More recently, Tobias and Brunnermeier [2016] used a standard regulatory measure of Value-at-Risk (VaR) to calculate the CoVaR, i.e., the change in the VaR of the overall financial system induced by a single bank being under distress. Acharya et al. [2017] and Brownlees and Engle [2017] calculate the systemic expected shortfall of a firm in terms of its likelihood to be undercapitalized conditional on a distressed financial system. They call the respective systemic expected shortfall “SRISK”. This measure focuses on cross-sectional characteristics of financial institutions and has been widely used in the literature. For a more detailed literature review on systemic risk measures, please refer to Bisias, Flood, Lo, and Valavanis [2012] and Giglio, Kelly, and Pruitt [2016].

Our paper is most related to the systemic risk measures based on detailed balance sheet information. Duarte and Eisenbach [2021] construct an index of aggregate vulnerability (AV) to fire sales based on the BHCs' balance sheet information and the “vulnerable bank” framework of Greenwood, Landier, and Thesmar [2015]. Compared to the market-based systemic risk measures, balance-sheet-based measures signal increased systemic risk ahead of a crisis (e.g., at least five years ahead for AV). Our paper empirically measures the effect of heterogeneity on systemic risk

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[vii] The “runs externality” focuses on the externality based on the liability structure of a firm which contributes to the propensity of runs and forced fire sales without a presumption of an aggregate expected shortfall or a systemic shock. It is well-understood that the maturity mis-matching can lead to a financial crisis i.e., financial firms rely extensively on short-term financing such as deposits which induces the risk that the financing of these firms cannot be rolled over when the economy experiences a shock.

with more granular features, and we found opposite results compared to Duarte and Eisenbach [2021]. Finally, a new strand of literature applies machine learning methodologies to systemic risk measures [Liu and Pun, 2022].

We use the $SRISK_{i,t}$ measure (of BHC i at time t) of Acharya et al. [2017] and Brownlees and Engle [2017], which is a comprehensive systemic risk measure that merges both market and balance sheet information. $SRISK_{i,t}$ is defined as the expected capital shortfall of a financial institution conditional on a prolonged and distressing market decline. We mainly use the global model for $SRISK_{i,t}$ that applies the stress test using the MSCI All-Country World Index decline by around 40% (equivalent to US$ 100 billion)[viii]. We also show results based on a domestic version of $SRISK_{i,t}$ based on a decline of 40% of the S&P 500 Index. $SRISK_{i,t}$ is one of the most used reduced-form analytical measurements that captures the systemic importance of a financial institution in terms of its contribution to the undercapitalization of the financial system at times of distress. In contrast to a firm's own risk measurement, e.g., expected shortfall ($ES_{i,t}$), which treats institutions' risk in isolation, $SRISK_{i,t}$ helps the regulator to supervise excessive risk-taking at an institutional level along the systemic risk dimension. For instance, a firm with the highest value of $SRISK_{i,t}$ contributes most to the undercapitalization of the financial sector during a crisis. This measure hinges on market-based measurements (i.e., equity volatility and correlation of the firm and market returns) as well as balance sheet information (i.e., the size and the degree of leverage of a financial firm). It should be noted that $SRISK_{i,t}$ captures the tail-dependency in a non-causal sense: the calculation is based on the expected value of one endogenous variable conditioned on the value of another endogenous variable. This means that if the financial sector is distressed and cannot function anymore when a substantial economic recession arises, the sector can itself further worsen the economic downturn.

We gratefully acknowledge that we are allowed to use the NYU Volatility Laboratory (V-Lab)'s Systemic Risk database, which covers 1,218 publicly traded global financial institutions from 72 countries of which

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[viii] There can be different variations of SRISK by applying, *e.g.*, different time horizons, market indexes and threshold of financial distress.

156 are from the U.S. since March 2000. By merging the BHC database and the SRISK datasets, we ended up with an unbalanced quarterly time series of 74 U.S. BHCs from 2000Q2 to 2021Q4.[ix]
The $SRISK_{i,t}$ is a function of a firm's size, leverage and risk and it is formally defined as:

$$\boldsymbol{SRISK_{i,t} = E_t(Capital\ Shortfall_{i,t+h} | Crisis\ Return_{m,t+1:t+h})} \quad (3.1)$$

$$\boldsymbol{SRISK_{i,t} \approx [k(1 - L_{i,t}) - (1 - k)(1 - LRMES_{i,t})L_{i,t}]A_{i,t}} \quad (3.2)$$

where m stands for the market index that we use (MSCI All-Country World Index for the global model and S&P 500 Index for the domestic model), k is the prudential level of equity relative to assets (for the U.S., this is an 8% prudential capital ratio), h is the time horizon for the market decline (which we set at 6 months), $L_{i,t}$ is the ratio of the market value of equity to the quasi-market value of assets (defined as $A_{i,t}$) of BHC i at time t (i.e. the book value of total assets plus market value of equity minus the book value of equity) and $LRMES$ is the Long-Run Marginal Expected Shortfall (i.e. the decline in expected equity value if another financial crisis were to arise). The $LRMES_{i,t}$ is calculated as: $LRMES_{i,t} = -E_t(R_{i,t+1:t+h} | R_{m,t+1:t+h} < d)$ where $R_{i,t+1:t+h}$ is a multiperiod arithmetic equity return of BHC i between period $t+1$ and $t+h$, $R_{m,t+1:t+h}$ is a multiperiod arithmetic equity return of the market m between period $t+1$ and $t+h$ and d is the six-month crisis threshold for the global market with a default value of 40%. The above equations show that SRISK is a function of the size of the BHC, its leverage and its expected capital shortfall conditional on a systemic event. SRISK is higher for a BHC with a larger size, higher leverage ratio and higher sensitivity to a systemic event.
Meanwhile, we can use the aggregate bank-level systemic risk to construct a system-wide measure of financial distress [Brownlees and Engle, 2017]:

[ix] Please note that the bankrupt Lehman Brothers Holdings Inc. is not in our sample as it is not included in the Bank Regulatory database.

$$\boldsymbol{SRISK_t} = \sum_i^N \left(\boldsymbol{SRISK_{i,t}}\right)_+ \qquad (3.3)$$

where $(x)_+$ denotes $\max(x, 0)$, i and t are the same as introduced above. The aggregate SRISK can be interpreted as the total amount of capital that the government would need to inject into the financial system in order to bailout the distressed financial institutions after a systemic event. This aggregate amount excludes the capital surpluses of BHCs (i.e., negative $SRISK_{i,t}$), which is a fair approach considering that capital surpluses cannot easily be transferred from interbank loans or following mergers and acquisitions when the market turns very illiquid.

We can observe in Figure 1 that the aggregate SRISK is relatively low after the dot-com bubble because this crisis was mainly in the telecommunications, media, and technology (TMT) sectors. Our sample represents financial institutions that BHCs control. Therefore, our aggregate SRISK measure does not always capture all the systemic events outside the financial sector. The measure focuses on financial firms which are more sensitive to leverage. SRISK reached its highest peak after the Lehman Brothers bankruptcy of September 2008. It stayed high with peaks when the European sovereign debt crisis significantly worsened (June 2010 and October 2011). So, using a sub-sample of the financial institutions, the aggregate systemic risk results capture the significant patterns in the broader sample (95 large financial institutions) of Brownlees and Engle [2017]. This indicates that our sample of the 74 largest BHCs (which stand for 15.4% of the total assets of the U.S. financial sector) proxies for the whole financial sector reasonably well and hence also relates to its systemic risk.

During the COVID-19 recessions, the aggregate systemic risk reached about the same level as in the Great Recession. Therefore, the COVID-19 pandemic is a systemic-important event worth further attention. Our results are consistent with the latest empirical findings that the pandemic induced an increased systemic risk in the global financial sectors [Duan et al., 2021; Trinh et al., 2022].

Finally, we can see that the overall patterns of the global SRISK and domestic SRISK are almost identical. So, for the rest of the paper, we will focus the results on the global SRISK for reasons of parsimoniousness. Besides, the level of the domestic SRISK is almost always above the level of the global SRISK. We can interpret that the American BHCs are more sensitive to a decline in the domestic capital market. Nevertheless, we leave a more detailed investigation of the divergence of the two measures for further research.

[Insert Figure 1 about here]

Finally, we can also interpret the $SRISK$ in terms of a systemic risk share:

$$\boldsymbol{SRISK\%_{i,t} = \frac{SRISK_{i,t}}{SRISK_t}} \textbf{ if } \boldsymbol{SRISK_{i,t} > 0} \tag{3.4}$$

In Table 1, we show that the $SRISK\%_{i,t}$ rank is consistent with the systemic importance of financial institutions. For example, Citigroup Inc., JPMorgan Chase &Co, Bank of America Corporation, and Wells Fargo & Company have been the most systemically important BHCs since the demise of Lehman Brothers in the fourth quarter of 2008 (see also Brownlees and Engle, 2017). While at the end of 2016, Wells Fargo & Company and JPMorgan Chase & Co are no longer as systemically risky as in 2008, the other two BHCs have retained their systemic importance. Meanwhile, Goldman Sachs Group and Morgan Stanley increased their systemic riskiness over our sample period.

[Insert Table 1 about here]

3.3 Measurements of heterogeneity

Various heterogeneity measures quantify the dissimilarity of any pair of BHCs based on their granular balance and off-balance sheet information. The basic idea is that if two BHCs have different investment, funding, and lending strategies and pursue similar other business activities, such as broker-dealer services, these activities are visible on the granular balance sheet and off-balance sheet accounts. There is not a single heterogeneity measure that has been singled out in the literature as a superior measure, and Fricke [2016] shows that the Euclidean distance [Jian Cai et al., 2018], generalized Jaccard similarity [Pool, Stoffman, and Yonker, 2015], connectedness [Anton and Polk, 2014], and cosine similarity [Falato, Favara, and Scharfstein, 2018] measures are highly correlated (at 88% or higher). We therefore start with the Euclidean distance to capture the degree of heterogeneity of any pair of BHCs. The larger the Euclidean distance, the more dissimilar the two BHCs are. While we calculate the Euclidean distance as a measure of heterogeneity, Jian Cai et al. [2018] use the banks' syndicated loan portfolios as the basis for the Euclidean distance to calculate their interconnectedness. That choice significantly biases the proximity measurement because syndicated loans are merely a small fraction of a BHC's balance sheet and may not even be the most important systemic factor. In contrast, we include all BHC's activities, on and off the balance sheet. As we cannot cap the Euclidean distance to a range of 0 to 1 (as do Jian Cai et al. [2018] since they use portfolio weights adding up to 1), we use a z-score measurement (by subtracting the mean of the specific account[x] across BHCs and dividing by its standard deviation) to capture the financial information on the regulatory reports (FR Y-9) of the BHCs and avoid data issues regarding scale or dispersion. This transformation improves the identification of the effects of our heterogeneity measure.

The BHC-level heterogeneity measure, i.e., pairwise Euclidean distance (PED) between BHC i and BHC j $(i \neq j)$in the following F-dimension space is

$$\boldsymbol{PED_{i,j,t}} = \sqrt{\sum_{f=1}^{F} \left(\boldsymbol{x_{i,f,t}} - \boldsymbol{x_{j,f,t}}\right)^{2}} \tag{3.5}$$

where $x_{i,f,t}$ is the standardized feature f in the financial statements at quarter t for BHC i. The distance between the two BHCs is determined by the total value of the squared distance for each item in the financial statements. So, if all the features of the two BHCs are exactly the same, $PED_{i,j,t} = 0$ (complete feature matching).

The benchmark heterogeneity measure of one BHC to the rest of the BHCs is measured using value-weighted Euclidean distance (VWD). VWD is based on the BHC's total assets and above pairwise Euclidean distance:

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[x] Balance sheet, income statement, cash flow statement and supplementing information in the FR Y-9 reports – see Appendix 1

$$\boldsymbol{VWD}_{\boldsymbol{i},\boldsymbol{t}} = \sum_{j \neq i} \boldsymbol{x}_{\boldsymbol{i},\boldsymbol{j},\boldsymbol{t}} \cdot \boldsymbol{PED}_{\boldsymbol{i},\boldsymbol{j},\boldsymbol{t}} \tag{3.6}$$

where $x_{i,j,t}$ is the weight given to BHC j in the computation of BHC i's dissimilarity. The value weights in the above formula, $x_{i,j,t}^{VW}$, are the value weights between any BHC i and j and n_t is the total number of BHCs at time t, such that

$$\boldsymbol{x}_{\boldsymbol{i},\boldsymbol{j},\boldsymbol{t}}^{\boldsymbol{VW}} = \frac{\mathbf{a}_{\mathbf{j},\mathbf{t}}}{\sum_i \boldsymbol{a}_{\boldsymbol{i},\boldsymbol{t}}} \tag{3.7}$$

where $a_{i,t}$ is the total asset of BHC i in quarter t. As a robustness check, we will also use equal-weighted Euclidean distance (EWD) where $x_{i,j,t}^{EW}$ are the equal weights such that

$$\boldsymbol{x}_{\boldsymbol{i},\boldsymbol{j},\boldsymbol{t}}^{\boldsymbol{EW}} = \frac{\mathbf{1}}{(\boldsymbol{n}_{\boldsymbol{t}}-\mathbf{1})} \tag{3.8}$$

and n_t is the number of BHCs in our sample at quarter t. This EWD is a useful benchmark as it enables us to understand whether or not value weighing is important (Duarte and Eisenbach [2021], for instance, do not allow for heterogeneous bank sizes when measuring homogeneity).

3.4 Control variables

In principle, we do not need to include the traditional control variables from the BHCs' balance sheets in our empirical analysis to avoid "bad controls" [Ahern and Dittmar, 2012; Cinelli, Forney, and Pearl, 2021]; indeed, our heterogeneity measure already incorporates the detailed book information of the BHCs. Still, as the illiquidity of a systemically important financial institution may matter, several aggregate and cross-sectional factors could explain a firm's "systemicness" [Tobias and Brunnermeier, 2016]. It is well known that the bank size and leverage at both the aggregate and the cross-sectional levels are essential to systemic risk [Duarte and Eisenbach, 2021]. We therefore include BHCs' total assets to capture that larger firms contribute more to systemic risk and may associate with the "too-big-to-fail" concept [Berndt, Duffie, and Zhu, 2022]. We use the equity to total assets ratio as our leverage measure, loans to total assets (including leases) as liquidity measure [Ari, Chen, and Ratnovski, 2021], and return on equity (ROE) as profitability. We also include the ratio of deposits to total assets as a proxy for solvency, as in

Laeven, Ratnovski, and Tong [2016]. All control variables are obtained from the Bank Regulatory Database.

4. Empirical results

4.1 Summary statistics

The summary statistics of the systemic risk measures (described in Section 3.2), the proximity measurement (the value-weighted pairwise Euclidean distance ($VWD_{i,t}$) described in Section 3.3), and the control variables (see Section 3.4) are presented in Table 2 and are based on 5,898 bank-quarter observations for the SRISK series and 5,294 bank-quarter observations for the distance measures ($VWD_{i,t}$ and $EWD_{i,t}$ series) over the period 2000Q2 to 2021Q4. The two samples differ because some public financial institutions are not categorized as BHCs over the entire sample period. For example, the Bank Regulatory database only included Goldman Sachs Group from 2008. The average global $SRISK_{i,t}$ is around US$ 1.23 billion which is much lower than the corresponding value, namely US$ 25.33 billion, reported by Jian Cai et al. [2018] on an international sample. We attribute the differences to the fact that we also consider the most recent decade (2011 to 2021), during which sufficient capital buffers were accumulated subsequent to the Great Recession. Furthermore, Jian Cai et al. [2018] focus on lead arrangers (commercial banks) of syndicated loans, whereas our sample only includes U.S. BHCs. BHCs have been under increasing regulatory pressure to reduce systemic risk. For instance, the Dodd-Frank Wall Street Reform and Consumer Protection Act was passed in 2010, and the Volcker Rule was enacted on July 21, 2015. Table 2 shows high variation in our $VWD_{i,t}$ measure; the standard deviation amounts to 3.35. The changes of our heterogeneity index are related to the systemic risk measures. It should be noted, however, that the absolute threshold of an optimal heterogeneity level is not yet well understood (and is only discussed in Engle and Ruan [2018]) Therefore, we focus on the relative changes in our heterogeneity index and offer preliminary evidence on the threshold.

Finally, the median of the main dependent variable ($SRISK_{i,t}$) is negative and right-skewed, whereas our key variable of interest ($VWD_{i,t}$) only has positive values. Therefore, adjusting the dependent variable by using inverse hyperbolic sine transformation (or arcsinh) is suggested in econometrics literature [Bellemare and Wichman, 2020; Norton, 2022]. The arcsinh approximates the traditional natural logarithm but allows retaining zero and negative economic observations. However, the interpretation of the coefficients is not straightforward; in Section 4.2, we follow Bellemare and Wichman [2020] with regard to the interpretations of elasticities.

[Insert Table 2 about here]

4.2 Aggregate heterogeneity and systemic risk

The aggregate heterogeneity indices of the financial sector, both equally- and asset-weighted, and the quarterly averages of BHC-level systemic risk ($SRISK_{i,t}$) are summarized in Figure 2. We see that the overall patterns of the two aggregate indices are similar and that they diverge the most during the 2009 financial crisis. This can be interpreted as bank size being a crucial factor in heterogeneity measures. In the subsequent analyses, we will use the weighted average version of our sector-heterogeneity index for our benchmark analyses. The heterogeneity of the financial sector was low on average prior to the 2009 financial crisis. The weighted VWD index dropped to the lowest level of the first half of our sample period before the bankruptcy of Lehman Brothers and the peak of aggregate systemic risk in 2008. Immediately after the bankruptcy of Leman Brothers, the heterogeneity index increased significantly and reached its highest level in 2011. Subsequently, there is a decline in the sector-heterogeneity index spanning the past decade. Similar to the decline of our heterogeneity index prior to the Great Recession that commenced in 2008, the index declined to a relatively low level before the COVID-19 recession, which correlates with a peak in aggregate systemic risk in 2020. From these observations, we can derive two preliminary conclusions. First, the changes in the heterogeneity index are associated with changes in systemic risk. Second, the level of heterogeneity has implications for systemic risk and could be used to identify future crises. The relatively low level of sector-heterogeneity prior to the two most recent economic recessions shows some preliminary evidence of a threshold of sector-heterogeneity that can trigger economic recessions. The drop in heterogeneity of the financial sector shortly before the bankruptcy of Lehman Brothers can be potentially explained by fire sales and devaluation of common asset holdings such as mortgage-backed securities (MBS), collateral debt obligations (CDO), and credit default swaps (CDS). Finally, we can see a gradual decrease in the heterogeneity in the financial sector over the past decade, consistent with Gandhi and Purnanandam [2022]. Figure 2 implies that a uniform prudential policy without consideration of sector heterogeneity could eventually lead to a homogeneous financial sector and increase systemic risk.

[Insert Figure 2 about here]

4.3 BHC level heterogeneity and systemic risk

This section describes the cross-sectional relationship between the BHC-level heterogeneity measures and systemic risk. We also test which characteristics of BHCs (size, profitability, leverage, solvency, and liquidity) are associated with higher systemic risk by means of a panel regression where we control for the year-quarter and bank fixed effects:

$$\textbf{arcsinh}\ (\boldsymbol{SRISK_{i,t}}) = \boldsymbol{\alpha} + \boldsymbol{\beta_0} \cdot \boldsymbol{VWD_{i,t}} + \boldsymbol{\gamma} \cdot \boldsymbol{Control_{i,t}} + \boldsymbol{\lambda_t} + \boldsymbol{\omega_i} + \boldsymbol{\epsilon_{i,t}} \quad (4.1)$$

where the dependent variable $\text{arcsinh}\ (SRISK_{i,t})$ is the inverse hyperbolic sine transformation of the daily time series of systemic capital shortfall matched with the BHC accounting information at the last trading day in each quarter. The variable of interest $\text{VWD}_{\text{i,t}}$ is the quarterly time series of value-weighted pairwise Euclidean distances based on-balance and off-balance sheet accounts. In Table 3, we report, in addition to the transformed systemic risk measure, the original values of $SRISK_{i,t}$ for robustness checks. We also include year-quarter (λ_t) and individual BHC fixed effects (ω_i) and apply robust standard errors by using the Eicker-Huber-White estimator. We conduct a Hausman test to decide between fixed-effect or random-effect models. The Hausman test rejects the null hypothesis that the relationship between the dependent and independent variables is affected by random effects, which is why we opt for fixed-effects models.

Table 3 shows that the control variables do not change much of the model's explanatory power, as they could be "bad controls" (Section 4.1), we will mainly discuss the results from the models of columns (1) and (5). Our primary variable of interest, namely our BHC-level heterogeneity measure $VWD_{i,t}$, is negatively related to systemic risk (at the 95% level of statistical significance) in column (1), as hypothesized. An increase in VWD by one standard deviation decreases the systemic risk by, on average, around US$ 0.236[xi] billion for the average BHC (or almost 19.2%[xii] of the average value of $SRISK_{i,t}$). The $VWD_{i,t}$ mean is 20.39 with a standard deviation of about 3.35 in Table 2. This finding is economically significant since, as we can observe in Table 1 that an increase of US$ 0.236 billion raises a BHC's rank of the $SRISK\%$ ranking in 2008Q4 (during the Great Recession). For example, Fifth Third Bancorp's $SRISK\%$ ranking can be replaced by Keycorp with an increase of $0.236 billion regarding SRISK. Recall that the SRISK measures the expected capital shortfall at the firm-level conditional on a market crisis.

This panel regression includes both the negative (capital surplus) and positive (capital shortfall) observations of $SRISK_{i,t}$ for BHCs i at time t. As discussed in Section 4.1, we apply inverse hyperbolic sine transformation for our dependent variable in columns (5)-(8) and follow Bellemare and Wichman [2020] to retransform the coefficients into elasticity interpretations. For comparison, we also calculated semi-elasticities in the models of columns (1)-(4) using the sample means of the

[xi] $-0.0705 \times 3.35 = -0.236$

[xii] 0.236/1.23 = 19.2%

dependent variable. According to semi-elasticity[xiii] in column (1), a 1% increase in bank-level heterogeneity decreases the systemic risk by approximately 1.17% on average. After controlling for the skewness of the dependent variable, we observe from column (5) that a 1 % increase in bank-level heterogeneity decreases systemic risk by around 0.2936% on average. The significant changes (at the 99% level) in economic magnitudes and statistical significance of the coefficients in of the models of columns (5)-(8) emphasize the importance of controlling for the skewness of our dependent variable.

[Insert Table 3 about here]

4.4 Heterogeneity and systemic risk during recessions

In this section, we focus on the cross-sectional relationship between the BHC-level heterogeneity and the systemic risk during the recessions measured by the NBER (the dot-com bubble, the bankruptcy of Lehman Brothers in September 2008, and the COVID-19 recession). In addition to the independent variables included in the models discussed in Section 4.3, we add an interaction term between an NBER recession indicator and our BHC-level heterogeneity measure and estimate the following equation:

$$\boldsymbol{SRISK_{i,t} = \alpha + \beta_1 \cdot Recession_t \cdot VWD_{i,t} + \beta_2 \cdot VWD_{i,t} + \gamma \cdot Control_{i,t} + \phi \cdot Cluster_{i,t} + \lambda_t + \omega_i + \epsilon_{i,t}} \tag{4.2}$$

where $Recession_t$ is a dummy variable equal to one during NBER recessions and 0 otherwise; $Recession_t \cdot VWD_{i,t}$ is the interaction term between the recession dummy and the BHC-level heterogeneity measure. The other independent and dependent variables are the same as the ones defined in Section 4.3. Our BHC-level heterogeneity measure $\mathrm{VWD}_{\mathrm{i,t}}$ is still negatively related to bank-level systemic risk, but with higher statistical significance (at the 99% statistical significance level) and

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[xiii] We construct the semi-elasticity using the regression coefficients of the original dependent variables $SRISK_{i,t}$ divided by the sample mean.

economic magnitudes in Table 4 compared to the levels in Table 3. In addition, the coefficient of the interaction term $Recession_t \cdot VWD_{i,t}$ is also positively related to systemic risk (at the 95% statistical significance level in column (1) and 99% level in column (3)). Therefore, our BHC-level heterogeneity measure contributes more to the systemic risk during recession periods. A one standard deviation increases in $VWD_{i,t}$ can increase the systemic risk by around US$ 1.08 billion for the average BHC. We can attribute the positive correlation to rational herding behavior that could be induced by government guarantees. If a BHC is very different from its peers, it may be less likely to be saved by the government during a recession. Nevertheless, after we control for the skewness of the dependent variable in columns (5)-(8), the interaction terms' coefficients are no longer statistically significant. Thus, the net effects of heterogeneity during recessions are yet inconclusive.

[Insert Table 4 about here]

5. Conclusions

A decrease in the heterogeneity of bank holding companies can amplify the aggregate expected capital shortfalls and is therefore correlated with systemic risk. While individual banks may diversify by holding different loan, lending, and investment books, this diversification choice may make them more similar, augmenting systemic risk. Hence, holding similar (optimal) portfolios, banks' managers (possibly inadvertently) herd by investing in correlated asset holdings and adopting a similar capital structure to exploit implicit or explicit government guarantees. Furthermore, by maximizing the private benefits from reward-based compensation schemes, bank managers may induce negative externalities to the real economy through augmenting systemic risk.

We observed a drop in heterogeneity in the financial sector prior to the financial crisis related to the Great Recession and the COVID-19 recession. We also noted a continued decrease in heterogeneity during the past decade, and that BHC-level heterogeneity negatively correlates with bank-level systemic risk. Therefore, this paper suggests that cross-sectional heterogeneity at BHC and at aggregate levels are relevant to the micro and macro prudential policies. It is crucial to consider heterogeneity to better monitor, intervene or regulate and eventually reduce the magnitude of a future possible joint failure of financial institutions and hence the whole financial system.

6. *Further research*

As the heterogeneity at the BHC level and the aggregate level for the financial sector contributes to systemic risk, a natural next step would be to delve deeper into the economic mechanisms. First, regarding the issue of diversification, one could collect data on detailed investment, funding, and lending portfolios of each of the BHCs. Furthermore, following Chu et al. [2020], incorporating geographic diversification of BCHs in the systemic risk analysis is an interesting path forwards crucial. Moreover, a more in-depth time series analysis with higher frequency (e.g., with daily, weekly data) could be pursued.

Second, in relation to the rational herding behavior mechanism, we can test the hypothesis that BHCs that implement a relative performance evaluation (RPE) for the top managers' compensation have investment portfolios that are more correlated with those of their peers (Albuquerque et al. [2019]). This would give insight into how incentive pay contributes to systemic risk, which has hardly been discussed in the extant literature. Moreover, a further extension of the framework of Duarte and Eisenbach [2021] with a focus on the heterogeneity effects is warranted.

Finally, one could also expand the focus towards the incorporation of other financial institutions such as insurance companies and pension funds. For example, the interconnectedness of the financial section with the insurance sector could be an important contributor to systemic risk (Billio, Getmansky, Lo, and Pelizzon [2012]). As Hufeld et al. [2017] state, insurance companies and pension funds invest in illiquid assets and cannot tolerate considerable downside risk; an increase in their aggregate risk can contaminate other financial institutions during a recession and bring the whole financial system down.

Figures and Tables
Figure 1: Aggregate SRISK

Figure 1 shows the quarterly time series of aggregate $SRISK_t$ from June 2000 to December 2021, which amounts to 87 quarters. The five vertical lines indicate (i) the peak of Dot-com bubble in January 2000, (ii) the bankruptcy of the Lehman brothers in September 2008, (iii) the European sovereign debt crises in June 2010 and (iv) October 2011, and (v) the WHO declaring COVID-19 as a pandemic, respectively.

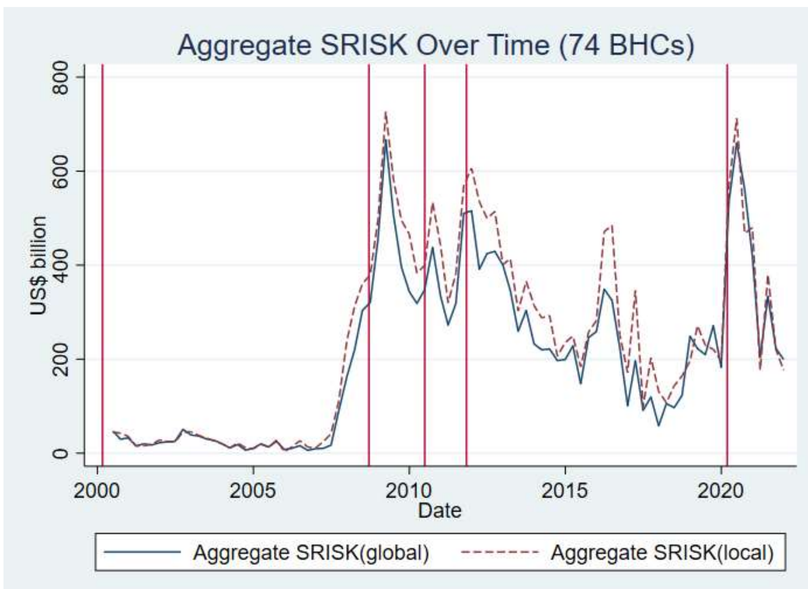

Figure 2: Decreasing heterogeneity of the financial sector

Figure 2 shows the decreasing heterogeneity of the financial sector. The heterogeneity (VWD) is measured by the weighted average of bank-level pairwise Euclidean distance (PED) across bank holding companies (BHCs) based on asset size (yellow dashed line) and equally-weighted bank-level PED across BHCs (brown dot-dashed line) respectively. The y-axis on the left shows the value of the systemic risk, the y-axis on the right shows the level of the sector-heterogeneity index, and the x-axis shows the time (in years). The gray areas from left to right are the recessions defined by the National Bureau of Economic Research, including the peak of the Dot-com bubble in January 2000, the bankruptcy of Lehman Brothers in September 2008, and the COVID-19 recession respectively. The solid lines capture the level of aggregate systemic risk. The red line represents the SRISK based on the assumption of a global recession and the purple line is the SRISK based on a domestic recession in the U.S. [Acharya et al., 2017; Brown and Engle, 2017].

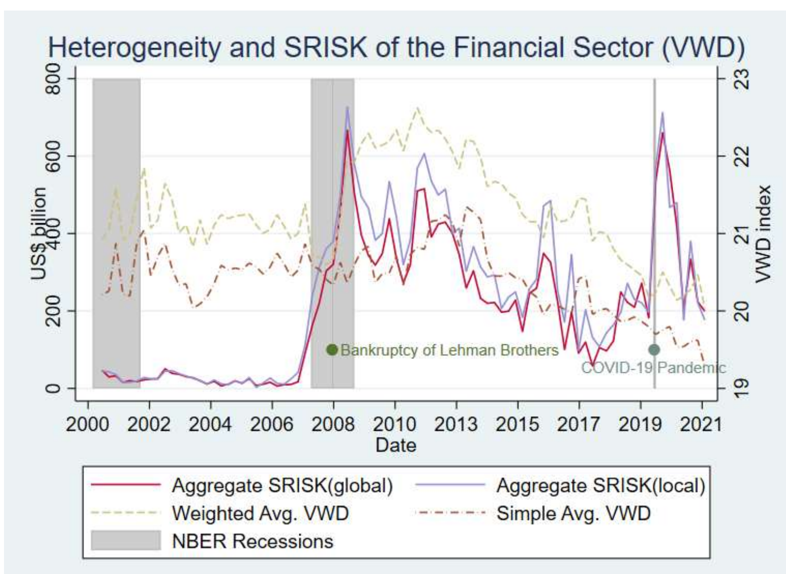

Table 1: The SRISK% rankings of the top ten bank holding companies

This table reports the ranking, the BHC-level systemic risk, the systemic risk share for each of the top ten bank holding companies (BHCs) that contributed the most to the aggregate systemic risk in the last quarter of 2008, 2012, 2016 and 2020, respectively. The sample period is from 2000Q2 to 2021Q4. The systemic share $SRISK\%_{i,t}$ is calculated as:

$$SRISK\%_{i,t} = \frac{SRISK_{i,t}}{SRISK_t} \text{ if } SRISK_{i,t} > 0,$$

where $SRISK_{i,t}$ stands for the daily time series BHC-level systemic risk (basd on global model) for each BHC i at the last trading day at the end of quarter t and the aggregate systemic risk is calculated as $SRISK_t = \sum_i^N \left(SRISK_{i,t}\right)_+$. There are 87 cross-sectional tables whose results are similar to the tables below and can be found in the Online Appendix.

Rank	**BHC Name**	**SRISK (US$ billion)**	**SRISK%**
	2008Q4		
1	Citigroup Inc.	134.67	29.45%
2	JPMorgan Chase & Co.	117.25	25.64%
3	Bank Of America Corporation	100.84	22.06%
4	Wells Fargo & Company	38.58	8.44%
5	Pnc Financial Services Group, Inc., The	11.21	2.45%
6	Suntrust Banks, Inc.	7.63	1.67%
7	Regions Financial Corporation	7.22	1.58%
8	Capital One Financial Corporation	5.81	1.27%
9	Fifth Third Bancorp	5.73	1.25%
10	Keycorp	5.57	1.22%

	2012Q4		
1	Bank Of America Corporation	99.15	24.78%
2	Citigroup Inc.	91.03	22.75%
3	Jpmorgan Chase & Co.	85.35	21.33%
4	Goldman Sachs Group, Inc., The	41.35	10.34%
5	Morgan Stanley	39.67	9.92%
6	Bank Of New York Mellon Corporation, The	8.59	2.15%
7	Suntrust Banks, Inc.	4.96	1.24%
8	Capital One Financial Corporation	4.43	1.11%
9	Pnc Financial Services Group, Inc., The	3.83	0.96%
10	Regions Financial Corporation	3.56	0.89%
	2016Q4		
1	Citigroup Inc.	32.95	32.65%
2	Bank Of America Corporation	30.09	29.82%
3	Morgan Stanley	16.39	16.24%
4	Goldman Sachs Group, Inc., The	10.60	10.51%
5	Ally Financial Inc	7.37	7.31%
6	State Street Corporation	2.83	2.81%
7	Capital One Financial Corporation	0.68	0.67%
8	Associated Banc-Corp	-0.17	0.00%
9	Bankunited, Inc.	-0.37	0.00%
10	Valley National Bancorp	-0.37	0.00%
	2020Q4		
1	Citigroup Inc.	107.77	25.80%
2	Wells Fargo & Company	80.47	19.27%
3	Bank Of America Corporation	63.41	15.18%
4	Goldman Sachs Group, Inc., The	37.82	9.06%
5	Jpmorgan Chase & Co.	37.75	9.04%
6	Morgan Stanley	14.00	3.35%
7	Bank Of New York Mellon Corporation, The	11.19	2.68%
8	Capital One Financial Corporation	7.39	1.77%
9	State Street Corporation	7.26	1.74%
10	Ally Financial Inc	6.80	1.63%

Table 2: Summary statistics

Table 2 shows the summary statistics of the systemic risk measures. Both global $SRISK_{i,t}$ based on a 40% decline in the MSCI World Index and the domestic $SRISK_{i,t}$ based on a 40% decline in the S&P 500 Index are reported as are the corresponding normalized systemic risk measures based on inverse hyperbolic transformation following Bellemare and Wichman [2020]. We also show the heterogeneity measurements (the value-weighted pairwise Euclidean distance, $VWD_{i,t}$ and the equally-weighted pairwise Euclidean distance, $EWD_{i,t}$), Total assets values, book equity, return on equity, equity ratio, loans to total assets, and deposits ratio. These summary statistics are mainly based on two databases the Bank Regulatory Database for BHC features and the NYU Volatility Laboratory (V-Lab)'s Systemic Risk database. We create a merged panel dataset of 74 BHCs based on the above datasets and report $SRISK_{i,t}$ which stands for the systemic capital shortfall for each BHC i at the last trading day at the end of quarter t. The time series consists of 87 bank-quarter observations for 74 unique BHCs (see appendix 2).

Variable	**Obs.**	**Mean**	**St. Dev.**	**Min**	**25th perc.**	**Median**	**75th perc.**	**Max**
Systemic risk measures								
Global $SRISK_{i,t}$ (US$ billion)	5898	1.23	16.37	-131.62	-4.89	-0.45	4.40	153.85
Global asinh ($SRISK_{i,t}$)	5898	-0.278	1.835	-5.573	-2.29	-0.432	2.187	5.729
Domestic $SRISK_{i,t}$ (US$ billion)	5995	2.25	17.15	-135.68	-3.77	-0.20	5.85	160.73
Domestic asinh ($SRISK_{i,t}$)	5995	-0.036	1.825	-5.603	-2.038	-0.196	2.467	5.773
BHC characteristics								
$VWD_{i,t}$	5294	20.39	3.35	8.42	15.25	21.31	23.55	26.45
$EWD_{i,t}$	5294	15.18	3.89	10.03	11.88	13.66	22.75	26.13
Total Assets (US$ billion)	5294	187.22	463.46	0.19	4.87	30.43	391.28	3757.58
Book Equity (US$ billion)	5294	18.31	44.37	0.02	0.48	3.30	44.48	294.13
Return on Equity (ROE)	5294	0.06	0.08	-1.99	0.02	0.06	0.13	0.62
Book Equity/Total Assets	5294	0.11	0.05	0.03	0.07	0.10	0.14	0.92
Loans/Total Assets	5280	0.59	0.19	0.00	0.32	0.66	0.77	0.96
Deposits/Total Assets	4993	0.53	0.14	0.00	0.37	0.54	0.69	0.85

Table 3: Bank-level heterogeneity and systemic risk

The baseline regression is:

$$\mathrm{arcsinh}(\mathrm{SRISK}_{i,t}) = \alpha + \beta_0 \cdot \mathrm{VWD}_{i,t} + \gamma \cdot \mathrm{Control}_{i,t} + \omega_t + \sigma_i + \epsilon_{i,t}$$

where the dependent variable $arcsinh(\mathrm{SRISK}_{i,t})$ is the inverse hyperbolic sine transformation of daily time series of systemic capital shortfall matched to the last trading day in each quarter. The $\mathrm{VWD}_{i,t}$ is a quarterly time series of value-weighted pairwise Euclidean distance based on balance and off-balance sheet accounts provided in the Bank Regulatory Database. We also report the results for the original values of $SRISK_{i,t}$ and equally-weighted pairwise Euclidean distance ($EWD_{i,t}$). The control variables include total assets, the equity ratio (leverage), return on equity (ROE), loans to total assets (liquidity), and deposits ratio to (solvency). Semi-elasticities are calculated based on sample means, while retransformed elasticities for inverse hyperbolic sine transformation are calculated based on Bellemare and Wichman [2020]. We also include year-quarter (λ_t) and individual fixed effects (σ_i) for the regression and estimate robust standard errors using the Eicker-Huber-White estimator. A Hausman test rejects the null hypothesis that the relation between the dependent and independent variables is influenced by random effects, which suggests the use of fixed-effects models. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

(US$ billion)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Key variables		$\mathbf{SRISK_{i,t}}$				$\mathbf{arcsinh(SRISK_{i,t})}$		
$VWD_{i,t}$	-0.0705**		-0.0653**		-0.0123***		-0.0103**	
	[0.0304]		[0.0321]		[0.00450]		[0.00472]	
$EWD_{i,t}$		-0.134***		-0.142***		-0.00565		-0.00324
		[0.0361]		[0.0390]		[0.00438]		[0.00461]
Control variables								
Total Assets (TA)	0.0290***	0.0289***	0.0296***	0.0295***	0.00190***	0.00189***	0.00185***	0.00184***
	[0.00306]	[0.00305]	[0.00312]	[0.00311]	[0.000260]	[0.000260]	[0.000262]	[0.000262]
Profitability (ROE)			-7.604**	-7.636**			-1.797***	-1.817***
			[3.542]	[3.575]			[0.631]	[0.632]
Leverage (Equity/TA)			-35.10***	-35.04***			-4.564***	-4.534***
			[7.630]	[7.616]			[0.968]	[0.965]
Liquidity (Loans/TA)			-0.508	-0.273			-0.452	-0.438
			[2.758]	[2.754]			[0.307]	[0.306]
Solvency (Deposits/TA)			-6.132***	-6.602***			0.847***	0.839***
			[1.612]	[1.653]			[0.204]	[0.207]
Calculated (semi-)elasticities								
$\xi(SRISK_{i,t}, VWD_{i,t})$	-1.169**		-1.082**		-0.2936***		-0.2475**	
					[0.1077]		[0.1130]	
$\xi(SRISK_{i,t}, EWD_{i,t})$		-1.654***		-1.752***		-0.1015		-0.0582
						[0.0787]		[0.0827]
Fixed effects								
Year-quarter	YES	YES	YES	YES	YES	YES	YES	YES
Bank-level	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-2.863***	-2.233***	4.575*	5.546**	-0.362***	-0.524***	0.0330	-0.134
	[0.820]	[0.804]	[2.720]	[2.689]	[0.104]	[0.0856]	[0.303]	[0.299]
Obs.	4693	4693	4404	4404	4693	4693	4404	4404
Adj. R-squared	0.541	0.541	0.543	0.544	0.616	0.616	0.623	0.622

Table 4: The impact of recessions

The regression is constructed as follows:

$$arcsinh(SRISK_{i,t}) = \alpha + \beta_1 \cdot Recession_t \cdot VWD_{i,t} + \beta_2 \cdot VWD_{i,t} + \gamma \cdot Control_{i,t} + \lambda_t + \omega_i + \epsilon_{i,t}$$

where the dependent variable $arcsinh(SRISK_{i,t})$ is the inverse hyperbolic sine transformation of daily time series of systemic capital shortfall matched to the last trading day in each quarter. $\mathrm{VWD}_{\mathrm{i,t}}$ is a quarterly time series of value-weighted pairwise Euclidean distance ($VWD_{i,t}$) based on balance and off-balance sheet accounts provided in the Bank Regulatory Database. We report the results for the original values of $SRISK_{i,t}$ and equally-weighted pairwise Euclidean distance ($EWD_{i,t}$). $Recession_t$ is the NBER-based recession indicator that covers the Dot-com bubble (April 2000 - November 2000), the 2008 financial crisis (Jan 2009 - June 2009), and the COIVD-19 pandemic (March 2020 - April 2020). The control variables include total assets, equity ratio (leverage), loans to the total assets (liquidity), and deposits ratio (solvency). Semi-elasticities are calculated based on sample means, while retransformed elasticities for inverse hyperbolic sine transformation are calculated based on Bellemare and Wichman [2020]. We also control for year-quarter (λ_t) and individual fixed effects (σ_i) and estimate robust standard errors by using the Eicker-Huber-White estimator. A Hausman test rejects the null hypothesis that the relation between the dependent and independent variables is influenced by random effects, which suggests the use of fixed-effects models. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

(US$ billion)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Key variables		$SRISK_{i,t}$				$arcsinh(SRISK_{i,t})$		
$VWD_{i,t}$	-0.106***		-0.105***		-0.0125***		-0.0108**	
	[0.0323]		[0.0345]		[0.00464]		[0.00492]	
$VWD_{i,t} \times Rec.$	0.263**		0.279***		0.00163		0.00310	
	[0.104]		[0.104]		[0.0148]		[0.0148]	
$EWD_{i,t}$		-0.128***		-0.141***		-0.00733		-0.00539
		[0.0373]		[0.0409]		[0.00456]		[0.00487]
$EWD_{i,t} \times Rec.$		-0.0345		-0.00498		0.0103		0.0123
		[0.123]		[0.124]		[0.0132]		[0.0131]
Control Variables	NO	NO	YES	YES	NO	NO	YES	YES
Calculated (semi-)elasticities								
$\xi(SRISK_{i,t}, VWD_{i,t})$	-1.757***		-1.741***		-0.2989***		-0.2581**	
					[0.1111]		[0.1176]	
$\xi(SRISK_{i,t}, EWD_{i,t})$		-1.580***		-1.740***		-0.1316		-0.0968
						[0.0819]		[0.0874]
Fixed Effects								
Year-quarter	YES	YES	YES	YES	YES	YES	YES	YES
Bank-level	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-2.900***	-2.248***	4.575*	5.540**	-0.362***	-0.519***	0.0330	-0.121
	[0.819]	[0.794]	[2.721]	[2.666]	[0.105]	[0.0847]	[0.303]	[0.299]
Obs.	4693	4693	4404	4404	4693	4693	4404	4404
Adj. R-squared	0.541	0.541	0.543	0.544	0.616	0.616	0.622	0.622

Appendices

Appendix 1: The FR Y-9 report

Description: This report collects basic financial data from domestic bank holding companies (BHC), savings and loans holding companies (SLHC), intermediate holding companies (IHCs), and security holding companies (SHC) on a parent-only basis in the form of balance sheet data, income statements, and the supporting schedules relating to investments, cash flows, and memoranda items.

Purpose: The information is used to assess and monitor the financial condition of parent holding companies.

Background: The report was initiated as the FR Y-9 in 1978. In 1985, the report was revised to parallel the Report of Condition and Income (Call Report) for commercial banks, and in June 1986, it was extensively revised and split into: FR Y 9LP (parent-company-only statements) and FR Y 9C (consolidated statements). In September 1990, a cash flow statement was added to the FR Y-9LP. In keeping with the revisions to the filing criteria for the FR Y-9C, the asset-size threshold for filing the FR Y-9LP was increased from $150 million to $500 million, from $500 million to $1 billion, and from $1 billion to $ 3 billion effective from March 2006, March 2015 and September 2018 report date, respectively. Consistent with the Call Report, the content and structure of this report are frequently revised in consideration of developments in the banking industry and changes in supervisory, regulatory, and analytical needs. This report is required under Regulation Y and the Bank Holding Company Act of 1956, as amended. The Dodd-Frank Wall Street Reform and Consumer Protection Act (the Dodd-Frank Act) was enacted on July 21, 2010. Title III of the Dodd-Frank Act abolished the Office of Thrift Supervision (OTS) and transferred all former OTS authorities (including rulemaking) related to SLHCs to the Federal Reserve, effective as of July 21, 2011. The Federal Reserve also became responsible for the consolidated supervision of SLHCs beginning July 21, 2011. During 2011, the Board finalized its proposal exempting a limited number of SLHCs from regulatory reporting using the Board's existing regulatory reports and providing a two-year phase-in approach for regulatory reporting for all other SLHCs, starting from March 31, 2012. Section 165 of the Dodd-Frank Act directs the Federal Reserve to establish enhanced prudential standards for bank holding companies (BHCs) and foreign banking organizations (FBOs) with total consolidated assets of $50 billion or more. On June 1, 2016, the Federal Reserve approved the proposal to require FBOs with total consolidated assets of $50 billion or more to establish a U.S. intermediate holding company (IHCs) over all their U.S. subsidiaries. The IHCs are subject to U.S. Basel III, capital planning, Dodd-Frank stress testing, liquidity, risk management requirements and other U.S. regulations. Effective July 1, 2016, U.S. Intermediate Holding companies were required to file certain reports under the Federal Reserve's Regulation YY.

Respondent Panel: This report is filed by the parent company of large BHCs, SLHCs, IHCs and SHCs and is required for large BHCs, SLHCs, IHCs with total consolidated assets of $3 billion or more. In addition, BHCs, SLHCs, IHCs and SHCs meeting certain criteria may be required to file this report regardless of size. When such BHCs, SLHCs, IHCs or SHCs are tiered holding companies, each of the subsidiary holding companies' files separate reports.

Frequency: Quarterly, from the last calendar day of the quarter onwards.

Public Release: Data are published in the Federal Reserve Bulletin and the Federal Reserve's Uniform Bank Holding Company Performance Report (BHCPR). With a few exceptions, microdata are considered public information and are available through the Board's Freedom of Information Office.

Appendix 2: The sample of bank holding companies

Ticker	Legal Name	Ticke	Legal Name
AIG	American International Group Inc	MI	Marshall & Ilsley
ALLY	Ally Financial Inc	MS	Morgan Stanley
AMP	Ameriprise Financial Inc	MTB	M&T Bank Corp
ASB	Associated Banc-Corp	NCC	National City Corporation
BAC	Bank of America Corp	NTRS	Northern Trust Corp
BK	Bank of New York Mellon	NYCB	New York Community Bancorp Inc
BKU	BankUnited Inc	OZK	Bank OZK
BOH	Bank of Hawaii Corp	PAC	PacWest Bancorp
BOKF	BOK Financial Corp	PB	Prosperity Bancshares Inc
C	Citigroup Inc	PBCT	People's United Financial Inc
CBSH	Commerce Bancshares Inc/MO	PNC	PNC Financial Services Group
CFFN	Capitol Federal Financial Inc	PNFP	Pinnacle Financial Partners Inc
CFG	Citizens Financial Group Inc	RF	Regions Financial Corp
CFR	Cullen/Frost Bankers Inc	RJF	Raymond James Financial Inc
CIT	CIT Group Inc	SCH	Charles Schwab Corp/The
CMA	Comerica Inc	SEIC	SEI Investments Co
COF	Capital One Financial Corp	SF	Stifel Financial Corp
CYN	City National Corp/CA	SIVB	SVB Financial Group
DFS	Discover Financial Services	SNV	Synovus Financial Corp
ETFC	E*TRADE Financial Corp	STI	SunTrust Banks Inc
EWBC	East West Bancorp Inc	STL	Sterling Bancorp/DE
FAF	First American Financial Corp	STT	State Street Corp
FCNC	First Citizens BancShares Inc/NC	TCBI	Texas Capital Bancshares Inc
FHB	First Hawaiian Inc	TCF	TCF Financial Corp
FHN	First Horizon National Corp	TFC	Truist Financial Corp
FITB	Fifth Third Bancorp	TRO	T Rowe Price Group Inc
FNB	FNB Corp/PA	UBSI	United Bankshares Inc/WV
FNFG	First Niagara Financial Group Inc	UMB	UMB Financial Corp
FULT	Fulton Financial Corp	UMP	Umpqua Holdings Corp
GS	Goldman Sachs Group Inc/The	USB	US Bancorp
HBAN	Huntington Bancshares Inc/OH	VLY	Valley National Bancorp
HCBK	Hudson City Bancorp Inc	WAF	Washington Federal Inc
HWC	Hancock Whitney Corp	WAL	Western Alliance Bancorp
IBKC	IBERIABANK Corp	WBS	Webster Financial Corp
ISBC	Investors Bancorp Inc	WFC	Wells Fargo & Co
JPM	JPMorgan Chase & Co	WTFC	Wintrust Financial Corp
KEY	KeyCorp	ZION	Zions Bancorporation

Appendix 3: Online appendix

Online appendix link (a shared Dropbox folder):
https://www.dropbox.com/sh/ldu00q0mqewnogz/AACV4jXqDcmBbzR-RZgFMsUka?dl=0

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