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by Iñaki Aldasoro, Bryan Hardy and Maximilian Jager

Monetary and Economic Department

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The Janus face of bank geographic complexity*

Iñaki Aldasoro
Bank for International Settlements

Bryan Hardy
Bank for International Settlements

Maximilian Jager
University of Mannheim

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Abstract

We study the relationship between bank geographic complexity and risk using a unique dataset of 96 global bank holding companies (BHCs) over 2008-2016. From data on the affiliate network of internationally active banking entities, we construct a measure of geographic coverage and complexity for each BHC. We find that higher geographic complexity heightens banks' capacity to absorb local economic shocks, reducing their risk. However, higher geographic complexity is also associated with a higher vulnerability to global shocks and less impact of prudential regulation, increasing their risk. Geographic complexity helps more (with respect to local shocks) and hurts less (with respect to global shocks) if countries' business cycles are misaligned. Large, international regulatory reforms such as the implementation of the GSIB framework and the European Single Supervisory Mechanism reduce bank risk, but geographic complexity weakens this effect. Bank geographic complexity therefore has a Janus face, decreasing some but increasing other aspects of bank risk.

JEL-Codes: G21, G28
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1 Introduction

Global banks' complexity is a major concern for policy makers, as shown by its prominence within the framework to regulate global systemically important banks (GSIBs). Complexity, however, is not a clearly defined concept and can take different forms. It could arise from the size and diversity of a bank's loan portfolio (Doerr and Schaz (2018)), it could be related to the extent and nature of investment activities (BCBS (2013)), or it could be determined by the organizational and geographic structure of the bank (Cetorelli and Goldberg (2014, 2016)). This paper focuses on the latter and examines how the geographic complexity of banks' organizational structure helps them to cope with the two main factors governing their business: the economic and regulatory environments.

Geographic complexity can affect bank risk through three channels acting in opposite directions. First, it can provide diversification value to financial institutions and can thus be beneficial for bank risk and financial stability. We document that a higher degree of geographic complexity helps banks dampen the adverse impact of local economic shocks (i.e. in the country of headquarters) on their riskiness.

Second, just as a wider geographic footprint enhances diversification potential, it also increases exposure. We find that banks with a higher degree of geographic complexity are more vulnerable to shocks to the global economy.

Third, geographic complexity can also increase risk by changing the way regulation impacts the bank. Tighter regulation is associated with higher capitalization. However, when there is higher geographic complexity, the increase in the risk-based capital ratio (regulatory Tier 1 capital) is smaller. This implies that a wider geographic reach can provide banks with a broad range of ways to respond to the regulation, potentially impacting their resilience and risk.

We further establish this third effect by analyzing forward-looking market measures of bank risk following the introduction of the GSIB framework and the Single Supervisory Mechanism (SSM) in Europe. We find that these reforms generally reduced bank risk, but less so for more geographically complex banks.

Bank geographic complexity therefore has a Janus face. On the one hand, it helps mitigate the impact of local economic shocks and hence strengthens banks' resilience. On the other hand, it can also pose a risk by increasing exposure to global shocks and affecting banks' response to regulation.

To perform our analysis, we build a new, unique bank-level dataset on geographic complexity using the BIS Banking List (see Section 2 for more details). Based on this list of internationally active banking entities, we obtain a dataset comprising the 96 largest bank holding companies (BHCs)[1] in the world, including most of the sample used by the Basel Committee on Banking Supervision (BCBS) in the GSIB assessment exercise. The data are unique in that they provide a large, global sample of the most relevant international BHCs in a cross-country panel. We match these data with balance sheet and market information at the BHC level, as well as macro indicators and information about the regulatory environment at the country level. This allows us to test how bank geographic complexity relates to measures of bank health and risk and their main driving forces. We exploit the cross-country nature of the dataset to control for various confounding factors in our analysis and obtain results that hold across different country settings.

We compute a Herfindahl-Hirschman based measure of geographic representation and complexity at the BHC-year level. This measure conceptually covers the size of the organizational structure (number of affiliates) as well as their geographic reach (number of host countries) and the concentration within their host countries. Our measure of geographic complexity contains information complementary to that captured by the BCBS's measures of complexity and cross-jurisdictional activity in the context of the GSIB assessment exercise, which focus mostly on the investment activities of global banks.

Our analysis is split into four sections. The first three each focus on the role of geographic complexity in affecting the relation between bank risk and one external factor: i) local economic shocks; ii) global economic shocks; and iii) local prudential regulation in individual

[1] Throughout we use bank, BHC and banking group interchangeably. Our unit of analysis is always the BHC.

countries (home country, host countries, or both). The fourth section examines the implementation of global regulatory reforms (the GSIB framework and the SSM in Europe) to further establish the weakening of regulatory actions via geographic complexity.

We use alternative measures of risk for different parts of our analysis. When looking at local and global shocks, we focus on the z-score. This measure is the most comprehensive and commonly used measure of realized risk. It better reflects changes to risk due to the changing economic environment. When examining the effects of regulation, we focus instead on risk-based capitalization, as this is a key target of regulators that proxies an ex-ante perspective to bank risk. Finally, when looking at large regulatory reforms such as the GSIB framework and the SSM, we focus on forward-looking market-based measures of bank risk. Such reforms introduce large, structural and new frameworks with long-lasting effects on affected banks' business models, as well as on the market structure as a whole. This is likely to be reflected in the forward-looking market assessment of the banks.[2]

We document that negative shocks to the growth of real GDP in the home country (i.e. local shocks) drive up bank risk.[3] The more geographically diversified a bank is, however, the more it can cushion this increase in risk. This diversification may occur passively (i.e. diversified shocks to borrowers) or actively (banks actively move resources according to changing circumstances and opportunities). We find evidence for active diversification, as operating abroad in the form of subsidiaries weakens the diversification benefit. This is because subsidiaries operate more independently, and so make it more difficult for a BHC to actively move funds around in response to changes. We also find evidence for passive diversification, as a higher business cycle correlation between home and host locations (which implies less diversified economic shocks to borrowers) is associated with a weaker diversification effect.

[2] In particular, we use measures of systemic risk, idiosyncratic risk and systematic risk, where the latter two are extracted from CDS spreads. Systemic risk indicators aim to capture the contribution of individual financial institutions to the likelihood of large system-wide financial disruptions. Systematic risk indicators capture market risk that cannot be diversified away. Idiosyncratic risk, in turn,captures the part of bank risk that is uncorrelated to the systematic component.

[3] Shocks to GDP growth are defined as the deviation of actual growth from forecasted growth.

In the second empirical section, we analyze shocks to the global financial cycle as captured by the global factor from Miranda-Agrippino and Rey (2015) and Miranda-Agrippino, Nenova, and Rey (2020). An increase in the global factor is symptomatic of thriving economic conditions globally. We show that a higher degree of geographic complexity amplifies the negative effects of a global shock. Greater geographic reach appears to expose banks to global shocks to a greater degree.

Geographic complexity in the form of many affiliates in emerging markets reduces this effect. EMEs are less integrated into the global financial system and hence developments in the global financial cycle are more representative of advanced economy conditions (Aldasoro, Avdjiev, Borio, and Disyatat (in press)). Operations in EMEs are thus less exposed to global shocks. This is the case particularly for subsidiaries, which are often funded locally and are thus less dependent on global markets. More generally, we find that the higher the host economies' business cycle loading on the global factor is, the more harmful is geographic complexity in the face of a global shock. Thus, geographic complexity helps more (local shocks) and hurts less (global shocks) if the business cycles are misaligned.

In the third part of the analysis we turn to local prudential regulatory actions in both home and host countries. These policy actions comprise measures to enhance banks' resilience, such as minimum capital requirements, as well as measures to prevent excessive risk-taking, such as LTV ratio caps (Cerutti, Correa, Fiorentino, and Segalla (2017)). We find prudential measures to be effective in increasing banks' risk-based capitalization (Tier 1 capital ratio). We do not find evidence that more geographically complex banks show a different degree of capitalization than less complex banks. However, we find that the positive effect of regulation on risk-based capitalization is weakened the more geographically complex a bank is. Just as a wider geographic footprint gives a BHC more room for maneuver in dealing with local shocks, it also allows for a broader range of options to respond to regulation, such that the desired level of risk is preserved for the group as a whole.

Similar to the case of business cycle correlation and economic shocks discussed earlier, we find that the synchronization of regulatory actions interacts with geographic complexity as a moderator of the effects of regulation. The more host country actions (tightening vs. loosening) are correlated with the home country's policies, the more geographic complexity dampens their impact on risk-weighted capitalization. In the presence of a tightening in several countries at the same time, e.g. because of the implementation of a global standard, or as a macroprudential reaction to economic developments in a whole region, banks which are more geographically complex will have an easier time finding a less tightly regulated host market in which to adjust their business.

The strength of this channel is also linked to the quality of regulation in home and host countries.[4] Our results suggest that if the regulator does not stringently enforce its tightening or implements less robust policies, banks do not need to be geographically complex to circumvent the regulatory action. This is consistent with our interpretation that these impacts reflect regulatory circumvention enabled by geographic complexity.

Lastly, the organizational structure again proves to be important. The moderating effect of geographic complexity is larger if the share of subsidiaries within the affiliate network is higher. Since subsidiaries hold their own capital, banks with a higher share of subsidiaries have more room for maneuver in the wake of regulatory changes in order to keep their returns and maintain desired risk levels.[5] This underscores the importance of trading-off branches versus subsidiaries which was already brought to the fore in the analysis of economic shocks.

The last part of the empirical analysis leverages more global and structural regulatory changes.[6] Concretely, we analyze the implementation of the GSIB framework, as well as the SSM in Europe. The implementation of the GSIB framework was intended to reduce the probability of failure of the largest global banks by increasing their going-concern loss

[4] We use the regulatory quality index of the World Bank. We combine the information of this index for the headquarter jurisdiction and all the host jurisdictions in which a BHC has affiliates.

[5] This stands in contrast to the relative value of branches versus subsidiaries observed for the analysis on local economic shocks. When facing these shocks, branches allow for a more seamless reallocation of business across borders, as they do not have an independent balance sheet.

[6] By "structural" we refer to regulatory changes involving the introduction of a new framework altogether, as opposed to improvements to an already existing framework.

absorbency, whereas that of the SSM was meant to improve regulatory quality and scrutiny of the largest banks in the euro area. We examine market reactions to banks at the time these measures were announced. For analysing the GSIB framework, we employ an inverse probability weighting approach (Hirano, Imbens, and Ridder (2003)) to deal with the endogeneity of the GSIB assignment. Both reforms lead to a reduction of risk as measured by CDS spreads (idiosyncratic risk for the GSIB framework, systematic risk for the SSM). However, the effect is attenuated for more geographically complex banks, providing further support to the finding that a wider geographic spread provides more avenues for adjustment and thus different effects on aspects of bank risk.

Throughout the analyses, we leverage our cross-country panel of BHCs to control for confounding factors and better identify these relationships. Bank fixed effects control for time-invariant bank-specific characteristics, such as the bank's home country or corporate culture. Time fixed effects capture variation that is common to all banks, such as changes in global financial conditions or global risk aversion. We also control for bank-specific time-varying characteristics such as banks' size, profitability and business model proxies. As a major robustness exercise, we saturate our regressions with *country* $\times$ *time* fixed effects in our benchmark regressions. This specification is highly demanding, but it allows us to control for time varying shocks specific to each headquarter country (e.g. credit demand, regulation, growth, etc.). All key results for local economic shocks and regulatory actions and many of the respective channel-specific analyses survive this robustness test. We thus provide compelling evidence for diversification and regulatory circumvention channels linking geographic complexity with bank risk.

To the best of our knowledge, our paper is the first to link bank geographic complexity with altered effects of regulation. Furthermore, the cross-country nature of our dataset allows us to abstract from a single institutional environment (e.g. banks from just one country) and control for time-varying shocks to individual countries (e.g. regulation or demand). The diversification possibilities afforded to banks by a more complex and wider geographic structure can be both beneficial and detrimental from a financial stability perspective. While complexity allows banks to diversify certain economic shocks, it can also be a countervailing force to the positive effects that regulation can have on riskiness.

Related literature. Our paper closely relates to the young but growing literature on bank complexity and bank geographic expansion.[7] Carmassi and Herring (2016), Cetorelli, McAndrews, and Traina (2014) and Claessens and Van Horen (2014a, 2014b, 2015) among others, highlight the rapidly increasing degree of geographic complexity and reach of banks over the last twenty years, as well as the impact this had on domestic and global market structures. Cetorelli and Goldberg (2016) show that the organizational complexity of the family of a bank is a fundamental driver of the business model of the bank itself, as reflected in the management of the banks' own balance sheet.[8]

There are opposing views on whether geographic complexity and foreign expansion can be regarded as beneficial for bank health and risk. Advantages of complexity include a higher degree of competition in the funding market (Faia, Laffitte, and Ottaviano (2019)), an easier access to funding in general (Levine, Lin, and Xie (2019)), the ability to maintain higher loan supply during periods of stress (Doerr and Schaz (2018)), and less geographic concentration of risk (Goetz, Laeven, and Levine (2016)).[9] Disadvantages can be higher exposure to shocks in foreign markets (Berger, El Ghoul, Guedhami, and Roman (2017)) or a loss of market power in the domestic market (Buch, Koch, and Koetter (2012)).

We confirm the ambiguity of the relation between geographic complexity and risk. We contribute to the literature by simultaneously showing that complexity can be good in terms

[7] This literature does not always position itself explicitly in terms of complexity, as sometimes the focus is on geographic diversification or foreign – or in the case of the US, interstate – expansion. Furthermore, complexity can sometimes also be (other forms of) organizational complexity. We consider these strands of the literature together.

[8] A number of theoretical studies look at the relevance of (geographic) complexity for bank resolution frameworks (Carmassi and Herring (2015), Bolton and Oehmke (2018) and Flood, Kenett, Lumsdaine, and Simon (2017), among others). The measures we develop could also be used to evaluate different resolution approaches.

[9] In a related paper, Gropp, Noth, and Schüwer (2019) show that banks with high locally non-diversifiable risk expand significantly more to other states following the US interstate deregulation of the early 1990s (relative to banks that face a low level of such risk). The riskiness of these banks decreases as they expand geographically across states, again relative to banks with low locally non-diversifiable risks.

of shock diversification, but can also alter the impact of prudential regulatory measures. We do so by providing a broad picture of the role geographic complexity can play for local economic shocks, global economic shocks, local prudential regulation, and global regulation. The papers representing the aforementioned opposing views either look at single countries or single regions. Our contribution is important because we draw our insights from a unique, global cross-country dataset on bank geographic complexity.

Closest to our paper are the contributions by Cetorelli and Goldberg (2014) and Krause, Sondershaus, and Tonzer (2017). We build on the former for our main measure of bank complexity, which is a geographic version of the Herfindahl-Hirschman index they present. Krause et al. (2017) present time series evidence for European banks that, among different measures of complexity, geographic and foreign subsidiary share measures are significant in explaining bank risk. We confirm their aggregate findings for our larger sample of global banks and drill down into the potential channels affecting the link between geographic complexity and risk.

Roadmap. The remainder of the paper proceeds as follows: Section 2 describes the dataset and its construction; Section 3 describes the empirical approach and motivates the structure of results, which are presented and discussed in Section 4; and finally, Section 5 concludes.

2 Data

We build a novel dataset on the complexity of internationally active banks using the *BIS Banking List*. As part of the International Banking Statistics (IBS), the BIS annually collects information on the internationally active bank entities that report to the BIS locational banking statistics. As of end-2016, this banking list contained 8331 banking entities. For each year and bank, the list has information on the country from which the bank is reporting, the type of institution (i.e. branch, subsidiary, domestic bank, etc.), and the name and nationality of the controlling parent, among other items.

We build a measure of bank complexity in the spirit of Cetorelli and Goldberg (2014), within the constraints of our dataset.[10] The subsidiaries and branches in our data are internationally active banking entities. Thus, they are a subset of all BHC's affiliates, as we do not have information about non-bank affiliates or domestically oriented affiliates. Nevertheless, they have the advantage of focusing on the international aspect of the BHC's operations.[11]

The main complexity variable we construct is a geographic Herfindahl-Hirschman index based on Cetorelli and Goldberg (2014):

$$HHI = 100\frac{R}{R-1}\left(1 - \sum_{j=1}^{R}\left(\frac{Affiliates_j}{TotalAffiliates}\right)^2\right) \quad (1)$$

$Affiliates_j$ is the number of affiliates that the bank has in location j. R is the total number of countries in which any bank has affiliates in our sample. $TotalAffiliates$ is the total number of affiliates the bank has across all regions. Larger values in this index indicate higher complexity. If all of a bank's affiliates are located in a single country, this measure would record a zero, the lowest value. If each of a bank's affiliates operate in a different country, this measure would record one hundred, the highest value. Thus, the information captured by this metric is different from – and complementary to – information obtained from measures based on plain counts of affiliates. Since this measure accounts for concentration of affiliates in each location (rather than just counting total affiliates or total countries), it has the advantage that it captures geographic complexity separately from bank size.

To measure bank risk we look at balance sheet based and market based measures. Most of the analysis is based on balance sheet measures. In particular, we focus on the z-score when analyzing economic shocks. This is computed as $\frac{ROA+Equity/Assets}{sd(ROA)}$, where ROA is the return on assets. In line with the literature, and in order to interpret increases in the indicator as higher bank risk, we take the inverse of the logarithm of the z-score. When analyzing regulatory changes, we focus on a measure of bank capitalization, computed as:

[10] Figure A1 in Appendix A presents a stylized description of the banking list in its raw format and the transformations we apply before building measures of complexity.

[11] Furthermore, the extent of geographic diversity is bound by the number of countries which contribute to the BIS statistics and provide a banking list. Hence, the total number of affiliates reported will be a minimum for the BHC's banking affiliates or its total affiliates.

$1 - \textit{regulatory Tier}1\ \textit{capital ratio}$ (i.e. higher values indicate less capitalization and hence higher risk).

We further use market-based measures of systemic, idiosyncratic and systematic risk. Systemic risk indicators aim to capture the contribution of individual financial institutions to the likelihood of large system-wide financial disruptions. Systematic risk (also known as "market risk") refers to the risk that is part of the overall market and which cannot be diversified away. Idiosyncratic risk, in turn, is the (un-systematic) risk specific to an asset that does not affect the entire market (i.e. that part of bank risk which is uncorrelated to the systematic component). We use the SRISK systemic risk measure to capture a bank's contribution to systemic risk (Brownlees and Engle (2016)).[12] We compute idiosyncratic risk for CDS spreads and stock returns by calculating the first principal component of the respective series across all banks and orthogonalizing the original series to this principal component, thereby purging it from market-wide systematic effects. Finally, we compute systematic risk based on the fitted values from regressing the original series (CDS, stock returns) on the systematic component.

The risk indicators we consider capture different aspects of risk. The z-score, which is the most commonly used measure of bank risk, can be thought of as a proxy for realized risk. The ratio between Tier 1 capital and risk-weighted assets comes closest to an ex ante measure of risk. In turn, some market-based measures such as those based on CDS spreads capture perceived risk.

Our dataset has a yearly frequency, runs from 2008 to 2016 and comprises 96 BHCs headquartered in 22 countries.[13] A significant number of banks in our sample are part of the GSIB assessment sample: as of end-2016, 68 of the 76 BHCs that make up the GSIB assessment sample are part of our dataset.[14] All banks designated as GSIBs are included in our

[12]SRISK measures the capital shortfall of a firm conditional on a severe market decline, and is a function of its size, leverage and risk.

[13]The distribution by country (number of banks) is as follows: AT (1), AU (4), BE (2), BR (3), CA (5), CH (2), CN (12), DE (7), DK (1), ES (4), FI(1), FR (7), GB (6), IN (1), IT (4), JP (7), KR (4), NL (2), NO (1), RU (2), SE (3), SG (2), US (15).

[14]Chinese banks which are not GSIBs yet are part of the GSIB assessment sample are not part of our dataset.

sample.[15]

We match our data at the BHC-year level with balance sheet data from Fitch. We also incorporate country-level data on macroprudential regulations from the IBRN database (Cerutti et al. (2017)), as well as additional macroeconomic indicators and global macro controls such as the global factor from Miranda-Agrippino et al. (2020) (i.e. the ”global financial cycle”).

Table A1 presents all variables used in the paper, their definition and the source from which the series were obtained.

2.1 Data summary

Figure 1 provides a bird's eye view of the network of international affiliates for the group of 96 BHCs in our study, as of end-2016.[16] Node size indicates the number of incoming and outgoing connections. Black nodes denote jurisdictions in which one or more of the BHCs in our sample are headquartered, whereas red nodes denote countries where only affiliates of BHCs headquartered in the "black node" jurisdictions are located. Links between countries denote the existence of affiliates. A significant amount of the connections link North America and Europe, and these two with Asia.

[15] The exception is Dexia, which is excluded from our sample. Dexia was part of the first list of GSIBs published in 2011 but was removed in 2012 (never to return) when it started undergoing an orderly resolution process.

[16] See Figure A2 in Appendix A for additional descriptives on the distribution of branches and subsidiaries.

Figure 1: The global network of foreign affiliates (as of end-2016)

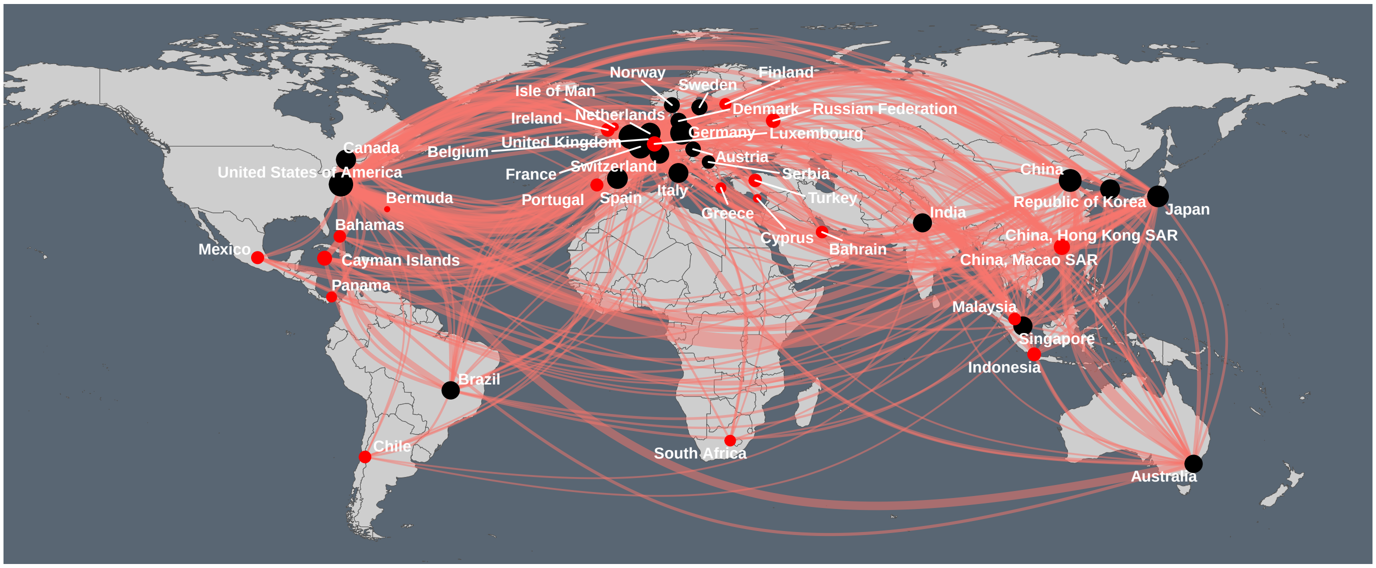


Table 1 summarizes the descriptive statistics for two types of geographic complexity measures, namely the HHI as specified in Equation 1, and count and share measures. We look at the time series behaviour as well as regional differences to highlight the importance of a cross-country panel approach to bank complexity and risk.

The first two rows in the upper panel of Table 1 compare the distribution of HHI values at the beginning and end of the sample. While the mean goes down only marginally, the standard deviation goes up considerably. That is, even though there is no homogeneous trend, there seem to be heterogeneous developments in complexity.

Rows three to five in the upper panel of Table 1 show regional differences at the end of our sample. US banks show high dispersion – with banks both at the higher and lower ends of the spectrum – but a comparably low mean. Euro area banks, instead, appear to be significantly more complex and exhibit a lower degree of dispersion. Lastly, banks from other regions (Asia, Latin America, non-Euro Europe, Canada) seem to reside in the middle of the two extremes. The HHI of the median bank does not vary much over time as can be seen by the standard deviation in the sixth row of the upper panel of Table 1. The modest time series variation for some individual banks highlights the importance of exploiting the cross-sectional differences interacted with various time varying factors (see section 3).

Table 1: Geographic complexity - descriptive statistics

	Mean	Median	Min	Max	Std
HHI 2008	85.38	88.03	44.83	97.07	10.46
HHI 2016	83.57	88.58	44.83	97.44	13.38
HHI 2016 US	80.66	86.60	50.43	97.44	16.86
HHI 2016 EA	86.71	90.19	44.83	95.78	11.47
HHI 2016 Rest	82.07	85.04	50.43	95.71	13.37
HHI median Time Series	87.68	88.03	86.74	88.58	0.75
Share of Branches 2008	0.56	0.57	0.00	1.00	0.19
Share of Branches 2016	0.59	0.58	0.00	1.00	0.23
Share of Subs 2008	0.36	0.33	0.00	1.00	0.23
Share of Subs 2016	0.29	0.26	0.00	1.00	0.22
Share of Subs 2008 Rest	0.35	0.32	0.00	1.00	0.26
Share of Subs 2016 Rest	0.32	0.30	0.00	1.00	0.23
No of countries 2008	11.93	10.00	2.00	33.00	7.56
No of countries 2016	12.95	11.00	2.00	37.00	8.96

The lower panel of Table 1 focuses on count and share measures. The share of foreign branches in the overall network structure has barely moved over our sample (first and second rows). The share of foreign subsidiaries, however, has gone down (third and fourth rows). Rows five and six, in turn, highlight that this is strongly driven by banks headquartered in the US and the Euro area, since the remaining regions have moved considerably less than the average. The last two rows of the lower panel look at the number of host countries a bank is present in. This number has slightly gone up, again with a notable increase in dispersion. Together with the statistics on subsidiaries and the HHI, this suggests that some banks closed down subsidiaries abroad while others even increased their complexity by expanding to new countries, leading to a larger variance in the HHI. The reasons for such heterogeneous behavior will be touched upon in section 3.

Table 2 presents summary statistics for the main controls and left-hand side variables. Size – measured as the logarithm of total assets – as well as the return on assets, show that we have a rather uniform set of very large and profitable banks. US banks tend to be a bit smaller and more profitable than the rest of the sample. Banks have very different structures in terms of reliance on deposit funding and loan business (columns six to eight). This highlights the richness of our cross-country data, as we can observe banks with different business models across countries. The first two columns further highlight the relevance of a cross-country analysis, since the number of branches and subsidiaries varies substantially across regions, with the Euro area being at the upper end, the US in the middle, and the rest at the lower end of affiliate counts. Furthermore, column three shows the usefulness of the time series dimension to the analysis, since the share of affiliates in emerging markets went up considerably over time, for banks from all regions.

Table 2: Bank variables - average for region × year

	# branch.	# subs.	EME	Size	ROA	Loans	Sec	Dep	Z-score	Cap
US 2008	9.07	5.71	0.11	12.83	0.37	44.70	32.95	55.09	0.60	0.88
US 2016	10.57	5.36	0.20	13.08	1.61	42.33	34.57	57.93	0.35	0.86
EA 2008	13.31	8.47	0.04	13.55	0.10	50.16	34.75	30.86	0.50	0.92
EA 2016	12.88	6.32	0.13	13.18	0.37	52.63	31.04	40.25	0.44	0.84
Rest 2008	7.16	4.21	0.08	12.96	0.57	50.65	33.07	56.06	0.48	0.90
Rest 2016	8.30	5.34	0.22	13.50	0.94	50.81	32.62	55.65	0.37	0.87

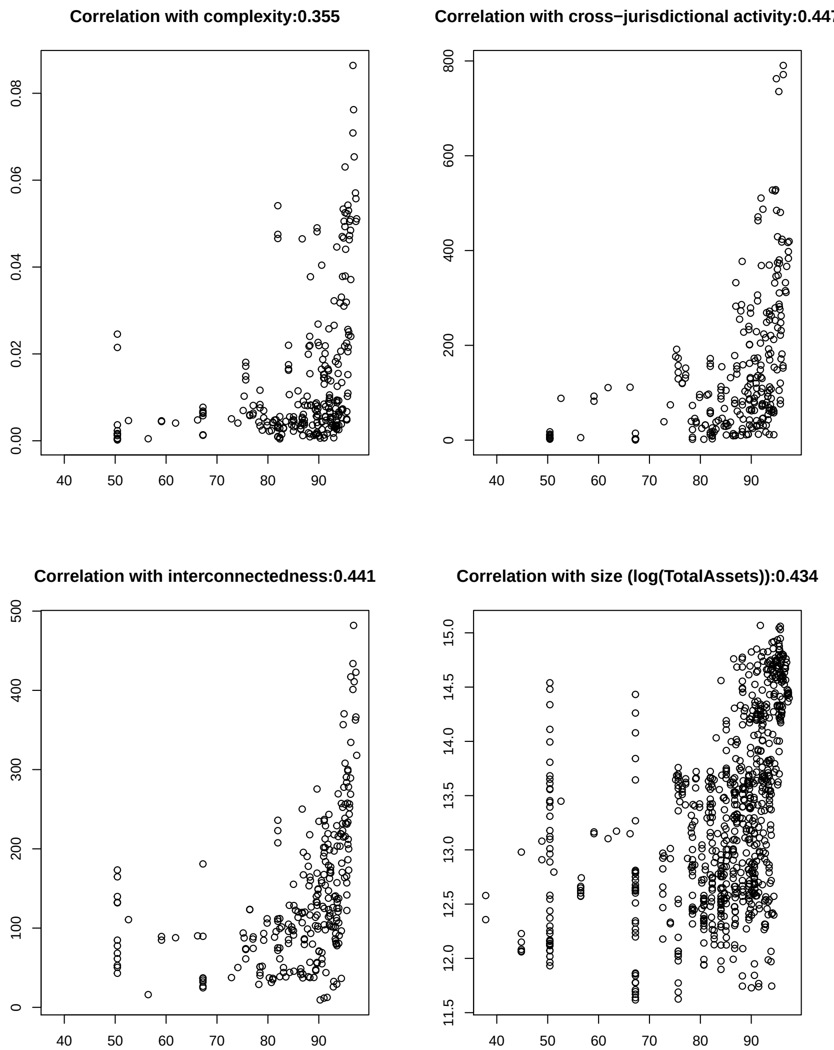
Note: *EME* stands for the share of affiliates in EMEs. *Size* is measured as the logarithm of total assets. *ROA* is the return on assets, expressed as percentage. *Loans*, securities (*Sec*) and deposits (*Dep*) are all expressed as a percentage of total assets. *Z-score* stands for 1/log(z-score). *Cap* stands for 1 - Tier1 Capital Ratio.

The riskiness of the banks in our sample – as measured by the z-score – varies significantly over the sample period. Euro area banks, which started from almost the lowest level of riskiness at the beginning of the sample, are by a good margin the riskiest banks at the end of the sample. Lastly, the capitalization variable indicates that banks in our sample are well capitalized. That said, we also observe quite some variation in this measure, where the general trend shows that average capitalization rates have gone up considerably over time. Additional summary statistics for our main variables can be found in Table A2 in the Appendix.

Our measure of geographic complexity contains information which differs from, and complements that, defined in the GSIB framework. The BCBS defines complexity as the simple average of scores calculated using the notional amount of OTC derivatives, level 3 assets, and trading as well as available-for-sale securities. This measure therefore captures operational complexity. Figure 2, Panel 1 compares our geographic complexity variable (HHI) with the BCBS complexity variable as of end-2016; the correlation between the two stands at 0.36.[17] For banks in the lower spectrum of complexity as defined by the BCBS (score roughly below 200), the HHI measure of geographic complexity provides much more variation and allows for an additional layer of differentiation. In the northeast corner of the figure, both measures align in pointing to the most complex bank. Our paper thus makes a case for the importance of also considering geographic complexity beyond organizational or operational complexity to fully capture the risk-relevant components of bank complexity. There are other indicators within the BCBS framework that could be associated with our HHI measure, namely cross-jurisdictional activity, interconnectedness and size. Panels 2 to 4 in Figure 2 present scatter plots for each of these, respectively. They do exhibit a slightly higher correlation with HHI, around 0.44. However, they all underscore the valuable variation that the HHI offers for banks in the lower spectrum of complexity.

[17] The figure shows the BCBS complexity score for those banks that are part of the GSIB assessment sample.

Figure 2: HHI geographic complexity vs. alternative complexity measures



Note: each panel plots our HHI measure on the x-axis versus the respective BCBS or balance sheet indicator on the y-axis.

3 Empirical approach

We use our dataset in order to examine how geographic complexity affects bank risk, in particular how it impacts the way external factors affect the bank. Our regressions take the following form:

$$\begin{aligned} Y_{it} = \alpha_t + \alpha_i + \beta_1 Complexity_{it-1} + \beta_2 ExternalFactor_{it} \\ + \beta_3 Complexity_{it-1} \times ExternalFactor_{it} + \gamma \mathbf{X}_{it-1} + \epsilon_{it} \end{aligned} \tag{2}$$

where i indicates the banking group, t indicates time and $\mathbf{X}_{it}$ is a vector of bank-specific controls.[18] Our outcome variable Y_{it} is either a measure of bank risk or capitalization. We include time fixed effects (α_t) and bank fixed effects (α_i) in all regressions. The former control for global shocks that are common to all banks which may affect their complexity or risk, such as broad-based changes in global financial conditions. Bank fixed effects, in turn, control for any bank-specific differences in risk and complexity that do not vary over time, as well differences in, say, corporate culture. We further exploit the cross-country nature of our dataset by including country-time fixed effects (α_{ct}) as a robustness exercise. These control for macroeconomic or regulatory shocks which may affect all banks headquartered in a given jurisdiction.

To determine relevant external factors, we start by investigating the drivers of banks' decisions to expand or contract along the geographic dimension. Geographic complexity is a choice variable of banks, as they select themselves into strategies leading to more or less complexity, which could be correlated with the propensity to take risk.

We create dummy variables for expanding the foreign affiliate network, for expanding business to a larger set of host countries, for contracting the foreign affiliate network, and for decreasing the number of countries a bank is present in. We then run regressions of the form:

$$Dummy_{it} = \alpha_i + \beta_1 ExternalFactor_{1,it-1} + ... + \beta_p ExternalFactor_{p,it-1} + \gamma \mathbf{X}_{it-1} + \epsilon_{it}, \quad (3)$$

where the structure of the specification is equivalent to the one in Equation 2, including the fixed effects and the bank-specific controls.[19] Furthermore, we also control for geographic complexity by including the HHI in $\mathbf{X}_{it-1}$, which we report separately. The results from running Equation 3 for each of the four dummy variables are presented in Table 3.

When local economic conditions – as proxied by shocks to home country real GDP growth – are on an upward trajectory, banks tend to close existing foreign affiliates and leave

[18]This includes measures of: size (logarithm of total assets), profitability (return on assets), loans to assets, deposits to assets and securities to assets.

[19]The exception are time fixed effects, which are not included as we include a global factor that only varies on the time dimension.

countries they are operating in (columns (3) and (4)). In a prosperous economic situation in the headquarter country, there could be less need for access to additional funding sources and/or different credit demand markets. Local economic conditions are an important factor banks' geographic expansion decisions.

If global conditions improve (as proxied by increases in the global factor of Miranda-Agrippino et al. (2020)), banks are less likely to move to new countries and to open new affiliates in general (columns (1) and (2)), presumably because they see less need for diversification. Global economic conditions are a natural determinant of banks' global reach.

A tightening of the regulatory stance in the current network[20] is associated with reduced expansion to new countries (column (2)) as well as more contraction from existing countries (column (4)). A higher regulatory burden throughout the network adds costs to geographic expansion. The insignificant coefficients on expanding/contracting the affiliates network in countries in which the BHC is already present (columns (1) and (3)) are in line with a regulatory circumvention argument, since a new affiliate in a country which was already a host country would add fewer opportunities. Prudential bank regulation is thus a relevant external factor for banks' choice of geographic expansion.

Existing bank geographic complexity naturally affects the decision to become more complex by expanding/contracting the affiliate network. As columns (2) and (4) show, banks which are already complex are less likely to expand to new countries and more likely to contract the number of countries they are present in. From the additional bank-specific controls included in the regression, only deposits to assets play a moderate role in affecting decisions to expand the foreign affiliate network. A larger deposit-to-asset ratio is negatively associated with the expansion of the foreign affiliate network. This hints to the funding situation as being another driver of banks' decisions, which is, however, more bank-specific and not easy to capture as an external factor at the local or global level. We control for this and other bank-specific time-varying characteristics in all regressions.

[20] Measured as the weighted average of all regulatory tightenings/loosenings across a bank's affiliate structure.

Table 3: Incentives to expand geographically

	(1) Expanding affiliates	(2) Expanding countries	(3) Contracting affiliates	(4) Contracting countries
GDP Growth$_{it}$	0.000465	-0.000870	-0.0160**	-0.00990**
	(0.00786)	(0.00740)	(0.00621)	(0.00479)
GFCy$_{t}$	-0.214***	-0.118***	0.00704	-0.0136
	(0.0398)	(0.0341)	(0.0332)	(0.0250)
PruReg$_{it-1}$	-0.0386	-0.0757***	0.000736	0.0437***
	(0.0326)	(0.0278)	(0.0194)	(0.0144)
HHI$_{it-1}$	-0.0114	-0.0259**	0.0121	0.0228***
	(0.00993)	(0.0105)	(0.00792)	(0.00611)
Observations	625	625	625	625
R^2	0.245	0.279	0.210	0.204
BankFE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Banks	83	83	83	83

Notes: The sample consists of annual data from 2008 to 2016. *GDP growth* is the growth in real GDP in the country in which the bank is headquartered. *GFCy* is the global financial cycle as captured by the global common factor in Miranda-Agrippino et al. (2020). *PruReg* stands for overall prudential regulation and captures the regulatory tightness faced by the bank, which combines home country regulation with the weighted average of all regulatory changes (tightenings and loosenings) across a bank's affiliate structure. *HHI* is the Herfindahl-Hirschman index as defined in Equation 1. All bank-specific control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Our empirical analysis comprises four subsections. They respectively study the relevance of complexity for bank risk when the bank is exposed to the following external factors: i) local economic shocks; ii) global economic shocks; iii) local prudential regulatory actions in home or host countries (or both); and iv) "global" regulatory actions such as the implementation of the GSIB framework or the SSM in Europe.

4 Results

4.1 Complexity and local shocks

The complexity of a bank holding company can help the organization to dampen the effect of economic shocks. In particular, if shocks occur in the country of headquarters, a broader geographic footprint could act as a shock absorber or mitigant. When viewed in this light, complexity can be alternatively thought of as providing diversification value to the organization.

In this section we look at how BHCs cope with shocks in their home country and the role that bank complexity plays in affecting the link between these local shocks and bank risk. Our baseline regression takes the following form:

$$z\text{-}score_{it} = \alpha_t + \alpha_i + \beta_1 HHI_{it-1} + \beta_2 GDP\_Shock_{it} + \beta_3 GDP\_Shock_{it} \times HHI_{it-1} + \boldsymbol{\gamma}\mathbf{X}_{it-1} + \epsilon_{it} \tag{4}$$

with controls and variables as defined before. Our outcome variable is the $z\text{-}score_{it}$, expressed as the inverse of the log value so that higher values indicate higher risk. GDP_Shock_{it} is a measure of the domestic or local shock (i.e. the shock in the country of headquarters of BHC i). It is defined as the difference between the realized annual real GDP growth and the consensus forecast of GDP growth for the same year; a negative GDP shock thus indicates actual real GDP growth falling short of expectations.

The result from estimating Equation 4 is presented in column (1) of Table 4. A negative GDP shock does indeed drive up bank risk, as indicated by the negative and significant coefficient on β_2. However, the positive and significant coefficient on the interaction term indicates that BHC complexity can help mitigate this effect. A standard deviation shock to GDP increases the risk of an average bank by roughly 7.5%. Each additional point of HHI reduces this effect by roughly 0.2 percentage points. The way the measure is constructed implies that banks that either have a larger overall affiliate network, a larger geographical reach, or a more evenly spread distribution of affiliates across the host countries, can buffer a home country shock more easily. All these factors help in diversifying income, while expanding the affiliate network at home, e.g. by opening additional domestic affiliates, will not give the BHC access to other income sources than its headquarter already grants.

More complexity gives banks more flexibility in dealing with local shocks. Banks' geographic spread can passively diversify their shocks by giving them claims on borrowers in many different jurisdictions who experience different shocks. Banks can also actively diversify by moving resources throughout their geographic network as opportunities arise and economic circumstances change.

The business model through which a BHC company chooses to have presence abroad can be an important determinant of the ability to actively smooth shocks. The ease with which business and resources can be shifted abroad depends on the type of affiliates. Banks can choose to go abroad via branches or subsidiaries (Cerutti, Dell'Ariccia, and Peria (2007)). Subsidiaries are locally chartered (i.e. in host jurisdictions), are separately capitalized, typically report earnings on a standalone basis and are regulated by host entities. Branches, on the other hand, are not independently capitalized, do not have an independent balance sheet, can be limited in their ability to raise local retail (insured) funding and are regulated by entities in the home jurisdictions where the BHC is headquartered. Branches should therefore provide more flexibility in the reallocation of business and funds within the banking organization.

If the geographic complexity of a BHC is mainly in the form of subsidiaries rather than branches, complexity is less likely to act as a mitigant of local shocks. In column (2) we explore this by including a variable capturing the share of subsidiaries among all foreign affiliates for a given BHC i, as well as interactions between this variable and our main variables of interest. Indeed, the larger the share of subsidiaries a bank has, the smaller the role of its geographic complexity as a force that can mitigate local shocks.

Banks will be more passively diversified if they operate in countries less similar to those of their headquarters, such as EMEs. However, column (3) shows that operating in EMEs (measured as having a larger share of international affiliates located in EMEs) attenuates the diversification benefit of geographic complexity. Columns (4) and (5) looks at this result separately for subsidiaries and branches in EMEs. This effect is driven by subsidiaries rather than branches.[21] Thus, it appears that the subsidiary effect dominates the passive

[21]In untabulated results we find that such effect is not reproducible with an advanced economy subsidiary

Table 4: Local Economic Shocks, Geographic Complexity and Bank Risk

	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{it-1}	0.000603	0.00147	0.000477	0.000664	0.0000175	0.000733
	(0.000922)	(0.000882)	(0.000745)	(0.000765)	(0.000857)	(0.00109)
GDP $Shock_{it}$	-0.0165*	-0.0422***	-0.0380***	-0.0341***	-0.0290**	
	(0.00879)	(0.0127)	(0.0136)	(0.0124)	(0.0127)	
HHI_{it-1} × GDP $Shock_{it}$	0.000206*	0.000551***	0.000473***	0.000421***	0.000360**	
	(0.000108)	(0.000170)	(0.000171)	(0.000155)	(0.000164)	
Sub_{it}		0.268				
		(0.180)				
HHI_{it-1} × Sub_{it}		-0.00298				
		(0.00235)				
GDP $Shock_{it}$ × Sub_{it}		0.0815**				
		(0.0309)				
HHI_{it-1} × GDP $Shock_{it}$ × Sub_{it}		-0.00110***				
		(0.000410)				
EME $Share_{it}$			0.581			
			(0.468)			
HHI_{it-1} × EME_{it}			-0.00500			
			(0.00510)			
GDP $Shock_{it}$ × EME_{it}			0.123**			
			(0.0511)			
HHI_{it-1} × GDP $Shock_{it}$ × EME_{it}			-0.00165**			
			(0.000680)			
EME Sub_{it}				1.130**		
				(0.544)		
HHI_{it-1} × EME Sub_{it}				-0.0131**		
				(0.00638)		
GDP $Shock_{it}$ × EME Sub_{it}				0.215***		
				(0.0765)		
HHI_{it-1} × GDP $Shock_{it}$ × EME Sub_{it}				-0.00288***		
				(0.00102)		
EME $Branch_{it}$					0.239	
					(1.127)	
HHI_{it-1} × EME $Branch_{it}$					0.00116	
					(0.0113)	
GDP $Shock_{it}$ × EME $Branch_{it}$					0.0765	
					(0.331)	
HHI_{it-1} × GDP $Shock_{it}$ × EME $Branch_{it}$					-0.00111	
					(0.00373)	
ΔGDP_{it}						-0.0117***
						(0.00436)
HHI_{it-1} × ΔGDP_{it}						0.000135**
						(0.0000521)
ΔGDP $Corr_{it}$						-0.230***
						(0.0821)
HHI_{it-1} × ΔGDP $Corr_{it}$						0.00246**
						(0.00122)
ΔGDP_{it} × ΔGDP $Corr_{it}$						0.0173***
						(0.00576)
HHI_{it-1} × ΔGDP_{it} × ΔGDP $Corr_{it}$						-0.000180**
						(0.0000750)
Observations	584	551	551	551	551	599
R^2	0.876	0.876	0.878	0.876	0.878	0.877
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks	79	73	73	73	73	80

Notes: The dependent variable is bank risk, measured as the inverse of the logarithm of the z-score (higher values indicate higher risk). The sample consists of annual data from 2008 to 2016. *HHI* is the bank's geographic Herfindahl-Hirschman index. *GDP Shock* is the deviation of real GDP growth from consensus forecast for the bank's headquarter country. Δ*GDP* stands for real GDP growth. Δ*GDP Corr* is the average correlation (weighted by number of affiliates) of real GDP growth between the headquarter country and the countries in which the bank has affiliates. *Sub* is the fraction of foreign affiliates of the bank that are subsidiaries. *EME Share* is the fraction of the bank's total foreign affiliates that are located in EMEs. *EME Sub* and *Branch* are the fraction of the bank's foreign affiliates that are subsidiaries and branches in EMEs, respectively. All bank control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

diversification from operating in EMEs.

Next, we more formally test if the diversification benefit of geographic complexity occurs passively as well as actively. Geographic diversity is less useful if the countries the bank operates in experience similar shocks and business cycles as the home country. In column (6) we slightly change the specification of column (1) by replacing GDP shocks by raw GDP growth and including a variable capturing the weighted correlation between the real GDP growth of the country in which bank i is headquartered and the real GDP growth of all the host countries.[22] The weights are given by the number of affiliates per host country (e.g. a high value indicates that the business cycle of the country in which bank i is headquartered is similar to the business cycles of the countries in which the bank is present through affiliates). In addition, we include interactions of this variable with the measure of complexity.

As shown by the triple interaction term, the larger the correlation between the business cycles of home and host countries, the smaller the role of bank complexity as a cushion for the effect of local shocks on bank risk. This result suggest that passive diversification is also at play, as the value of geographic complexity is reduced (increased) when the host countries on average experience downturns (upturns) at the same time as the home country.

The effect of local shocks on bank risk, as well as the heterogeneity of the effect by bank complexity, is observed only for the z-score as a measure of idiosyncratic risk. When looking at market-based measures, no such effects can be observed. Market-based measures can be seen as longer term, forward looking assessments of the bank, whereas the z-score is a backward looking measure of realized risk and more reflective of a contemporaneous assessment of the bank. Hence, we would expect the market measures to react less to a transitory economic shock. Table B3 in the Appendix presents results for a different set of market measures capturing systemic, idiosyncratic and systematic risk (as defined above) as well as for banks' leverage.

share. Furthermore, for the BHCs in our sample, less than half of EME affiliates are subsidiaries.

[22] We switch to GDP growth to match the economic concepts of our shock variable and the variable for which we calculate the correlation across the business cycle network. A correlation of shocks as defined before would imply looking at a correlation of forecast errors, which is not the relevant economic concept.

We leverage the cross-country nature of our dataset to further control for headquarter country-specific macroeconomic shocks that these banks may face from their headquarter country. The results from Table 4 survive the inclusion of *country* $\times$ *time* fixed effects (Table C7). The one exception is column (6), where the triple interaction with GDP correlation retains its sign but loses economic significance under such a demanding specification. Columns (1)-(5) remain consistent in showing the diversification benefit of complexity and the attenuation role of subsidiaries. Thus, our results are not driven by unobserved shocks affecting banks in a given country. This is a very stringent test which provides better identification of and strong evidence for our results.

4.2 Complexity and global shocks

While geographic complexity can be beneficial for banks to diversify local shocks, it may also integrate them more into the international financial system and thus expose them more to global shocks. In this section we look at the effect of bank geographic complexity in dampening or exacerbating the link between global shocks and bank risk. Our baseline regression is as follows:

$$bank\_risk_{it} = \alpha_t + \alpha_i + \beta_1 HHI_{it-1} + \beta_2 GFCy_t \times HHI_{it-1} + \gamma \mathbf{X}_{it-1} + \epsilon_{it} \tag{5}$$

where $GFCy_t$ is the global factor common across asset prices, constructed by Miranda-Agrippino et al. (2020). This measure serves to capture developments in the global financial cycle and is our measure of global shocks. Increases in the global factor can act as proxy for thriving global economic and financial conditions. Since the dynamics of the global factor are in large part driven by developments in the United States (Miranda-Agrippino and Rey (2015)), we exclude US banks from the following regressions so our measured shock is more exogenous and global for the sample. The rest of the variables are specified as before.[23]

Table 5 presents the result from estimating Equation 5. The risk (z-score) of more com-

[23]Since the global factor varies only on the time dimension, its direct effect is absorbed by the time fixed effects. Hence, it only enters the regression when interacted with other variables.

plex banks is impacted more by a shock to global economic conditions (column 1). This points to an amplifier effect of complexity, as opposed to the cushioning effect observed for local shocks. Assuming a negative correlation between the global factor and bank risk, the effect of a standard deviation shock to the global factor on the z-score is amplified by 0.08 percentage points per additional point of HHI. Thus, more geographically complex banks are more exposed to global financial shocks and so are more affected by them.

Column (2) explores whether the share of subsidiaries matters for the extent of the amplification, as they mattered for the extent of the diversification benefits in section 4.1. While the sign indicates that more subsidiaries would weaken the amplification effect, the coefficient estimate is not significantly different from zero. Regardless of the organizational form chosen to have affiliates across the globe, higher geographic complexity does not shield banks from the effects of global shocks.

Banks operating in countries that are less integrated in the international financial system may be less exposed to these global shocks than equally complex banks operating in more integrated countries. Column (3) indicates that this is the case, as this effect is weaker for banks with a higher share of affiliates in emerging markets.[24]. Further, EME subsidiaries tend to have more local funding, including local currency funding, making them more stable in the event of external funding shocks.[25] Columns (4) and (5) show that, indeed, subsidiaries in EMEs drive the effect of the EME affiliate share on the complexity-risk relationship.[26]

Column (6) further formalizes this analysis by measuring the loadings on the global factor of individual country business cycles. A BHC that is more geographically complex will tend to see global shocks impact its riskiness more if the business cycles of the countries in which it is present show a high loading on the global shock. We compute a weighted (by

[24] This is in line with the recent finding that the global financial cycle as commonly measured is more reflective of developments in advanced economies (Aldasoro et al. (in press))

[25] See Ehlers and McGuire (2017), McCauley, Benetrix, McGuire, and von Peter (2017), Ongena, Peydro, and van Horen (2015) and Schnabl (2012).

[26] The EME subsidiary (branch) share is given by the number of subsidiaries (branches) a BHC has in EMEs relative to the total foreign affiliates of the holding company.

number of affiliates) average of factor loadings across host locations, and interact this with the HHI and the global factor. We find the results to be consistent: geographic complexity exposes banks more to global shocks, and more so if they operate in countries highly integrated into the international financial system.

Taken together, our results point to geographic complexity as a factor creating vulnerabilities to global shocks, confirming the evidence presented in Berger et al. (2017), among others. As with the case of local shocks, market-based indicators of bank systemic, systematic and idiosyncratic risk do not react to transitory global economic shocks, nor are they affected by geographic complexity (see Table B4).[27]

The results of saturating the model with *country* $\times$ *time* fixed effects can be found in Table C8. The results are largely not robust, though column 2 remains consistent. Since the global factor varies only at the time level, including country-time fixed effects can absorb too much variation to detect the effects. Nevertheless, the sign of the coefficients remains the same.

Our analysis of economic shocks indicates that bank geographic complexity has a Janus face. A wider geographic reach has diversification value in the face of local shocks, but increases exposure to global shocks. The effect varies depending on which countries the bank is operating in and on whether the foreign presence is in the form of subsidiaries or branches.

4.3 Complexity and home/host prudential regulation

This section examines how bank geographic complexity affects the impact of regulation on risk. We look at prudential regulation in both the country of headquarters as well as the different host countries in which a BHC is present through its affiliates. A more geographically complex bank has a broader range of options to respond to regulations, with potentially

[27] An exception is the systematic risk component of stock returns. The more geographically complex a bank is, the smaller the impact of the global factor on the systematic part of the banks' stock return.

Table 5: Global shocks, geographic complexity and bank risk

	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{it-1}	0.00171	0.00255*	0.00177	0.00192	0.00128	0.000739
	(0.00130)	(0.00133)	(0.00136)	(0.00132)	(0.00139)	(0.00116)
$\text{HHI}_{it-1} \times \text{GFCy}_t$	-0.000787**	-0.00263**	-0.00194**	-0.00189**	-0.00108	0.0000833
	(0.000364)	(0.00113)	(0.000955)	(0.000900)	(0.000789)	(0.000334)
Sub_{it}		0.277				
		(0.252)				
$\text{HHI}_{it-1} \times \text{Sub}_{it}$		-0.00300				
		(0.00311)				
$\text{GFCy}_t \times \text{Sub}_{it}$		-0.447				
		(0.311)				
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{Sub}_{it}$		0.00595				
		(0.00367)				
EME Share_{it}			0.429			
			(0.445)			
$\text{HHI}_{it-1} \times \text{EME Share}_{it}$			-0.00339			
			(0.00466)			
$\text{GFCy}_t \times \text{EME Share}_{it}$			-1.264*			
			(0.752)			
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{EME Share}_{it}$			0.0145*			
			(0.00852)			
EME Sub_{it}				0.259		
				(0.306)		
$\text{HHI}_{it-1} \times \text{EME Sub}_{it}$				-0.00290		
				(0.00363)		
$\text{GFCy}_t \times \text{EME Sub}_{it}$				-1.540**		
				(0.593)		
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{EME Sub}_{it}$				0.0190**		
				(0.00735)		
EME Branch_{it}					0.331	
					(0.930)	
$\text{HHI}_{it-1} \times \text{EME Branch}_{it}$					0.000444	
					(0.00941)	
$\text{GFCy}_t \times \text{EME Branch}_{it}$					-1.148	
					(1.981)	
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{EME Branch}_{it}$					0.0123	
					(0.0221)	
Factor Load_{it}						-0.183**
						(0.0829)
$\text{HHI}_{it-1} \times \text{Factor Load}_{it}$						0.00259**
						(0.00120)
$\text{GFCy}_t \times \text{Factor Load}_{it}$						0.116
						(0.105)
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{Factor Load}_{it}$						-0.00239*
						(0.00138)
Observations	508	487	487	487	487	508
R^2	0.875	0.874	0.875	0.874	0.877	0.877
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks	68	63	63	63	63	68

Notes: The dependent variable is bank risk, measured as the inverse of the logarithm of the z-score (higher values indicate higher risk). The sample consists of annual data from 2008 to 2016. *HHI* is the bank's geographic Herfindahl-Hirschman index. *GFCy* captures the global financial cycle as measured by the global factor common to asset prices as constructed by Miranda-Agrippino et al. (2020). *Sub* is the share of subsidiaries in the BHC's affiliate network. *EME Share* is the fraction of the bank's total foreign affiliates that are located in EMEs. *EME Sub* and *Branch* are the fraction of the bank's foreign affiliates that are subsidiaries and branches in EMEs, respectively. *Factor Load* is the loading of countries' business cycles on the global financial cycle. All bank control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

negative implications for financial stability.[28] With the shift from economic shocks to regulation, we also modify our left-hand side variable to focus on bank capitalization, as this is a key target measure of regulators that proxies an ex-ante perspective of bank risk. A better capitalized bank is, other things equal, a less risky bank.

Our baseline specification is:

$$\begin{aligned} bank\_cap_{it} = &\alpha_t + \alpha_i + \beta_1 HHI_{it-1} + \beta_2 OverallPru.Reg_{it-1} + \beta_3 HHI_{it-1} \times OverallPru.Reg_{it-1} \\ &+ \gamma \mathbf{X}_{it-1} + \epsilon_{it} \end{aligned} \tag{6}$$

where $bank\_cap_{it}$ is 1 minus the regulatory Tier 1 capital ratio (e.g. higher values indicate less capitalization, more leverage, higher risk). $PruReg_{it}$ captures the changes in prudential policies in year t, combining both home (i.e. headquarter) and host countries. A tightening of policy is captured by +1, a loosening by a -1, and no change is captured by 0.[29] We use the database on prudential regulations from Cerutti et al. (2017), and combine information from all policy actions. These policy actions include measures aimed at strengthening banks' resilience, such as increases in minimum capital requirements, as well as measures aimed at reducing risk-taking, such as LTV ratio caps. The rest of the elements of Equation 6 are as in the previous regressions.

Table 6 summarizes the results. As shown in column (1), a tightening of overall prudential regulation is associated with an increase in bank capitalization, indicating that the regulation is indeed having an effect towards less risk. However, geographic complexity weakens the impact. More complex banks appear to find alternative adjustments besides their capitalization in response to regulatory tightenings in the jurisdictions in which they operate. A standard deviation of more regulatory tightening increases the risk-weighted

[28]In addition to altering the balance sheet impact of regulation, another instance in which bank complexity can be detrimental to financial stability is by making resolution more complicated (Bolton and Oehmke (2018)). We do not investigate this aspect here.

[29]A 50% weight is given to headquarter and host country policy changes, and host country changes are a weighted average (by number of affiliates) of the policy changes enacted in the countries in which the bank has foreign affiliates.

capitalization of an average bank by 0.6 %-points. Each additional unit of HHI dampens this effect by approximately 0.08%-points.[30]

It is plausible to argue that more complex banks (in our context, high HHI banks) are more closely scrutinized and therefore build capital buffers earlier than other banks in the sample. When regulatory changes are introduced, these international banks would then simply reduce their buffers and be seen in the data to respond less than their less complex peers. However, if this were the case we should then see a correlation between HHI and capitalization, captured by the coefficient on the non-interacted HHI in the first row of Table 6. In no specification is this coefficient statistically significant. Furthermore, it is quantitatively very small and can even change signs. There is thus no evidence that high HHI banks show a different degree of capitalization than less complex banks.

The effect complexity has on moderating the increase in bank capitalization is affected by how strictly and effectively prudential regulations are applied. Column (2) includes an indicator aimed at capturing the quality of the regulatory environment: $LowRegQuality_{it}$ is an average of two dummies each equal to 1 if the headquarter country, respectively the affiliate-weighted host country average, is below the 25^{th} percentile in regulatory quality, as measured by the World Bank. For a given level of complexity, bank leverage increases less in response to a regulatory tightening if the bank operates in low quality regulatory environments. This suggests that the alternative avenues of responses by complex banks are less important when regulation is less strictly enforced.

In column (3), we again include the share of subsidiaries. We document that a higher subsidiary share is associated with a lower impact of regulatory tightenings on bank capitalization. Since it is more difficult to transfer capital into and out of subsidiaries (relative to branches), this result indicates that banks aim to maintain their consolidated risk-weighted capitalization in the face of tighter regulation by making adjustments within individual units. That is to say, it does not seem that the banks move capital towards the less reg-

[30]Banks at the higher end of the geographic complexity spectrum in our sample are able to fully avoid the balance-sheet impact of the regulatory action and keep their capitalization constant.

Table 6: Prudential policy changes, geographic complexity and bank capitalization

	(1)	(2)	(3)	(4)
HHI_{it-1}	-0.000210	0.000119	-0.00000965	-0.0000324
	(0.000315)	(0.000393)	(0.000425)	(0.000397)
PruReg_{it-1}	-0.00776*	-0.00318	-0.0258***	0.00491
	(0.00427)	(0.00458)	(0.00827)	(0.0124)
$\text{HHI}_{it-1} \times \text{PruReg}_{it-1}$	0.0000927*	0.0000280	0.000280***	-0.0000711
	(0.0000471)	(0.0000550)	(0.0000980)	(0.000145)
$\text{LowRegQuality}_{it}$		0.0344		
		(0.0379)		
$\text{HHI}_{it-1} \times \text{LowRegQuality}_{it}$		-0.000384		
		(0.000435)		
$\text{PruReg}_{it-1} \times \text{LowRegQuality}_{it}$		0.0220***		
		(0.00820)		
$\text{HHI}_{it-1} \times \text{PruReg}_{it-1} \times \text{LowRegQuality}_{it}$		-0.000225**		
		(0.0000974)		
Sub_{it}			0.0572	
			(0.0400)	
$\text{HHI}_{it-1} \times \text{Sub}_{it}$			-0.000525	
			(0.000555)	
$\text{PruReg}_{it-1} \times \text{Sub}_{it}$			-0.0431**	
			(0.0170)	
$\text{HHI}_{it-1} \times \text{PruReg}_{it-1} \times \text{Sub}_{it}$			0.000561**	
			(0.000239)	
RegCorr_{it-1}				-0.281
				(0.273)
$\text{HHI}_{it-1} \times \text{RegCorr}_{it-1}$				0.00239
				(0.00315)
$\text{PruReg}_{it-1} \times \text{RegCorr}_{it-1}$				-0.0941
				(0.0570)
$\text{HHI}_{it-1} \times \text{PruReg}_{it-1} \times \text{RegCorr}_{it-1}$				0.00126*
				(0.000674)
Observations	618	618	603	445
R^2	0.777	0.780	0.775	0.802
BankFE	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Banks	84	84	80	61

Notes: The dependent variable is 1 - regulatory Tier 1 capital ratio (higher values indicate more leverage, higher risk). The sample consists of annual data from 2008 to 2016. *HHI* is the bank's geographic Herfindahl-Hirschman index. *PruReg* captures changes in prudential policies in the year (where a tightening is a +1 and a loosening is a -1) in both headquarter and host countries. 50% weight is given to headquarter and host country policy changes, and host country changes are a weighted average (by number of affiliates) of the policy changes enacted in the countries in which the bank has foreign affiliates. *LowRegQuality* is an average of two dummies, each equal to 1 if the headquarter country, respectively the affiliate-weighted average of the host countries, is below the 25th percentile in regulatory quality, as measured by the World Bank. *Sub* is the fraction of foreign affiliates of the bank that are subsidiaries. *RegCorr* is the average correlation (weighted by number of affiliates) of the regulatory change measure between the bank's headquarter country and the countries in which it has foreign affiliates. All bank control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

ulated locations, but rather that they adjust their risk profile within locations in order to maintain their desired risk-weighted leverage at the BHC level. Branches do not maintain their own capital, so their positions are already constrained by limits on the parent. Subsidiaries operate with their own capital, and so may have more room for adjustment. They may thus be better able to find and make such marginal risk adjustments in their portfolio.[31]

If a bank is present in jurisdictions with more synchronized policy actions, the importance of geographic complexity found in column (1) is intensified. Column (4) captures this by including an interaction term $PruRegCorr_{it}$, which captures the average correlation (weighted by the number of affiliates) of the regulatory change measure between the bank's headquarter country and the countries in which it has foreign affiliates. In the presence of an environment of widespread regulatory tightening, a wider geographic reach is particularly helpful in moderating the reduction in bank risk.

The results of saturating our model with headquarter *country* $\times$ *time* fixed effects can be found in Table C9. Columns (1) and (4) are robust to this specification, which more strongly suggests that these results are general and not specific to factors in individual countries.[32] Geographic complexity allows banks to weaken the effect that regulation has on their capital position. This effect is stronger the more correlated regulatory measures are through the host network.

Contrary to the diversification value provided by geographic bank complexity for local economic shocks, the effect uncovered in this section is detrimental from a financial stability perspective, as it weakens the positive effects of regulation. To the best of our knowledge, our paper is the first to link bank geographic complexity with a weakening of regulation. Furthermore, the cross-country nature of our dataset allows us to control further for any observed and unobserved factors varying at the country level over time which may otherwise contaminate the results.

[31] Table B5 in the Appendix presents results for a similar specification but using market-based measures and the z-score as left-hand side variables. Systemic risk increases on average in response to regulatory tightenings. This effect is weaker for more geographically complex banks.

[32] As was observed for the economic shock analyses, those coefficients losing significance keep their sign and suffer from the loss of variation this demanding specification induces.

4.4 Complexity and global regulation

In this section, we expand our scope to global regulatory actions. We investigate the implementation of the GSIB framework as well as the Single Supervisory Mechanism (SSM) in Europe.

Since 2011, the BCBS and the Financial Stability Board compile and publish a yearly list of the most systemically relevant banks worldwide, which are subject to additional regulatory scrutiny and additional capital requirements – the so-called GSIB buffer. The first list was published in 2011, without additional information. In 2012 the list was updated and further information on GSIB bucket allocation[33] by bank was disclosed. Finally, in 2013 the list was updated and the methodology for bucket allocation was made fully transparent (BCBS (2013)). Since the first list of banks was already disclosed in 2011, we take this year as the implementation date.

GSIB assignment is not random, and so presents some endogeneity challenges for identification. To address this, we employ an inverse probability weighting (IPW) approach (Hirano et al. (2003)). This method builds upon the idea of "exogenizing" the assignment by applying weights to the sample which are inversely related to the likelihood of being designated as a GSIB a priori. A lower weight is assigned to treated banks which were very likely to be treated and to untreated banks which were very likely to be untreated. Conversely, a higher weight is assigned to banks for which the treatment status was hard to predict, given their pre-GSIB situation. We are further advantaged by the fact that GSIB assignment involves a judgement call in addition to the raw score, so receiving a score near the (ex-post) threshold would still carry some uncertainty around GSIB designation.

To formalize this idea, consider $\widehat{Prob}_i$ as the probability that bank i at the end of 2010 is classified as a GSIB in the first list in 2011. We obtain these values by fitting a logit model of the treatment dummy onto a set of balance sheet indicators, which are as close as possible to the measures actually used in the GSIB assessment exercise.[34] We then run a regression

[33] The GSIBs are classified into separate buckets, requiring different levels of additional capital.

[34] The actual GSIB scores for 2010 are not available to construct these weights.

of the form:

$$\tilde{Risk}_{i,t} = \alpha_t + \epsilon_i + \beta_1 \tilde{Treatment}_i \times \tilde{Post}_t + +\beta_2 \tilde{Post}_t \times \tilde{Complexity}_i + \beta_5 \tilde{Treatment}_i \times \tilde{Post}_t \times \tilde{Complexity}_{i,t-1} + \tilde{Post}_t \times \tilde{\mathbf{X}}_i \Gamma + \tilde{v}_{i,t}, \tag{7}$$

where $\tilde{Z}_{it} = \frac{Z_{it}}{IPW_i}$ with $IPW_i = \frac{1}{\widehat{Prob}_i}$ for treated and $IPW_i = \frac{1}{1-\widehat{Prob}_i}$ for non-treated. We take the pre-period average of complexity and of our controls to match the difference-in-differences specification.

We now focus on market-based instead of balance sheet measures as our benchmark left-hand side variables of interest. This is because the GSIB assessment and the SSM are large, structural and new frameworks with long-lasting effects on affected banks' business models, as well as on the market structure as a whole. This is likely to be reflected in the forward-looking market assessment of the banks. As an indicator of realized risk, the z-score is less likely to be affected since, for instance, the GSIB designation will not immediately affect banks' business over and above the additional regulatory capital buffer, which was phased in slowly.

The first three columns of Table 7 show the results of the IPW approach applied to Equation 7. We use three different left-hand side variables capturing market based measures of risk: a measure of systemic risk (SRISK); idiosyncratic risk (idiosyncratic component of CDS spreads); and systematic risk (systematic component of CDS spreads) - the latter two respectively the idiosyncratic and systematic components of CDS spreads as discussed in Section 2.[35] Systemic risk indicators aim to capture the contribution of individual financial institutions to the likelihood of large system-wide financial disruptions. Systematic risk indicators capture market risk that cannot be diversified away. Idiosyncratic risk, in turn, captures the part of bank risk that is uncorrelated to the systematic component.

Column (1) shows that systemic risk was not impacted by the GSIB designation on average, nor was there heterogeneity along the geographic complexity dimension. Column

[35] We prefer to use the components of CDS spreads over the components of stock returns as measures of risk, since a CDS contract specifically captures default risk, while a stock return captures a more complex economic outlook. However, results for risk measures extracted from stock returns can be found in Table B6 in the Appendix.

(2), however, indicates that the GSIB designation reduced idiosyncratic bank risk (i.e. the idiosyncratic component of CDS spreads went down). However, the more geographically complex a bank is, the weaker this effect – up until the point where the most complex GSIBs actually saw an increase in their market-based risk assessment. We do not observe any significant effect in the systematic component of bank CDS.

Similarly to the GSIB framework, the implementation of the SSM in the euro area was perceived as a major market-wide regulatory reform. This implied a higher degree of regulatory scrutiny and stringency for a large number of euro area banks. The designation of becoming an SSM-supervised bank was highly deterministic in the sense that no non-euro area bank had the chance of becoming an SSM bank.[36] Moreover, the non-deterministic part of regulatory judgement within the assignment was not linked to transparent, quantitative assessments as it was for the GSIB exercise, such that we cannot apply the same estimation approach (i.e. inverse propensity weights) as before. Thus, we examine its impact with a straightforward difference-in-differences framework.

Measures of idiosyncratic and systematic risk suggest that market participants looked favourably on the implementation of the SSM. As shown in columns (5) and (6) in 7, both risk measures decrease following SSM implementation. Geographic complexity weakens this effect, in particular for systematic risk (for idiosyncratic risk there is no significant heterogeneity, although the estimate is also positive).

The evidence on SRISK from Table 7 suggests that the common framework increased the systemic risk of the banks involved. This could be because it brought these banks under the same supervisor and regulations, making the single supervisor more vulnerable in case of simultaneous trouble across banks. However, our results also show that complexity reduces this effect, perhaps due to the diversification benefits.

Bank risk as captured by CDS spreads shows a decline in the systematic component (no impact on the idiosyncratic component) following the implementation of the SSM. This effect is likewise attenuated by increasing complexity. This is consistent with the regulation

[36] All euro area banks in our sample are SSM banks.

Table 7: GSIB and SSM implementation, geographic complexity and bank risk

	GSIB framework implementation			SSM implementation		
	(1) SRISK	(2) Idio. Risk	(3) Sys. Risk	(4) SRISK	(5) Idio. Risk	(6) Sys. Risk
$\text{GSIB}_i \times \text{Post}_t$	-25552.4	-232.4***	6.681			
	(133913.7)	(69.93)	(15.88)			
$\text{Post}_t \times \text{HHI}_i$	276.4	0.572	0.00874			
	(340.0)	(0.708)	(0.0842)			
$\text{GSIB}_i \times \text{Post}_t \times \text{HHI}_i$	406.3	2.654***	-0.103			
	(1523.2)	(0.859)	(0.179)			
$\text{SSM}_i \times \text{Post}_t$				119985.0**	-29.10	-189.0*
				(54557.9)	(148.3)	(97.53)
$\text{Post}_t \times \text{HHI}_i$				169.5	0.0967	-0.319*
				(129.7)	(0.317)	(0.173)
$\text{SSM}_i \times \text{Post}_t \times \text{HHI}_i$				-1312.8**	0.447	2.014*
				(620.6)	(1.627)	(1.079)
Observations	431	477	477	653	702	702
R^2	0.865	0.118	0.944	0.907	0.026	0.957
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks	49	53	53	74	78	78

Notes: Higher values in the left-hand side variable indicate higher risk. The sample consists of annual data from 2008 to 2016. *GSIB* is a dummy variable equal to 1 (for all periods) if the bank was designated as a GSIB in 2011, and 0 otherwise. *SSM* is a dummy variable equal to 1 (for all periods) if the bank was subject to SSM regulation, and 0 otherwise. *Post* is a dumy equal to 1 for 2011-2016 in the GSIB regressions and 2014-2016 in the SSM regressions, and 0 otherwise. *HHI* is the bank's geographic Herfindahl-Hirschman index, pre-period average. All bank control variables (Size, Loans, ROA, Securities, Deposits) are pre-period averages interacted with the post dummy. Loans, Securities and Deposits controls are all normalized by assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

itself reducing risk, but having a weaker grip on more complex banks. This effect shows up in the systematic component, as this regulation was a system-wide change, rather than a mark on individual banks as the GSIB designation was.

Table C10 in the appendix shows that results on the impact of the GSIB designation are robust. Indeed, in this specification systemic risk also appears to follow the same pattern (regulation decreases risk, complexity attenuates the effect). The results for the SSM are not robust to this demanding specification, but the coefficients retain the same signs. Altogether, these results provide corroborating evidence to that of Section 4.3 that geographic complexity weakens the impact of regulation on measured risk, for both local and global regulatory efforts.

5 Conclusion

This paper constructs a unique dataset of bank geographic complexity based on the BIS Banking List. We build a Herfindahl-Hirschman indicator which conceptually covers the size of the organizational structure (number of affiliates) as well as their geographic reach (number of host countries) and the concentration within their host countries. This indicator, which we construct for the largest 96 bank holding companies in the world (headquartered in 22 different countries), provides information different from and complementary to that captured by the BCBS measure of complexity used in the assessment of global systemically important banks.

We find robust evidence that bank geographic complexity can help cushion the negative effects of local economic shocks. The importance of bank geographic complexity in this regard depends on the business model that the bank chooses: the lower the share of subsidiaries, the weaker the role of complexity as a shock dampening force. Geographic complexity is less helpful in this regard if the business cycles of the countries the bank operates in are highly correlated with that in the home country. These findings are in line with the literature on the role of diversification as a moderator of bank risk, as a more geographically complex bank is also a more diversified bank.

A wider geographic reach has diversification value in the face of local shocks, but increases exposure to global shocks. This effect holds regardless of the organizational form chosen for foreign affiliates, but is weaker for banks with a higher share of affiliates in emerging markets.

Bank geographic complexity thus has a Janus face. This is exacerbated when assessing the role such complexity plays when dealing with changes in regulation. In particular, a wider geographic reach can also be a vehicle allowing banks to alter the effects of regulation on their balance sheet, potentially increasing risk. We find robust evidence that bank geographic complexity can moderate the positive effect that tighter prudential regulation has on bank capitalization. More geographically complex banks can more easily adjust to regulatory tightenings in the jurisdictions in which they operate. Evidence from global and multinational regulatory changes such as the implementation of the GSIB framework and the establishment of the SSM in Europe, is consistent with this finding.

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A Additional summary statistics, definitions and sources

Table A1: Variable definitions and sources

Variable	Definition	Source
Bank balance sheet, complexity and market variables		
HHI	Geographic Herfindahl-Hirschman index (see Equation 1)	BIS
$z-score$	1/log(z-score); z-score = (ROA + Equity/Assets)/sd(ROA); standard deviation computed over 40 rolling quarters	Fitch
bank_cap	1 - regulatory Tier1 capital ratio	Fitch
Size	Logarithm of total assets	Fitch
ROA	Average return on assets	Fitch
Loans	Loans scaled by total assets	Fitch
Securities	Securities scaled by total assets	Fitch
Deposits	Deposits scaled by total assets	Fitch
CDS spread/Stock return, idiosyncratic	Orthogonalization between the first principal component of the respective series across all banks and the original series	Markit, Datastream, Authors' calculation
CDS spread/Stock return, systematic	Fitted values from regressing the original series onto the systematic component	Markit, Datastream, Authors' calculation
SRISK	Capital shortfall of a firm conditional on a severe market decline	NYU Stern V-lab
Country-bank variables		
LowRegQuality	Average of two dummies; dummy =1 if home country, respectively affiliated-weighted average of host countries, is in the lower 25^{th} percentile of the regulatory quality index	World Bank
Sub	Share of subsidiaries among all foreign affiliates of each bank	BIS
EME Share	Share of affiliates, subsidiaries, respectively branches in EMEs out of all foreign affiliates, subsidiaries, or branches a bank has	BIS
PruReg	Average of headquarter and host country prudential regulation (using the 9 categories from the macroprudential regulation dataset). 50% weight is given to headquarter and host country policy changes, with the latter being a weighted average (by number of affiliates) of the policy changes enacted in the countries in which the bank has foreign affiliates	Cerutti et al. (2017), BIS
PruRegCorr	Bilateral correlations of the IBRN prudential policy changes in the headquarter country with each of the host countries, aggregates as a weighted average, with weights being the number of affiliates in a given country for each bank	Cerutti et al. (2017), BIS
ΔGDP *corr.*	Weighted bilateral correlations of the real GDP growth of the headquarter country with all the host countries, with weights given by the number of affiliates in the different host countries	IMF, BIS
Factor Load	Weighted average (by number of affiliates by country) of country factor loadings. A country's factor loading is the coefficient from regressing the country's business cycle measure (extracted from real GDP using a Christiano-Fitzgerald Bandpass filter over a 2-32 quarter range) on the global factor (GFCy).	IMF, BIS, Miranda-Agrippino et al. (2020)
GDP Shock	Realized real GDP growth minus forecast for the same year	IMF (actual), OECD (forecast)
Other		
GFCy	Global factor in asset prices (global financial cycle)	Miranda-Agrippino et al. (2020)
GSIB (SSM)	Dummy=1 if the bank was designated as a GSIB (SSM bank) in 2011 (from 2014 onwards)	BCBS, ECB
Post	Dummy = 1 if year is 2011 or later (for SSM exercise, dummy =1 if year is 2014 or later)	Author's calculation

Table A2: Bank variables - sample-wide descriptives

	# branch.	# subs.	EME	Size	ROA	Loans	Sec	Dep	Z-score	Cap
Mean	10.34	5.79	10.14	13.32	0.78	49.97	32.72	48.51	0.41	0.88
Median	7	3	8	13.29	0.73	51.35	29.35	49.15	0.37	0.88
Std	10.47	6.40	11.87	0.84	0.86	17.86	16.37	18.77	0.15	0.03
Min	0	0	0	11.62	-4.19	0.99	2.41	4.23	0.24	0.71
Max	77	36	100	15.07	5.65	88.39	87.17	86.93	1.51	0.95
No of Obs	782	782	741	768	768	764	768	756	705	728

Note: *EME* stands for the share of affiliates in EMEs. *Size* is measured as the logarithm of total assets. *ROA* is the return on assets, expressed as percentage. *Loans*, securities (*Sec*) and deposits (*Dep*) are all expressed as a percentage of total assets. *Z-score* stands for 1/log(z-score). *Cap* stands for 1 - Tier1 Capital Ratio.

Figure A1 presents a stylised description of the list data for a given year in its raw format and the transformations we apply to it. Every observation comprises a banking entity reporting from a given country within the list of countries that report to the BIS locational banking statistics. In the stylised example we have three reporting countries (X, Y and Z) and three BHCs indexed 1, 2 and 3. BHC1 is headquartered in country X and has three domestic entities reporting from that country. It also has presence in the other two countries via a combination of branches, subsidiaries, and other bank types. BHC2 is headquartered in country Y, but also has branches reporting from country X and subsidiaries reporting from country Z. Finally BHC3 is headquartered in country Z, but has one and two subsidiaries reporting in countries X and Y respectively. We first reorganise the list around BHCs, as indicated in the middle part of Figure A1. Then, based on this, we compute complexity indicators at the BHC(-year) level as shown in the rightmost part of Figure A1.[37]

In the banking list, we can identify 5 types of affiliates: domestic affiliates, foreign subsidiaries, foreign branches, consortium banks (only located in Japan), and non-bank affiliates (only those located in the United States). Given the limited number of consortium banks and non-banks in the dataset, we restrict our analysis to either the total count available or the count of foreign subsidiaries and branches. Furthermore, we do not consider non-bank affiliates in our regression analysis.

[37]In practice the construction of the international footprint of BHCs is not as automatic nor as straightforward as Figure A1 implies. A substantial amount of manual work goes into matching each of the bank entities in the banking list in each year into the BHCs they are a part of.

Figure A1: From raw banking list to holding company-level indicators

Stylised version of list in raw form

Reporting country	*Bank name*	*Bank type*	*Parent country*	*Parent name*	...
X	AA	D	-	BHC1	
X	AB	B	Y	BHC2	
X	AC	B	Y	BHC2	
X	AD	S	Z	BHC3	
X	AE	D	-	BHC1	
X	AF	B	Y	BHC2	
X	AG	S	Z	BHC3	
X	AH	D	-	BHC1	
X	AI	D	-	AI	
Y	BA	B	X	BHC1	
Y	BB	S	X	BHC1	
Y	BC	O	X	BHC1	
Y	BD	D	-	BHC2	
Y	BE	D	-	BE	
Y	BF	D	-	BF	
Y	BG	S	Z	BHC3	
Z	CA	D	-	CA	
Z	CB	D	-	CB	
Z	CC	D	-	BHC3	
Z	CD	D	-	BHC3	
Z	CE	O	X	BHC1	
Z	CF	S	Y	BHC2	
Z	CG	B	X	BHC1	
Z	CH	S	Y	BHC2	

Stylised version of tranformed list

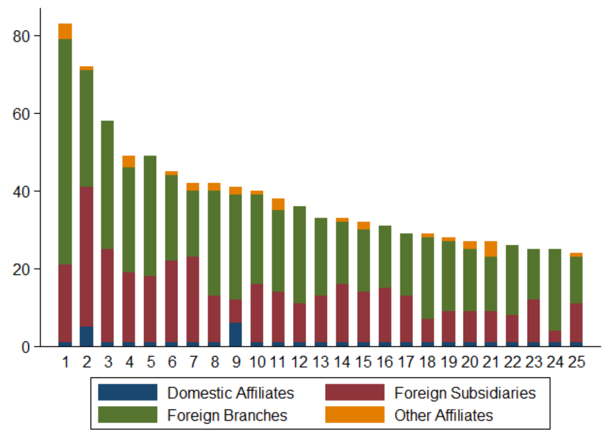
BHC name	*HQ country*	*Reporting country*	*Bank Type*	...
BHC1	X	X	D	
BHC1	X	X	D	
BHC1	X	X	D	
BHC1	X	Y	B	
BHC1	X	Y	S	
BHC1	X	Y	O	
BHC1	X	Z	B	
BHC1	X	Z	O	
BHC2	Y	X	B	
BHC2	Y	X	B	
BHC2	Y	X	B	
BHC2	Y	Y	D	
BHC2	Y	Z	S	
BHC2	Y	Z	S	
BHC3	Z	X	S	
BHC3	Z	X	S	
BHC3	Z	Y	S	
BHC3	Z	Z	D	
BHC3	Z	Z	D	

Data ready for merging

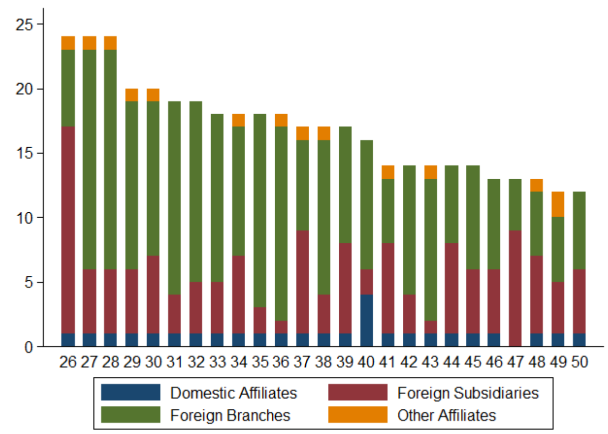
BHC	*Complexity indicators*			
name	*#1*	*#2*	*#3*	*#...*
BHC1	...	...	...	...
BHC2	...	...	...	...
BHC3	...	...	...	...

Figure A2 plots the affiliate structure of the BHCs, sorted by the total number of affiliates. The BHC with the most internationally active affiliates has over 80 affiliates, followed by about 70 for the second and about 60 for the third. After that, there is a more gradual decline, but with variation in the composition of the affiliates. The largest segment of affiliates for most BHCs is foreign branches, though a few have more foreign subsidiaries than branches.

Figure A2: Affiliate structure, by rank of total affiliates



(a) Rank 1-25



(b) Rank 26-50

Rank based on affiliates in 2016. Affiliates include internationally active banking entities across BIS reporting countries. Other affiliates include consortium banks in Japan and non-banks in US.

B Additional risk indicators

Table B3: Local Economic Shocks, Geographic Complexity and Bank Risk - Alternative LHS variables

	(1) SRISK	(2) CDS Spread Idio	(3) Stock Return Idio	(4) CDS Spread Sys	(5) Stock Return Sys	(6) Capital
HHI_{it-1}	628.8*	1.000*	0.0589	-0.0665	0.0321	0.0000503
	(350.9)	(0.586)	(0.334)	(0.438)	(0.0936)	(0.000252)
GDP Shock_{it}	953.8	5.110	-0.201	-1.210	0.635	0.000293
	(1646.0)	(4.340)	(3.185)	(1.807)	(0.805)	(0.00157)
$\text{HHI}_{it-1} \times$ GDP Shock_{it}	-15.92	-0.0635	-0.00540	0.0161	-0.00276	-0.00000261
	(19.74)	(0.0491)	(0.0356)	(0.0208)	(0.00952)	(0.0000183)
Observations	539	573	520	581	520	613
R^2	0.924	0.242	0.143	0.939	0.891	0.772

Notes: The sample consists of annual data from 2008 to 2016. *HHI* is the bank's geographic Herfindahl-Hirschman index. *GDP Shock* is the deviation of the real GDP growth forecast from actual for the bank's headquarter country. *Capital* denotes capitalization as measured by 1 minus the regulatory Tier 1 capital ratio. For additional variable definitions see Table A1. All bank control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Table B4: Global Economic Shocks, Geographic Complexity and Bank Risk - Alternative LHS variables

	(1) SRISK	(2) CDS Spread Idio	(3) Stock Return Idio	(4) CDS Spread Sys	(5) Stock Return Sys	(6) Capital
HHI_{it-1}	618.7*	0.503	-0.656	0.168	-0.0712	-0.0000316
	(350.7)	(1.016)	(0.397)	(0.556)	(0.164)	(0.000399)
$\text{HHI}_{it-1} \times \text{GFCy}_t$	81.45	0.347	-0.0539	0.206	-0.166***	-0.00000848
	(77.36)	(0.326)	(0.261)	(0.138)	(0.0513)	(0.000136)
Observations	561	503	436	511	436	529
R^2	0.924	0.258	0.151	0.942	0.890	0.790
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks	74	65	57	66	57	72

Notes: The sample consists of annual data from 2008 to 2016. *HHI* is the bank's geographic Herfindahl-Hirschman index. *GFCy* is the global factor common to asset prices as constructed by Miranda-Agrippino et al. (2020). Capital denotes capitalization as measured by 1 minus the regulatory Tier 1 capital ratio. All bank control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Table B5: Prudential Policy Changes and Geographic Complexity-
Alternative LHS variables

	(1) SRISK	(2) CDS Spread Idio	(3) Stock Return Idio	(4) CDS Spread Sys	(5) Stock Return Sys	(6) Z score
HHI_{it-1}	373.1	-0.0308	0.148	-0.115	-0.0103	0.000756
	(269.2)	(0.559)	(0.244)	(0.368)	(0.0758)	(0.00139)
PruReg_{it-1}	8100.9*	-4.342	12.93*	-3.665	2.359	0.00950
	(4247.7)	(11.89)	(7.255)	(7.609)	(2.835)	(0.0110)
$\text{HHI}_{it-1} \times \text{PruReg}_{it-1}$	-142.0**	-0.0400	-0.161*	0.0269	-0.00618	-0.000146
	(55.23)	(0.137)	(0.0835)	(0.111)	(0.0327)	(0.000137)
Observations	614	662	594	671	594	658
R^2	0.910	0.222	0.112	0.938	0.899	0.733
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks	72	76	69	77	69	79

Notes: The dependent variable is 1 - regulatory Tier 1 capital ratio (higher values indicate more leverage, higher risk). The sample consists of annual data from 2008 to 2016. *HHI* is the bank's geographic Herfindahl-Hirschman index. *PruReg* captures changes in prudential policies in the year (where a tightening of one policy is a +1 and a loosening is a -1) in both headquarter and host countries. 50% weight is given to headquarter and host country policy changes, and host country changes is a weighted average (by number of affiliates) of the policy changes enacted in the countries in which the bank has foreign affiliates. All bank control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Table B6: GSIB and SSM implementation, geographic complexity and bank risk - Alternative measures

	GSIB framework implementation				SSM implementation			
	(1) Stock Idio.	(2) Stock Sys.	(3) Leverage	(4) Z score	(5) Stock Idio.	(6) Stock Sys.	(7) Leverage	(8) Z score
$GSIB_i \times Post_t$	-14.97**	7.650**	-0.0519	0.215				
	(7.087)	(3.375)	(0.0446)	(0.131)				
$Post_t \times HHI_i$	-0.0323	0.000432	-0.000283	-0.00103				
	(0.0231)	(0.00928)	(0.000411)	(0.00108)				
$GSIB_i \times Post_t \times HHI_i$	0.163**	-0.0871**	0.000650	-0.00255*				
	(0.0765)	(0.0366)	(0.000487)	(0.00151)				
$SSM_i \times Post_t$					0.145	-0.847	-0.0443	0.146
					(4.654)	(0.791)	(0.0418)	(0.181)
$Post_t \times HHI_i$					-0.0274***	0.00301	0.00000559	0.000561
					(0.00794)	(0.00262)	(0.000205)	(0.000610)
$SSM_i \times Post_t \times HHI_i$					-0.000245	0.0108	0.000302	-0.00150
					(0.0516)	(0.00877)	(0.000463)	(0.00221)
Observations	414	414	506	517	648	648	717	746
R^2	0.221	0.896	0.764	0.715	0.118	0.874	0.778	0.570
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banks	46	46	58	58	72	72	86	87

Notes: Higher values in the left-hand side variable indicate higher risk. The sample consists of annual data from 2008 to 2016. *GSIB* is a dummy variable equal to 1 (for all periods) if the bank was designated as a GSIB in 2011, and 0 otherwise. *SSM* is a dummy variable equal to 1 (for all periods) if the bank was subject to SSM regulation, and 0 otherwise. *Post* is a dumy equal to 1 for 2011-2016 in the GSIB regressions and 2014-2016 in the SSM regressions, and 0 otherwise. *HHI* is the bank's geographic Herfindahl-Hirschman index, pre-period average. All bank control variables (Size, Loans, ROA, Securities, Deposits) are pre-period averages interacted with the post dummy. Loans, Securities and Deposits controls are all normalized by assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

C Robustness with *country* $\times$ *time* fixed effects

Table C7: Local Economic Shocks, Geographic Complexity and Bank Risk

	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{it-1}	0.000850	0.00248**	0.00110	0.000706	0.000908	0.000749
	(0.000981)	(0.00122)	(0.00102)	(0.000920)	(0.00107)	(0.000997)
$HHI_{it-1} \times$ GDP $Shock_{it}$	0.000210**	0.000584***	0.000492**	0.000431**	0.000393**	
	(0.0000999)	(0.000188)	(0.000195)	(0.000164)	(0.000164)	
Sub $Share_{it}$		0.404**				
		(0.165)				
$HHI_{it-1} \times$ Sub $Share_{it}$		-0.00448*				
		(0.00229)				
GDP $Shock_{it} \times$ Sub $Share_{it}$		0.0774**				
		(0.0355)				
$HHI_{it-1} \times$ GDP $Shock_{it} \times$ Sub $Share_{it}$		-0.00110**				
		(0.000462)				
EME $Share_{it}$			0.778			
			(0.535)			
$HHI_{it-1} \times$ EME $Share_{it}$			-0.00817			
			(0.00624)			
GDP $Shock_{it} \times$ EME $Share_{it}$			0.141**			
			(0.0589)			
$HHI_{it-1} \times$ GDP $Shock_{it} \times$ EME $Share_{it}$			-0.00192**			
			(0.000797)			
EME Sub $Share_{it}$				1.112		
				(0.682)		
$HHI_{it-1} \times$ EME Sub $Share_{it}$				-0.0132		
				(0.00798)		
GDP $Shock_{it} \times$ EME Sub $Share_{it}$				0.226**		
				(0.0964)		
$HHI_{it-1} \times$ GDP $Shock_{it} \times$ EME Sub $Share_{it}$				-0.00306**		
				(0.00128)		
EME Branch $Share_{it}$					0.380	
					(0.938)	
$HHI_{it-1} \times$ EME Branch $Share_{it}$					-0.00241	
					(0.0103)	
GDP $Shock_{it} \times$ EME Branch $Share_{it}$					0.188	
					(0.266)	
$HHI_{it-1} \times$ GDP $Shock_{it} \times$ EME Branch $Share_{it}$					-0.00241	
					(0.00303)	
$HHI_{it-1} \times$ GDP $Growth_{it}$						0.000139**
						(0.0000542)
GDP $Corr_{it}$						-0.134***
						(0.0440)
$HHI_{it-1} \times$ GDP $Corr_{it}$						0.00158**
						(0.000709)
GDP $Growth_{it} \times$ GDP $Corr_{it}$						0.0114***
						(0.00382)
$HHI_{it-1} \times$ GDP $Growth_{it} \times$ GDP $Corr_{it}$						-0.0000972
						(0.0000617)
Observations	541	504	504	504	504	549
R^2	0.942	0.944	0.943	0.942	0.942	0.942
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
CountryTimeFE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks	73	66	66	66	66	74

Notes: The dependent variable is bank risk, measured as the inverse of the logarithm of the z-score (higher values indicate higher risk). The sample consists of annual data from 2008 to 2016. *HHI* is the bank's geographic Herfindahl-Hirschman index. *GDP Shock* is the deviation of real GDP growth from actual for the bank's headquarter country. ΔGDP is real GDP growth. ΔGDP *Corr* is the average correlation (weighted by number of affiliates) of real GDP growth between the headquarter country and the countries in which the bank has affiliates. *Sub* is the fraction of foreign affiliates of the bank that are subsidiaries. *EME Share* is the fraction of the bank's total foreign affiliates that are located in EMEs. *EME Sub* and *Branch* are the fraction of the bank's foreign affiliates that are subsidiaries and branches in EMEs, respectively. All bank control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Table C8: Global Economic Shocks, Geographic Complexity and Bank Risk

	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{it-1}	0.00258*	0.00436**	0.00328*	0.00313*	0.00302*	0.00167
	(0.00142)	(0.00183)	(0.00166)	(0.00159)	(0.00168)	(0.00127)
$\text{HHI}_{it-1} \times \text{GFCy}_t$	-0.0000238	-0.00193*	-0.00128	-0.000942	-0.000941	0.000598
	(0.000378)	(0.000977)	(0.000933)	(0.000733)	(0.000919)	(0.000390)
Sub_{it}		0.556*				
		(0.293)				
$\text{HHI}_{it-1} \times \text{Sub}_{it}$		-0.00633*				
		(0.00373)				
$\text{GFCy}_t \times \text{Sub}_{it}$		-0.379				
		(0.341)				
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{Sub}_{it}$		0.00498				
		(0.00400)				
EME Share_{it}			0.841			
			(0.601)			
$\text{HHI}_{it-1} \times \text{EME Share}_{it}$			-0.00849			
			(0.00692)			
$\text{GFCy}_t \times \text{EME Share}_{it}$			-1.013			
			(1.133)			
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{EME Share}_{it}$			0.0118			
			(0.0125)			
EME Sub_{it}				0.793		
				(0.720)		
$\text{HHI}_{it-1} \times \text{EME Sub}_{it}$				-0.00923		
				(0.00827)		
$\text{GFCy}_t \times \text{EME Sub}_{it}$				-0.396		
				(1.220)		
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{EME Sub}_{it}$				0.00561		
				(0.0135)		
EME Branch_{it}					0.810	
					(0.888)	
$\text{HHI}_{it-1} \times \text{EME Branch}_{it}$					-0.00684	
					(0.0103)	
$\text{GFCy}_t \times \text{EME Branch}_{it}$					-1.701	
					(2.006)	
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{EME Branch}_{it}$					0.0197	
					(0.0227)	
Factor Load_{it}						-0.129*
						(0.0738)
$\text{HHI}_{it-1} \times \text{Factor Load}_{it}$						0.00220*
						(0.00113)
$\text{GFCy}_t \times \text{Factor Load}_{it}$						0.0284
						(0.0815)
$\text{HHI}_{it-1} \times \text{GFCy}_t \times \text{Factor Load}_{it}$						-0.00154
						(0.00117)
Observations	459	434	434	434	434	459
R^2	0.944	0.944	0.944	0.944	0.944	0.946
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
CountryTimeFE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks	62	56	56	56	56	62

Notes: The dependent variable is bank risk, measured as the inverse of the logarithm of the z-score (higher values indicate higher risk). The sample consists of annual data from 2008 to 2016. *HHI* is the bank's geographic Herfindahl-Hirschman index. *GFCy* is the global factor common to asset prices as constructed by Miranda-Agrippino et al. (2020). *EME Share* is the fraction of the bank's total foreign affiliates that are located in EMEs. *EME Sub* and *Branch* are the fraction of the bank's foreign affiliates that are subsidiaries and branches in EMEs, respectively. For additional variable definitions see Table A1. All bank control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Table C9: Prudential Policy Changes, Geographic Complexity and Bank Capitalization

	(1)	(2)	(3)	(4)
HHI_{it-1}	0.000102	0.000323	0.000118	0.000123
	(0.000270)	(0.000260)	(0.000360)	(0.000337)
PruReg_{it-1}	-0.00769**	-0.00299	-0.0146**	0.00257
	(0.00373)	(0.00318)	(0.00690)	(0.0124)
$\text{HHI}_{it-1} \times \text{PruReg}_{it-1}$	0.0000571*	-0.0000462	0.000143*	-0.0000564
	(0.0000293)	(0.0000349)	(0.0000856)	(0.000127)
$\text{HHI}_{it-1} \times \text{LowRegQuality}_{it}$		-0.0000143		
		(0.000288)		
$\text{PruReg}_{it-1} \times \text{LowRegQuality}_{it}$		0.0109		
		(0.00773)		
$\text{HHI}_{it-1} \times \text{PruReg}_{it-1} \times \text{LowRegQuality}_{it}$		-0.0000988		
		(0.0000843)		
Sub_{it}			-0.00986	
			(0.0420)	
$\text{HHI}_{it-1} \times \text{Sub}_{it}$			0.000235	
			(0.000530)	
$\text{PruReg}_{it-1} \times \text{Sub}_{it}$			-0.0262	
			(0.0175)	
$\text{HHI}_{it-1} \times \text{PruReg}_{it-1} \times \text{Sub}_{it}$			0.000311	
			(0.000231)	
PruRegCorr_{it-1}				-0.111
				(0.136)
$\text{HHI}_{it-1} \times \text{PruRegCorr}_{it-1}$				0.000897
				(0.00162)
$\text{PruReg}_{it-1} \times \text{PruRegCorr}_{it-1}$				-0.0746*
				(0.0377)
$\text{HHI}_{it-1} \times \text{PruReg}_{it-1} \times \text{PruRegCorr}_{it-1}$				0.00117**
				(0.000451)
Observations	565	565	546	392
R^2	0.909	0.909	0.906	0.933
BankFE	Yes	Yes	Yes	Yes
CountryTimeFE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Banks	79	79	74	56

Notes: The dependent variable is 1 - regulatory Tier 1 capital ratio (higher values indicate more leverage, higher risk). The sample consists of annual data from 2008 to 2016. *HHI* is the bank's geographic Herfindahl-Hirschman index. *PruReg* captures changes in prudential policies in the year (where a tightening of one policy is a +1 and a loosening is a -1) in both headquarter and host countries. 50% weight is given to headquarter and host country policy changes, and host country changes is a weighted average (by number of affiliates) of the policy changes enacted in the countries in which the bank has foreign affiliates. *LowRegQuality* is an average of two dummies, each equal to 1 if the headquarter country, respectively the affiliate-weighted average of the host countries, is below the 25th percentile in regulatory quality, as measured by the World Bank. *Sub* is the fraction of foreign affiliates of the bank that are subsidiaries. *PruRegCorr* is the average correlation (weighted by number of affiliates) of the regulatory change measure between the bank's headquarter country and the countries in which it has foreign affiliates. All bank control variables (Size, Loans, ROA, Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Table C10: GSIB and SSM implementation, geographic complexity and bank risk

	GSIB framework implementation			SSM implementation		
	(1) SRISK	(2) Idio. Risk	(3) Sys. Risk	(4) SRISK	(5) Idio. Risk	(6) Sys. Risk
$GSIB_i \times Post_t$	-296167.7*	-381.2***	17.03			
	(158486.1)	(110.1)	(17.44)			
$Post_t \times HHI_i$	618.4	0.537	-0.0504			
	(511.5)	(0.667)	(0.0883)			
$GSIB_i \times Post_t \times HHI_i$	3428.7*	4.535***	-0.187			
	(1814.7)	(1.121)	(0.179)			
$SSM_i \times Post_t$				30238.2	-86.24	-102.5
				(55257.3)	(127.8)	(63.86)
$HHI_i \times Post_t$				351.4	0.539	-0.401
				(218.0)	(0.376)	(0.316)
$SSM_i \times HHI_i \times Post_t$				-433.5	1.298	1.074
				(604.2)	(1.414)	(0.699)
Observations	347	405	405	590	648	648
R^2	0.943	0.695	0.973	0.947	0.558	0.977
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
CountryTimeFE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks	39	45	45	67	72	72

Notes: Higher values in the left-hand side variable indicate higher risk. The sample consists of annual data from 2008 to 2016. *GSIB* is a dummy variable equal to 1 (for all periods) if the bank was designated as a GSIB in 2011, and 0 otherwise. *SSM* is a dummy variable equal to 1 (for all periods) if the bank was subject to SSM regulation, and 0 otherwise. *Post* is a dumy equal to 1 for 2011-2016 in the GSIB regressions and 2014-2016 in the SSM regressions, and 0 otherwise. *HHI* is the bank's geographic Herfindahl-Hirschman index, pre-period average. All bank control variables (Size, Loans, ROA, Securities, Deposits) are pre-period averages interacted with the post dummy. Loans, Securities and Deposits controls are all normalized by assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

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