# The Channels of International Comovement

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[PRELIMINARY AND INCOMPLETE - DO NOT CIRCULATE]

**Abstract**

How does exposure to international markets affect returns and cash flow comovements? Foreign bond owners, lenders, affiliates, investors, customers, and suppliers all transmit country shocks to companies. Most multinationals have many of these exposures simultaneously within the same foreign market. Returns and cash flows of two companies comove when exposed to the same country through the same channel. Within-country exposure through different channels is generally associated with lower comovement, in line with an operational hedging strategy. This evidence can help reconcile how, on average, increased market integration does not lead to increased comovement.

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# 1 Introduction

Aggregate shocks spread globally through a variety of channels. Natural disasters or labor shortages affect foreign customers and suppliers. Financial distress affects creditor banks and debtors. Headquarters' decisions impact foreign subsidiaries' performance. Financing, ownership, and trade connections form a complex and correlated network that complicates efforts to establish causality and assess the relative importance of different transmission mechanisms. Focusing on a well-identified event study can establish causality, but some linkages may be significant only under certain circumstances.

This paper studies how large companies expose all their activities to international markets. I use detailed firm-to-firm and firm-to-market data sets to explore the average relative importance of foreign investors, subsidiaries, debt financing, costs, and revenues in determining cash flows and return comovement. I find that a company with an active exposure to a particular country is likely to have several other kinds of exposures in the same country. In other words, companies match equity, debt, and operations to be related to the same market.[1]

Exposure to a common country and channel implies high return comovement. In order of importance, companies' stocks and cash flows correlate when their lenders, investors, subsidiaries, suppliers, and customers reside in the same country. However, returns and cash flows exposed to the exact location through different channels will correlate less. These patterns are consistent with operational hedging strategies, as firms exploit multiple business linkages to lower their dependence on country-specific conditions. The most robust hedging mechanisms are between the country of the investor and debt, revenue and debt, cost and debt, and revenue and affiliates.

I gather data from several micro- and macro-level sources, including Factset, Capital IQ, Dealscan, BIS, IMF, and the capital flow restated matrices by Coppola et al. (2021). I use these data to create harmonized measures of country exposure for a large set of multinationals that covers 70 percent of total world market capitalization. The channels of exposure covered are the country of subsidiaries, investors, revenue, cost, bond holders, and loan holders. These categories represent most multinational firms' primary sources of connections to foreign capital and goods markets. For most of these channels, I measure the ultimate region of risk, considering the entire network structure of the exposure.

I provide a detailed description of the methodology used to harmonize and impute

[1] One exception to this rule is large markets such as the United States, the eurozone, and China, where multinationals always tend to have considerable exposure through multiple channels regardless of their exposure distribution across other countries or channels.

foreign country exposure across different channels. Gathering and harmonizing such a large volume of data on heterogeneous exposures and from different sources is one of the main contributions of this paper. For this reason, each channel is built to maintain a tight connection to the raw data and to minimize ad hoc assumptions. But this also means that the measured exposures do not always allow a disaggregation into detailed economic channels.[2] Nevertheless, several observed firm-level patterns align with economic theory and aggregate macroeconomic flows.

I provide a battery of novel facts related to the exposure patterns of multinationals in my sample. The average degree of home bias is high across all channels. At the same time, 40 percent of large companies have strong ties (minimum 5 percent exposure) with foreign markets through at least three channels, and 20 percent through at least four. Only 8 percent of large listed companies do not have any significant foreign linkage through any of the channels considered. The most globally integrated flows are trade and equity investment. The highest degree of home bias is in loans and subsidiary linkages.

Country fixed effects are the most important source of variation explaining foreign exposure across all channels, followed by firm fixed effects. Country fixed effects are significant because of market size effects and the prominent role that countries such as the United States have in global financing. Firm size is also positively associated with foreign exposure across all channels, and sales growth is negatively related to foreign exposure. All exposure channels are positively correlated to each other, so much so that knowing any company-specific exposure channel provides more power than a gravity model in explaining other kinds of exposure.

In the last part of the paper, I study return and cash flow comovement determination. Based on evidence drawn from the harmonized micro-level data and aggregate patterns, I make the assumption that the average exposures observed after 2009 are representative of exposures observed from 2000 through 2019. I follow two strategies to measure and decompose the drivers of comovement. First, I study the in-sample return comovement of a nonparametric model associating a firm's return with a time-by-country-by-channel fixed effect. This kind of analysis can be done only by knowing the precise size of the exposure of any firm to any specific country, a novel contribution in its own right. Second, I study how different exposures can explain the cross-sectional betas of a multifactor capital asset pricing model (CAPM) of investor country returns. I verify that returns

[2]For example, geographic revenues aggregate arm's-length and affiliates trade, as this is how company reports declare revenue estimates. Outstanding bond obligations issued in foreign currency are assumed to be held by the nationals using that currency (when the currency is not the US dollar). But this means that, for bonds, I cannot distinguish between country and currency risk. Finally, I cannot distinguish between horizontal and vertical integration purposes behind the presence of subsidiaries.

and cash flows comove when exposed to a location through the same channel but will generally diverge if exposed to that location through different channels. This implies that being exposed to the same country through different channels tends to hedge an exposure instead of amplifying it.

This evidence can help reconcile how previous papers find low comovement of stock returns when market integration increases while other studies show high transmission and correlation exposures to specific international linkages. One explanation supported by this paper is that large companies systematically use a variety of linkages to any specific country, which can help them insure themselves from over-dependence. All these findings are unconditional and may change depending on any particular shock.

This paper makes three contributions to the literature. First, it measures and harmonizes six different channels of foreign-country exposure at the firm level: investors, subsidiaries, bond holders, loan holders, revenue, and cost. I provide details on the methodology and data harmonization assumptions. Second, I provide evidence on novel stylized facts, including how the exposure channels correlate positively with each other, explain return and cash flow comovements, and provide hedging when used simultaneously. Finally, having firm-level disaggregated information on six contemporaneous exposure channels enables an essential improvement in the identification of country shock transmission. I can study the contribution of any single channel, controlling for all others, conditional on firm- and industry-time-specific effects.

The rest of the paper proceeds as follows. Section 2 summarizes the relevant literature and the specific contributions of this paper. Section 3 outlines the methodology and data sources to build each measure of country exposure. Section 4 provides the descriptive stylized facts. Section 5 studies the return comovement of foreign market-exposed companies. Section 6 provides robustness tests. Section 7 concludes.

## 2 Literature

This paper relates to several branches of international finance research. One branch looks at the consequences of globalization on stock return comovements. The main purpose of this literature is to measure how comovement in stock markets evolves as goods markets become more integrated over time (Forbes and Rigobon, 2002; Bekaert, Hodrick and Xiaoyan, 2009; Pukthuanthong and Roll, 2009; Bekaert et al., 2016; Auer et al., 2022). The review chapter by Bekaert et al. (2016) finds "weak evidence of comovement measures reacting to globalization." (p. 221). While my paper also studies returns comovements, it focuses on the impact of several exposure channels on both the real and financial sides.

The aim is to establish the relative importance of different international connections in the cross section of returns rather than to study the evolution of stock comovement over time.

Another literature studies the effects of globalization on risk premia and average returns. Fillat and Garetto (2015) and Fillat, Garetto and Oldenski (2015) show how multinationals have higher risk premia than domestic companies, which can be explained by dominant hysteresis and sunk cost dynamics associated with entering foreign markets. Hoberg and Moon (2019) shows that selling output abroad is associated with higher stock returns while foreign purchases are hedges. Recent papers also relate risk premia to the input-output structure of the global economy. Herskovic (2018) finds that the sparsity of a network increases return spreads whereas concentration decreases it. Barrot, Loualiche and Sauvagnat (2019) finds that industries with high shipping costs have annual excess returns of –7 percent. The study concludes that this must be because foreign shocks are negatively correlated with investors' marginal utility. While my paper does not study how different channels of exposure affect the risk premium, my findings do not contradict the fact that multinational corporations have, on average, higher returns than domestic companies.

There is also a growing literature studying the transmission of specific country shocks to foreign and domestic companies. Hassan et al. (2023) focuses on the importance of foreign country shocks in explaining returns and real effects on multinational firms. The focus of Hassan et al. (2023) is to isolate the effects of country-specific risk and sentiment shocks as perceived by multinationals, but the study does not focus on any specific channel of transmission.

Several papers focus on one specific transmission channel of country-level shocks. One takeaway from this literature is that the transmission mechanism depends on the nature of the event. Using a spatial regression model, di Giovanni and Hale (2020) quantifies the foreign spillovers of US monetary policy through the trade network. Boehm, Flaaen and Pandalai-Nayar (2019) shows how the supply disruption due to the 2011 Tōhoku earthquake in Japan spilled over into the United States through firm-to-firm production linkages. Miranda-Agrippino and Rey (2020) shows how monetary contractions in the United States led to significant deleveraging of global financial intermediaries and tightening of foreign financial conditions. Kalemli-Ozcan, Papaioannou and Peydro (2013) shows that legislative-regulatory harmonization in financial services is associated with less synchronized output cycles. Ivashina, Scharfstein and Stein (2015) shows that shocks in credit conditions of eurozone banks affect lending conditions in the United States. Cravino and Levchenko (2016) shows that a 10 percent growth in the headquarters' sales is associated with a 2 percent growth in the affiliates' sales. Bena, Dinc and Erel (2022) shows that investment is 18 percent lower in subsidiaries of parent companies that are experiencing a downturn. My paper focuses instead on unconditional average correlations between companies' financials.

Many papers find evidence of operational hedges implemented by multinational companies (Alfaro, Calani and Varela, 2021; Hoberg and Moon, 2017; Colacito, Qian and Stathopoulos, 2021). However, these papers typically study a hedge between only two channels of exposure, and they focus primarily on hedging of foreign currency exposure.

Finally, Lane and Milesi-Ferretti (2008), Coppola et al. (2021), and Maggiori, Neiman and Schreger (2020) are examples of recent papers in the international macroeconomic literature that have significantly improved the quality of the data used to observe capital flows and the macroeconomic connection between trade and capital. My paper contributes to this literature by showing how the high interdependence between foreign capital and goods markets observed at the aggregate level also appears at the firm level.

# 3 Data Sources and Harmonization of Country Exposures

This section outlines the main data sources and methodology to build each firm-level channel of country exposure. Every channel (subsidiary, investor, revenue, cost, bond, loan) is defined as a firm-by-year-specific share of exposure to each country in the world. All firm-year shares for any given channel sum to 1. All shares are relative to the channel's financial variable of interest. For instance, revenue and cost shares are expressed as a fraction of total revenues. Loan and bond shares are expressed as a fraction of debt outstanding. Investor shares are expressed as a fraction of firm equity. For this reason, their relative size is not always comparable. However, there are two main advantages in specifying foreign exposure as a share. First, it is a straightforward normalization that accounts for the size of a company and allows for zeroes. Second, since some exposures represent stocks and others represent flows, each share is internally consistent and does not require any further normalization.

## 3.1 Subsidiary Exposure

Subsidiary exposure represents the direct and indirect share of subsidiaries located in different countries. The data sets used to build subsidiary exposure are Factset Data Management Solutions and the Factset Historical Entity Structure package. I complement the Factset data with financial information from Capital IQ when necessary. Each unit of observation in Factset is called an entity. An entity identifies public or private companies, subsidiaries, joint ventures, government institutions, funds, or individuals. An entity ID is time-permanent, regardless of a name or an ownership change.[3] An entity owns another entity if it has purchased more than 50 percent of its equity.

There are two main advantages to using Factset over most data sets in circulation. First, Factset contains the historical records of each entity's parent change, country of headquarters, and entity type since the early 2000s. Second, the headquarters country of each entity corresponds to the location of the firm's senior management rather than to the country of incorporation or legal offices.[4]

After building the yearly ownership network from Factset, I gather financial and employment information on each entity from Capital IQ. Financial information is necessary for two reasons: (1) to weigh each subsidiary's relative importance and (2) because different financial variables proxy for different economic concepts of exposure. For example, sales-weighted subsidiary shares capture market-access motivations for opening a foreign branch (horizontal integration). Equity-weighted subsidiary shares capture the direct accounting importance of each entity. The employment-weighted subsidiary share captures the location where most of the labor-intensive production takes place (vertical integration).

For each year in the sample, I can build an ownership matrix $O_{M\times M}$ in which each cell $o_{ij}$ in position $ij$ equals 1 if an affiliated entity in row $i$ is owned by an entity in column $j$ and 0 otherwise.[5] The matrix $H_{M\times C}$ contains headquarters country associations. Each element of $H$, $h_{jc}$ equals 1 when the headquarters of entity $j$ is in country $c$. The vector $W_{M\times 1}$ includes the financial information of interest for each entity. The vector $S^W_{M\times 1} = W - \text{Diag}(W)O'e$ contains the relative size of each entity net of its subsidiaries. Given these matrices, I can account for the direct and indirect exposure of each entity to any given country with the following formula for the share of subsidiary exposure:

$$S^{\text{Subs.}} = \text{Diag}(S^W)(I - \text{Diag}(W)\cdot O\cdot \text{Diag}(W)^{-1})^{-1}\cdot H. \tag{1}$$

Appendix C.1 shows the derivation of equation (1) from an accounting identity. $S^{\text{Subs.}}$ contains the subsidiary country share of either employment, sales, or other financial variables, accounting for direct and indirect linkages. The formula works under the assumption that each entity's financials include consolidated accounts of all its subsidiaries. The

[3]When a merger and acquisition (M&A) occurs, one or both entity IDs may be discontinued and registered as extinct subsidiaries of a new entity.

[4]Multinationals sometimes register their companies in tax haven countries for tax-advantage purposes (Coppola et al., 2021; Wier and Zucman, 2022).

[5]$M$ varies from 3.1 million in 2009 to 8 million in 2019.

midterm on the right-hand side is equivalent to a Leontief matrix for ownership capital flow. The first term, $\text{Diag}(S^W)$, weights the Leontief matrix by the net size of each affiliate. The matrix $H$ aggregates the entity-by-entity linkages to an entity-by-country exposure.

This measure of subsidiary exposure represents both direct and indirect subsidiary linkages while accounting for the fact that parent companies often consolidate all their subsidiaries' budgets. One disadvantage of this measure is that it requires financial information on the full network of subsidiaries. Appendix C.1 shows details on the subsidiary network coverage using different financial variables or by simply counting the number of subsidiaries. The appendix also discusses and tests the robustness of the main results using different measures of subsidiary exposure.

## 3.2 Investor Exposure

Investor exposure represents the share of a company's investors that are located in different countries. Capital IQ gathers information on equity holders and investors of most multinationals in the sample. I link each firm to its ultimate parent's investors.[6] The country of each investor corresponds to the headquarters country designated by Factset or Capital IQ.

There are several data limitations to this variable that require careful evaluation.[7] Capital IQ provides only a snapshot of current holders at the time of the data pull (late 2020). I exploit this variable only to make claims on cross-sectional variation and to assign each company to the country of the main investor in Section 5.2. I also verify that from 2020 to 2023, for which a time series of investor data is available, the share of investors by nationality remained persistent. Second, the exact percentage of ownership by minority shareholders is not always available or fully accountable. For this reason, I build two alternative measures of investor exposure:

- **Direct Investor Exposure**: When the investor ownership percentage is available, use headquarters country of the investor. Assign any missing ownership share to the "country of primary exchange" as defined by Factset (the country where most liquid equity listings trade). In most cases, the country of primary exchange corresponds to the headquarters country.

- **Full Investor Exposure**: When the investor ownership percentage is available, use headquarters country of the investor. Assign any missing ownership share to the investor country shares in the restated equity flow matrices by Coppola et al. (2021)

[6] Ninety-six percent of companies in the final sample are ultimate parents.
[7] Appendix C.2 explains in detail the methodology, limitations, and robustness tests.

and associated with the nationality of the issuer. The disadvantage of this approach is that the latter restated matrices are specified at the country-by-country level. However, since Coppola et al. (2021) links microlevel mutual fund holdings to each equity issuer in the world, the full investor exposure variables incorporate more information on the likely distribution of ultimate holders of an entity.

### 3.3 Revenue Exposure

Revenue exposure represents the decomposition of a company's sales across different countries. The Factset Geographic Revenue (GeoRev) data set captures revenue exposures of global entities to different countries/regions over time. Factset exploits annual reports and regulatory filings to achieve a consistent record. GeoRev covers 20,292 entities for 2009 and 72,606 entities for 2019. Most of these entities are publicly listed. Not all companies declare their revenue segments at the country level. For this reason, Factset harmonizes heterogeneous declarations of sales distribution across geographies at different levels of aggregation and assigns a "certainty rank" to each value according to whether it was declared directly by the firm, imputed from previous values, or imputed from more aggregate firm-level data. I use the country-level disaggregation as a benchmark, and I use the certainty index information to test the estimates' robustness.[8] The main advantage of this data set is the vast array of sources used to infer the geographic revenues of each company and its global coverage. The data set is not well suited to a study of the extensive margin of foreign-revenue exposure, as 70 percent of the country-level records have some degree of imputation, even though most of them are associated with a high to medium degree of certainty.

### 3.4 Cost Exposure

Cost exposure represents the share of value added in a company's sales originated from different countries. I call it cost exposure in contrast to revenue exposure.[9] The main data set used for building the cost exposure is Factset Supply Chain. Factset Supply Chain collects and verifies supply chain relationship information using various sources: 10-K filings, conference call transcripts, company press releases, company websites, and news media reports. In contrast to other supply chain data sets, such as Compustat Segment, it relies on various sources and covers both US and non-US firms. It provides records

[8] Appendix C.3 gives more details on the certainty levels associated with each record. Appendix D shows the robustness of the benchmark estimates to revenue shares defined under different levels of certainty.

[9] Cost exposure is a concept similar to value added exposure, but the two are equivalent only when profits are zero.

of supplier-customer relationships, competitors, joint ventures, creditors, and other factors that were in effect on any given date from 2003 to 2023.[10] I exclude intra-company relationships.

I build the allocation network of supplier-customer relationships $A^S$ assuming that the suppliers in the sample fully represent each customer's total cost of materials and that each supplier is equally important to the customer. The latter assumption is necessary because only 10 percent of the relationships have any information on the sales flow between companies.[11] To estimate the customer-supplier allocation matrix $A^S$, I assign the cost of raw material over revenue ratio according to the industry average of the customer. By doing so, each cell of $A^S$, $a_{ij}$, represents the ratio of purchased materials from supplier i over customer j's revenue. Similarly to the formula for the affiliate shares, the cost exposure, accounting for both direct and indirect exposure, is then computed as:

$$S^{\text{cost}} = \text{Diag}(V)\text{Diag}(S)^{-1}(I - A^S)^{-1} \cdot H. \tag{2}$$

where $\text{Diag}(V)\text{Diag}(S)^{-1}$ represents the share of value added over sales of each supplier. Appendix C.4 shows the derivation of equation (2) from an accounting identity. I also compute simpler, more direct measures of cost exposure by counting the number of suppliers in each country and weighting suppliers by their sales size. These two measures are computed for robustness purposes.

In a future iteration of this paper, I will provide a supply chain measure built from nominal sales flows between suppliers and customers and estimated from a smaller version of the Factset Supply Chain data set.

### 3.4.1 IO Industry Costs

As an additional control, I combine information from the OECD Inter-Country Input-Output (ICIO) tables and the industry-country combination of each entity in my sample. First, I compute the value-added matrix of each industry-country pair from the OECD ICIO tables. Each column of the value-added matrix represents the decomposition of a specific country-industry pair output by the country origin of value added. I assign each value-added source share to the corresponding industry-country of the entity of interest. This measure of cost share is the same for all entities belonging to the same industry-country pair.

[10] The most comprehensive data coverage appears to start in 2012.

[11] A methodology for the imputation of missing sales flow is a work in progress.

## 3.5 Debt Exposure

Debt exposure represents the amount of debt outstanding with foreign nationals. It is split between bond and loan exposure. Later in the paper, I aggregate bonds and loans into total debt exposure whenever the estimation requires more parsimonious specifications. Total debt exposure weights bond and loan exposure by their relative weights in total debt outstanding from Factset Debt Capital Structure (DCS).

### 3.5.1 Bond Exposure

To compute bond exposure, I use Factset DCS and aggregate information on bond holdings from Coppola et al. (2021) and Maggiori, Neiman and Schreger (2020). Factset DCS provides summary and detailed information on the debt structure of 43,835 reporting entities as of 2019. The data capture revolving credit (balances and availability), term loans, notes/bonds, and other borrowings as of a specific fiscal date. Each security in DCS is linked to a CUSIP identifier when available.

Maggiori, Neiman and Schreger (2020) matches mutual funds holdings with global bonds information and finds that investors disproportionately hold bonds in their currency. This finding holds for domestic bonds as much as for foreign bonds. In fact, after the authors account for issuance currency, they find that "knowledge of the issuer's nationality offers very little additional information for predicting the investor's nationality" (p. 1). This means that the bond currency issuance best predicts the bond *holder's* nationality. The one exception to this conclusion involves the US dollar. Global investors are uniquely willing to hold foreign securities denominated in US dollars.

To reflect these findings, I build bond country exposure as follows. If the bond was issued in a currency different from the US dollar, I assign the amount outstanding of the bond to the country of the currency. If the bond was issued in US dollars, I multiply the amount outstanding by the bond holder countries' shares from Coppola et al. (2021) that correspond to the ultimate parent nationality of the entity. The latter assignment is necessary to better capture global bond investors' shares in the bond nationality of any given entity. In section 6 and in the appendix, I show how the results change when I leave the exposure to US dollars as an exposure to the United States. In this latter exposure definition, the bond issuance variable better reflects exposure to a country's currency rather than reflecting the nationality of the bond holder.

### 3.5.2 Loan Exposure

I use Factset DCS and the Loan Pricing Corporation's (LPC) Dealscan database to build loan exposure. Dealscan contains detailed global syndicated loan market data. I include all Dealscan data related to borrowers matched with entities covered by Factset from 2009 through 2019. The appendix shows the number of matched borrowers and loans.

Syndicated loans represent the most common way large public companies receive loans (Caglio, Darst and Kalemli-Özcan, 2021). Approximately one-third of aggregate cross-border lending is in the form of a syndicated loan (Cerutti, Hale and Minoiu, 2015). Syndicated loans are organized in the form of packages and facilities in which multiple lenders generally participate. I adjust the facility's credit amount to reflect time until maturity, spread, and loan type to translate the credit line information to an estimated end-of-year amount outstanding. I correct for usage rates using aggregate usage rate estimates from Cerutti, Hale and Minoiu (2015). If not available, I impute the credit proportion of each lender according to an estimation methodology available in Appendix C.5. As a validation, I use the loan issuance currency to reconcile the imputed total outstanding syndicated credit to the total loans outstanding amount available in Factset DCS. I assign the estimated syndicated loans outstanding as an exposure to the country of the ultimate parent of the lender. I assign any residual outstanding credit not accounted for by syndicated loans to the country of the issuance currency, following the same methodology used to compute bond exposure.

# 4 Descriptive Statistics and Stylized Facts

This section describes the sample of public companies and their exposure to foreign markets. I then provide stylized facts to further an understanding of the analysis.

## 4.1 Sample

The sample consists of all listed nonfinancial entities for which data are available in both Factset and Capital IQ for 2009 through 2019. I drop all companies with a market capitalization of less than $1 million. To avoid double counting, I exclude all companies whose parents were ever in the sample. All companies are at the "top" of their ownership hierarchy, and 96 percent are ultimate parents. The sample covers, on average, 33 percent of all currently active nonfinancial public companies worldwide and represent 77 percent of global equity market value. Table 17 in the appendix shows the financial characteristics of the firms in the sample. As in other papers focusing on international listed companies (Bekaert, Hodrick and Xiaoyan, 2009; di Giovanni and Hale, 2020), all entities have sound financials and high liquidity buffers. They also tend to have high levels of investment and profitability.

Table 1: Average Total Foreign Exposure in Each Channel by Headquarters Country

| HQ Country | # Companies | Subsidiary Empl. W. | Subsidiary Sales W. | Investors Direct | Investors Full | Revenues | Costs | IO Costs | Bonds | Loans |
|---|---|---|---|---|---|---|---|---|---|---|
| United States | 4521 | 0.10 | 0.23 | 0.13 | 0.33 | 0.24 | 0.17 | 0.06 | 0.22 | 0.05 |
| China | 2892 | 0.02 | 0.08 | 0.09 | 0.34 | 0.16 | 0.16 | 0.01 | 0.02 | 0.07 |
| Japan | 2696 | 0.10 | 0.22 | 0.12 | 0.34 | 0.22 | 0.22 | 0.08 | 0.01 | 0.01 |
| Eurozone | 1876 | 0.18 | 0.27 | 0.23 | 0.60 | 0.45 | 0.30 | 0.11 | 0.05 | 0.13 |
| South Korea | 1284 | 0.09 | 0.17 | 0.07 | 0.31 | 0.29 | 0.24 | 0.17 | 0.02 | 0.02 |
| United Kingdom | 966 | 0.22 | 0.29 | 0.47 | 0.79 | 0.51 | 0.32 | 0.13 | 0.16 | 0.24 |
| Canada | 931 | 0.18 | 0.28 | 0.26 | 0.58 | 0.54 | 0.31 | 0.15 | 0.12 | 0.30 |
| India | 930 | 0.08 | 0.22 | 0.16 | 0.35 | 0.23 | 0.23 | 0.10 | 0.03 | 0.06 |
| Taiwan | 894 | 0.11 | 0.24 | 0.09 | 0.41 | 0.60 | 0.29 | 0.24 | 0.03 | 0.02 |
| Hong Kong SAR China | 752 | 0.16 | 0.27 | 0.33 | 0.52 | 0.76 | 0.36 | 0.17 | 0.16 | 0.31 |
| Australia | 719 | 0.07 | 0.12 | 0.31 | 0.79 | 0.38 | 0.29 | 0.08 | 0.14 | 0.14 |
| Sweden | 350 | 0.28 | 0.40 | 0.26 | 0.62 | 0.59 | 0.29 | 0.17 | 0.08 | 0.11 |
| Singapore | 341 | 0.19 | 0.20 | 0.22 | 0.54 | 0.59 | 0.30 | 0.28 | 0.10 | 0.29 |
| Indonesia | 314 | 0.00 | 0.04 | 0.21 | 0.46 | 0.12 | 0.24 | 0.08 | 0.12 | 0.23 |
| Thailand | 304 | 0.03 | 0.08 | 0.17 | 0.35 | 0.18 | 0.26 | 0.18 | 0.02 | 0.05 |
| Brazil | 253 | 0.06 | 0.17 | 0.25 | 0.45 | 0.15 | 0.27 | 0.07 | 0.07 | 0.12 |
| Israel | 248 | 0.13 | 0.25 | 0.22 | 0.50 | 0.47 | 0.33 | 0.13 | 0.05 | 0.42 |
| Others | 236 | 0.08 | 0.12 | 0.26 | 0.62 | 0.20 | 0.35 | 0.07 | 0.22 | 0.28 |
| Switzerland | 224 | 0.33 | 0.61 | 0.29 | 0.72 | 0.69 | 0.36 | 0.22 | 0.14 | 0.25 |
| Poland | 170 | 0.04 | 0.13 | 0.34 | 0.48 | 0.26 | 0.28 | 0.21 | 0.08 | 0.06 |
| Russia | 169 | 0.07 | 0.14 | 0.16 | 0.39 | 0.18 | 0.29 | 0.09 | 0.09 | 0.24 |
| Norway | 154 | 0.20 | 0.37 | 0.33 | 0.53 | 0.60 | 0.37 | 0.18 | 0.07 | 0.29 |
| Turkey | 154 | 0.01 | 0.09 | 0.19 | 0.43 | 0.20 | 0.23 | 0.12 | 0.11 | 0.14 |
| Mexico | 109 | 0.08 | 0.19 | 0.19 | 0.40 | 0.23 | 0.35 | 0.00 | 0.28 | 0.20 |
| Philippines | 103 | 0.05 | 0.10 | 0.17 | 0.32 | 0.11 | 0.34 | 0.11 | 0.07 | 0.16 |
| Saudi Arabia | 93 | 0.06 | 0.12 | 0.07 | 0.09 | 0.20 | 0.34 | 0.10 | 0.02 | 0.05 |
| Denmark | 91 | 0.28 | 0.45 | 0.27 | 0.88 | 0.69 | 0.42 | 0.19 | 0.19 | 0.29 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows the number of companies in the sample and the average foreign-country exposure, by headquarters country. Foreign exposure is the sum exposure to all non-headquarters countries. The average is over a year-by-company sample. The details on the construction of each exposure channel measure are in Section 3 and Appendix C.

The second column of Table 1 shows the number of companies covered by headquarters country. All the other columns of Table 1 show the average foreign exposure in each channel by headquarters country. This is an average over a year-by-company sample of total exposure to non-headquarters countries. I aggregate the raw country exposure into 27 countries/regions. The focus is primarily on developed markets, the BRICS countries (Brazil, Russia, India, China, and South Africa), and other large developing nations.[12]

[12] The eurozone is aggregated into one unique area due to its common currency and high level of financial integration. The criterion for the inclusion of a country as an exposure region requires that there are at least 50 companies that have at least 50 percent of exposure to that country in all channels. This allows for some balance in the study of cross-country channel correlation.

Table 1 shows relatively high levels of home bias and high heterogeneity across countries. The channels with the highest percentage of foreign exposures are investor exposures and geographic revenue. The full investor exposure presents much higher levels of foreign exposure than the direct investor exposure almost by construction. This is because any missing equity information is assigned to the investors' shares of the issuer, proportionally to aggregate capital flows information from Coppola et al. (2021).

The higher level of foreign revenue exposure is due to the global nature of the companies in the sample. Intra-firm trade and exports are predominant activities of large listed companies. But if foreign sales are dominant, why do we not see an equivalent foreign exposure on the cost side, which should represent the sales to global suppliers? The answer is that cost shares are weighted to represent the costs of materials over total sales. The weighting is necessary to compute the Leontief matrix representing direct and indirect cost exposure, which is presented in Appendix C.4. The weighting makes the magnitude of revenue and costs comparable to each other. Finally, GeoRev includes sales through arms'-length trade and subsidiaries. The cost exposure includes only purchases from arm's-length trade.

Countries (and regions) such as Switzerland, Singapore, and Hong Kong that are strongly integrated with large neighbor markets have companies with a high foreign exposure. High foreign exposure is also present in emerging markets and small open economies such as Taiwan and Poland.

## 4.2 Foreign Exposure Determinants

This section provides an overview of which level of variation in the database best explains the raw country exposure shares. I am interested in understanding which variable among country-of-exposure, firm, time, industry, and headquarters-country characteristics tends to explain most of the exposure variation. All such factors are highly correlated to each other. I estimate Shapley value regressions (Lipovetsky and Conklin, 2001) to tackle the multi-colinearity and evaluate the relative importance of these characteristics.

The importance coefficient in Shapley value regressions is computed first by recording the $R^2$ of all possible combinations of fixed effects that can be included in the model, with their interactions. One mix will include only the firm, another only the country, another the year, another year-country fixed effect, and so on. Each combination is indexed by $j$, and for each $j$, the indicator $\mathbb{1}_j^g$ is 1 if the fixed effect type $g$ is included in case $j$. The first part of the algorithm runs:

$$S_{ilt}^{\text{channel}} = \mathbb{1}_j^i \delta_i + \mathbb{1}_j^l \delta_l + \mathbb{1}_j^t \delta_t + \mathbb{1}_j^{il} \delta_{il} + \mathbb{1}_j^{it} \delta_{it} + \ldots \quad \forall j \quad \text{and store } R_j^2, \tag{3}$$

where $S_{ilt}^{\text{channel}}$ represents the channel exposure of company $i$ to location $l$ at time $t$. After storing the coefficient of variation $R_j^2$ for each fixed effect combination, I use it as a coefficient for the computation of the Shapley value of each fixed effect. The Shapley value represents the average marginal contribution of each fixed effect to any other model containing a subset of the other fixed effects. In this context, the coefficient of importance of the Shapley value applied to fixed effects represents a concept similar to an analysis of variance (ANOVA) decomposition.

Table 2: Relative Importance of Different Fixed Effects in Explaining Foreign Exposures

| **Fixed Effects** | **Subsidiary** | | **Investors** | | **Revenues** | **Costs** | **Bonds** | **Loans** |
|---|---|---|---|---|---|---|---|---|
| | Empl. W. | Sales W. | Direct | Full | | | | |
| *Panel A. Balanced Shares Sample* | | | | | | | | |
| Exp. Country | 0.57 | 0.58 | 0.76 | 0.62 | 0.68 | 0.58 | 0.59 | 0.63 |
| Company ID | 0.30 | 0.30 | 0.15 | 0.28 | 0.16 | 0.26 | 0.25 | 0.17 |
| Industry | 0.06 | 0.05 | 0.03 | 0.05 | 0.04 | 0.06 | 0.05 | 0.03 |
| Year | 0.04 | 0.05 | 0.02 | 0.00 | 0.07 | 0.05 | 0.06 | 0.14 |
| HQ Country | 0.03 | 0.02 | 0.04 | 0.05 | 0.06 | 0.05 | 0.04 | 0.02 |
| *Panel B. Unbalanced Sample* | | | | | | | | |
| Exp. Country | 0.51 | 0.55 | 0.71 | 0.55 | 0.58 | 0.54 | 0.55 | 0.53 |
| Company ID | 0.39 | 0.35 | 0.22 | 0.39 | 0.27 | 0.35 | 0.33 | 0.29 |
| Year | 0.03 | 0.03 | 0.01 | 0.00 | 0.07 | 0.03 | 0.05 | 0.14 |
| Industry | 0.03 | 0.04 | 0.02 | 0.03 | 0.03 | 0.04 | 0.03 | 0.03 |
| HQ Country | 0.03 | 0.03 | 0.04 | 0.03 | 0.06 | 0.04 | 0.04 | 0.02 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)

*Notes*: This table shows the relative importance of coefficients computed from Shapley value regressions of various interacted fixed effects in explaining the variation of exposure. For each channel of exposure, I compute all possible combinations of fixed effects interaction among the ones listed in the first column. I then compute the Shapley value associated with each type of fixed effect using the $R^2$ of the fixed effect coalition as gain in the Shapley value formula.

Table 2 ranks fixed effects according to their Shapley value for a balanced and unbalanced sample of exposure shares. The unbalanced sample is used throughout the paper, while the balanced sample forces exposure data to be available for every year in all channels simultaneously. The introduction of the balanced sample in this context is necessary to fairly evaluate the relative importance of the time fixed effect vis-à-vis other characteristics.

The most notable evidence in Table 2 is how well location fixed effects explain exposure across all channels. This means that the identity of the exposure country is the best predictor of foreign exposure magnitude in any given channel, regardless of the identity of the firm, its industry, or the year. Table 19 in the appendix shows how the importance of the United States and the eurozone fixed effects are not solely responsible for the strong explanatory power of the exposure country.

The second crucial factor is firm characteristics; all other fixed effects have relatively less explanatory power. In this context, one helpful interpretation of the Shapley value is that summing up two values will give an approximate estimate of the $R^2$ from equation (3) that includes the interaction between the two corresponding fixed effects. Summing up the coefficients for country and firm fixed effects shows that firm-country-specific characteristics can explain 85 percent to 95 percent of the variation in exposure shares. The low coefficients for the year fixed effects is a testament to how stable the country of exposure is, on average, in the sample. The next section further investigates time trends.

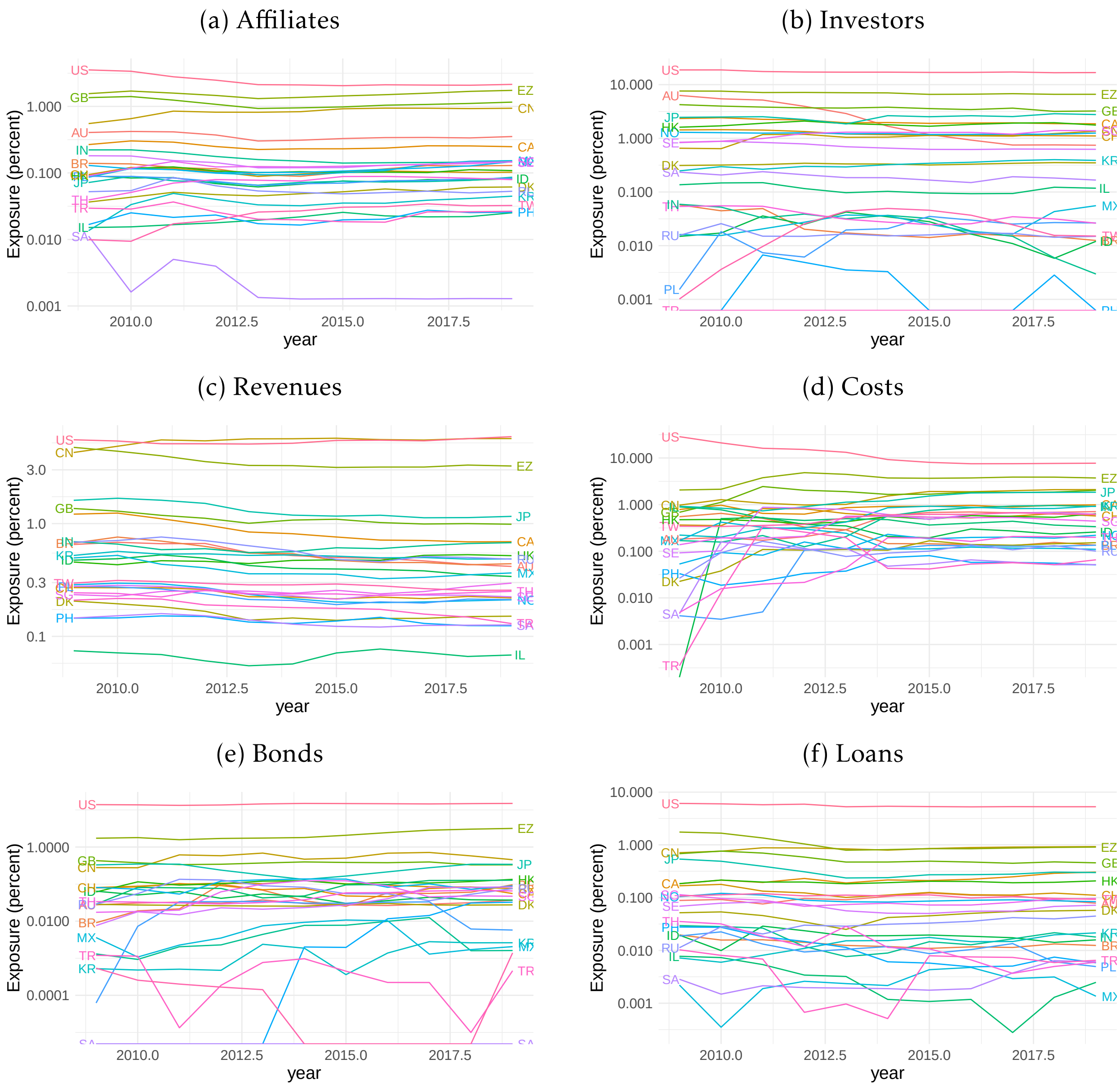
## 4.3 Exposure Shares over Time

This section explores time trends in foreign exposure channels. Figure 1 shows the average exposure to all countries and channels from 2009 through 2019. I consider only foreign exposures, defined as exposures to countries different from the headquarters country. The shares are plotted on a logarithmic scale to follow the average exposure distribution across all country sizes. There is no visually discernible trend for most countries, with a few exceptions.

First, countries with low exposures on average have higher exposure volatility in the sample. This results from having very few firms exposed to small countries such as Saudi Arabia or Israel, each of which has a small footprint in global capital flows. Second, affiliates and cost exposures displayed some exposure trends before 2012, but those trends flattened after 2012. This is due to Factset's lower entity coverage of non-US and private companies before 2012. Inadequate coverage of smaller companies affects both the affiliate and cost exposure because these measures rely on the full coverage of the entire network of private and public company linkages.[13] While I verify that data availability does not, per se, affect the conclusions of this paper, it is the main reason why I use 2019 as a benchmark reference year when studying cross-sectional exposures. Finally, most companies are increasingly exposed to eurozone bond holders but less exposed to eurozone bank lending. Most companies are increasingly exposed to costs originating from China. All other visible trends are present only before 2012.

[13]It is a harder task to cover consistently the full network of subsidiaries (with their financial information) and supply-chain relationships, as opposed to only the consolidated listed companies in the sample. Lower coverage before 2012 implies different shares, a problem that cannot be solved by focusing on a balanced sample of listed ultimate parents.

Figure 1: Mean Shares of Foreign Exposure across Companies




*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)

*Notes*: This figure shows the firm average in country of exposure for each channel over time. The y-axis is in logarithmic scale. Each line is equivalent to plotting the fixed effect $\delta^c_{gt}$ from the regression $s^c_{igt} = \sum_c \sum_g \sum_t \delta^c_{gt}$, for channel $c$, location $g$, and year $t$.

Nevertheless, country shares in the 2012–2019 period, the time frame that has the highest data quality in both the Factset and Capital IQ data sets, present high persistence. Tables 3 and 4 show the persistence coefficient of each channel of exposure, conditional on country-firm fixed effects. All persistence coefficients are close to 1 and have within-$R^2$ values greater than 80 percent when the sample is balanced. Similar but somewhat

Table 3: Time Persistence Coefficients 2009–2019, Balanced Shares Sample

| Dependent Variables: | Subsidiaries | Investors Full | Bonds | Bonds orig | Revenues | Loans | Costs |
|---|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Variables* | | | | | | | |
| lag | 0.9733*** | 0.9838*** | 0.9420*** | 0.9127*** | 0.9602*** | 0.9236*** | 0.9386*** |
| | (0.0014) | (0.0100) | (0.0075) | (0.0111) | (0.0076) | (0.0083) | (0.0067) |
| *Fixed-effects* | | | | | | | |
| factset_entity_id | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | |
| Observations | 175,082 | 1,103,687 | 304,317 | 50,423 | 874,775 | 95,518 | 822,647 |
| $R^2$ | 0.98856 | 0.99517 | 0.93687 | 0.79439 | 0.96667 | 0.96983 | 0.93022 |
| Within $R^2$ | 0.96524 | 0.99300 | 0.80630 | 0.51906 | 0.92356 | 0.76685 | 0.89021 |

Table 4: Time Persistence Coefficients 2009–2012, Unbalanced Shares Sample

| Dependent Variables: | Subsidiaries | Investors Full | Bonds | Bonds orig | Revenues | Loans | Costs |
|---|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Variables* | | | | | | | |
| lag | 0.9688*** | 0.9873*** | 0.9221*** | 0.8883*** | 0.9525*** | 0.8931*** | 0.9369*** |
| | (0.0016) | (0.0069) | (0.0102) | (0.0141) | (0.0081) | (0.0110) | (0.0066) |
| *Fixed-effects* | | | | | | | |
| factset_entity_id | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | |
| Observations | 324,297 | 3,156,929 | 489,751 | 87,373 | 2,130,999 | 234,124 | 1,432,651 |
| $R^2$ | 0.98701 | 0.99543 | 0.91734 | 0.70819 | 0.95765 | 0.96203 | 0.93212 |
| Within $R^2$ | 0.94791 | 0.99339 | 0.70091 | 0.35981 | 0.89410 | 0.67672 | 0.88367 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)

*Notes*: This table shows the average autoregressive coefficient of each exposure share channel for a balanced and unbalanced panel of exposure shares. Each column represents the coefficient $\rho^c$ from the regression $s^c_{i,g,t} = \alpha_{i,g} + \rho^c s_{i,g,t-1} + \epsilon_{i,g,t}$. The unbalanced panel represents the benchmark sample. It allows for some companies to have missing information on the exposure country from the 2009–2019 period. The balanced panel includes only firms that have information available for all years from 2009 through 2019.

lower persistence is observed when including firms that started being covered or that terminated operations in the middle of the sample.[14] Due to the high persistence of exposure shares, I will henceforth focus mostly on the cross section of exposure. Also, Section 4.2 showed how most of the variation in shares lies in the cross section rather than in the time component.

[14]Note that I considered the sample as balanced not conditional on a foreign exposure being always positive from 2009 through 2019. There is a balanced shared sample simply if a company's information is always present in the ownership, DCS, Georev, and supply chain package, but foreign shares are allowed to be 0 in the first panel too.

## 4.4 Country Determinants of Exposure

This section investigates the cross-sectional characteristics of exposures to different countries and channels. It identifies the countries in which firms are more likely to be exposed on average, and it illustrates how an exposure to any given country and channel tends to correlate with any other. All results refer to 2019, the year for which the database includes the most firms.

I illustrate cross-sectional country patterns as an estimation of the following:

$$S^{c}_{il} = \gamma^{cg}_{lr}\ S^{g}_{ir}|_{S^{g}_{ir}>0} + \epsilon_{il}, \tag{4}$$

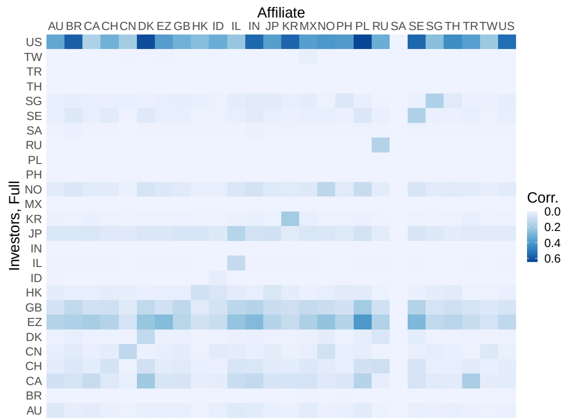
where $\gamma^{cg}_{lr}$ captures the correlation between exposure to country $l$ through channel $c$ and exposure to country $r$ through channel $g$. The correlation is measured conditional on company $i$ being positively exposed to country $r$ through channel $g$. I focus on the correlation conditional on $S^{g}_{ir} > 0$ to capture how the exposure intensity of one channel correlates with another. The coefficient $\gamma^{cg}_{lr}$ represents the average exposure to location $l$ through channel-$c$ if the same company is exposed to channel-$g$, location $r$. Note that fixed effects and controls are omitted to give an indication of the data's unconditional correlations. Section 4.6 studies conditional correlations in regression form.

Figure 2 shows a graphic representation of the correlation matrices obtained from estimating equation (4) for all country-channel combinations. The estimates consider only foreign exposures; that is, I do not include observations where either country $g$ or $l$ coincide with the headquarters country. The coefficients in every matrix cell indicate the likelihood that a nonzero foreign exposure in the x-axis channel-country combination will predict an exposure in the y-axis channel-country. Darker colors in an entire row imply that all companies are likely to be highly exposed to the y-axis channel-country combination regardless of the exposure in the x-axis. Darker colors in a vertical line imply that foreign exposure in the x-axis channel-country indicates high foreign exposure in the same x-axis channel for all other countries. A darker diagonal indicates a high correlation between the x- and y-axis channels within the same exposure country.

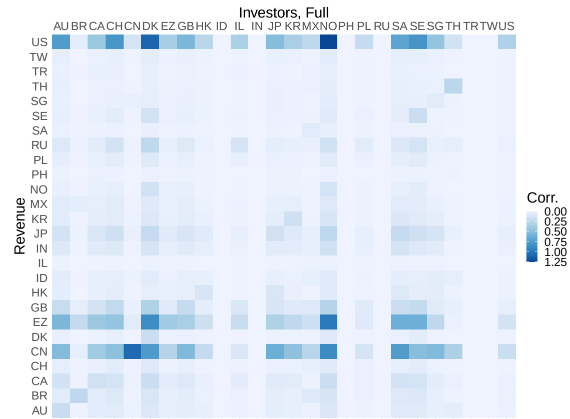
Figure 2 also shows the six combinations of exposure channels for which there are the highest degree of within-country cross-channel correlation. All other cases are presented in the appendix. The most striking pattern illustrates that most multinationals in the sample are exposed to the United States and the eurozone through all possible channels, regardless of their other global activities. Exposure to the United States is the most pronounced. Most companies are unconditionally exposed to China through only the revenue and cost channels. Great Britain, Japan, and Norway have a widespread footprint in

Figure 2: Cross-country Exposure Correlation across Channels

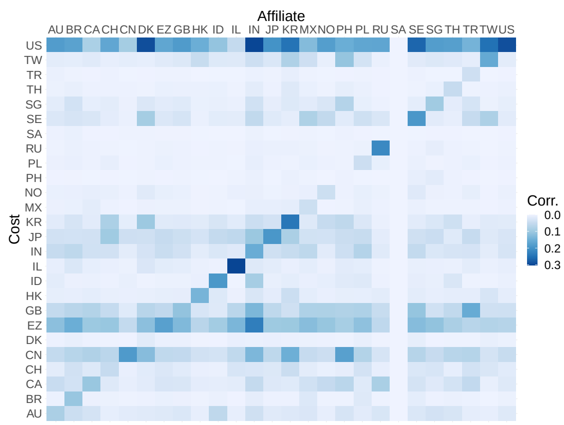
(a) Investors over Subsidiaries



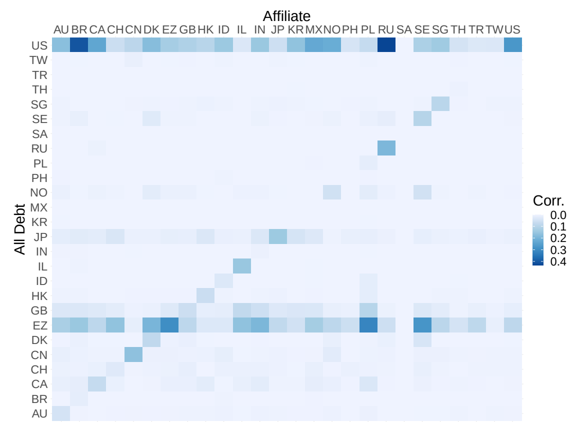

(b) Revenues over Investors



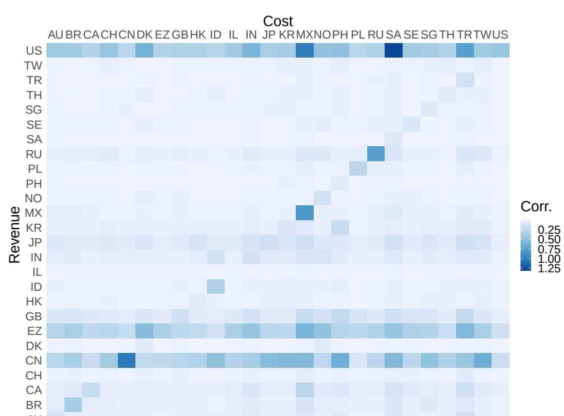

(c) Costs over Subsidiaries



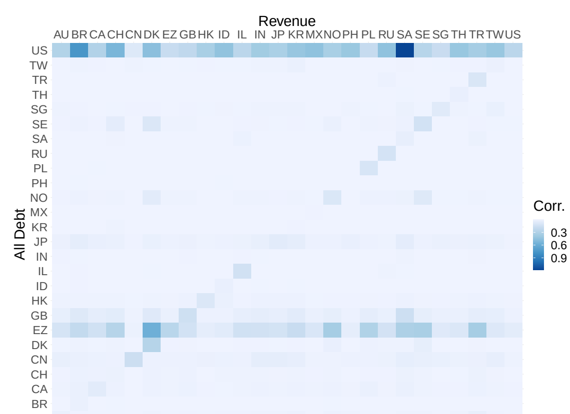

(d) Debt over Subsidiaries




(e) Revenues over Costs




(f) Debt over Revenue




*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)

*Notes*: Each cell of these panels represents the correlation between a foreign exposure in the x-axis country-channel combination and the y-axis country-channel combination, conditional on the x-axis exposure being nonzero.

capital flows but not as large in trade.

A second visible pattern involves the diagonal values. It indicates that exposure in any given country through a particular channel makes it highly likely that the same company will be exposed to the same region through another channel. For instance, non-Canadian firms with affiliates in Canada will likely have Canadian suppliers, Canadian equity investors, and/or Canadian debt financing. Most economic models and empirical studies focus on only one or two simultaneous channels of exposure.

The high within-country cross-channel correlation is not mechanically built into the exposure measures. One concern may be that a subsidiary's liabilities are classified as foreign debt in the debt measure or that cost exposure includes interest payments. But each exposure channel does not contain another exposure channel in its definition and measurement. For instance, when a firm has an affiliate in Country A, it does not mean we should observe debt exposure in Country A. Even when the subsidiary's functional currency is the same as in Country A, international accounting regulation demands that this debt is consolidated and translated into the currency of the ultimate parent.[15] For the bonds or loans exposure to be recorded, the ultimate parent must be associated with an active loan from a bank residing in Country A, or there must be an active corporate bond denominated in the currency of Country A for which the ultimate parent is responsible. Similarly, the network of subsidiaries and owners cannot overlap because, by definition, a subsidiary cannot be an investor, as investors are only ultimate parents that invest minority shares in other ultimate parents. Geographic revenues include arm's-length, intrafirm, and indirect revenues from different countries, as declared by each ultimate parent. Hence, they are not necessarily related to the number of affiliates weighted by the number of subsidiary employees. Finally, cost exposures exclude relations with subsidiaries, joint-venture partners, or financial partners, so there cannot be built-in overlap between suppliers and subsidiaries, or suppliers and creditor banks.

## 4.5 Determinants of Firm Exposure

As shown in Table 2, the second most important source of variation in foreign exposure are firms' characteristics. This section explores which of these characteristics are more likely to correlate with foreign exposure. I estimate the following:

$$S_{il}^{\text{channel}} = \beta X_i + \delta_l + \epsilon_{ir}, \tag{5}$$

[15] There are exceptions to this rule, but they generally do not apply to listed equity owners with a stake higher than 50 percent, as in this sample.

where $S^c_{ir}$ is the average share of firm $i$'s exposure to location $l$ in 2019; $X_i$ is a vector of average firm characteristics from 2009 through 2019, including mean sales growth, mean capital expenditure (CAPEX), market capitalization, leverage, number of employees, and book-to-market ratio; and $\delta_r$ is a region fixed effect. I collapse the time dimension to simplify the interpretation and because shares are stable over time (see Section 4.3).

Table 5: Correlation between Firm Characteristics and Foreign Exposure

| Dependent Variables: | Subsidiaries | Investors Full | Bonds | Revenue | Loans | Cost |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| Market Cap | 0.2045** | 0.1581* | 0.2332** | 0.0508 | 0.1854** | 0.1195** |
| | (0.0743) | (0.0896) | (0.1129) | (0.0551) | (0.0745) | (0.0453) |
| Employees | 0.1108** | -0.0179 | 0.0184 | 0.1825* | 0.0171 | 0.1202*** |
| | (0.0487) | (0.0144) | (0.0480) | (0.0903) | (0.0232) | (0.0321) |
| Book to Market | -0.0224 | -0.0600 | -0.0490 | -0.0654 | 0.0789* | -0.0153 |
| | (0.0491) | (0.0451) | (0.0866) | (0.0906) | (0.0389) | (0.0379) |
| Leverage | -0.0094 | -0.0107 | -0.0158 | -0.1623*** | 0.0484** | -0.0301 |
| | (0.0167) | (0.0161) | (0.0271) | (0.0501) | (0.0193) | (0.0198) |
| CAPEX | 0.0125 | 0.0233* | 0.0549 | -0.1636** | -0.0830 | -0.0191 |
| | (0.0313) | (0.0136) | (0.0409) | (0.0665) | (0.0652) | (0.0287) |
| Sales Growth | -0.1277** | -0.0154 | 0.0707 | -0.0730 | 0.0966 | -0.0663** |
| | (0.0529) | (0.0658) | (0.0542) | (0.0581) | (0.0587) | (0.0278) |
| *Fixed-effects* | | | | | | |
| iso_country | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 162,642 | 163,838 | 92,597 | 163,864 | 163,286 | 143,032 |
| $R^2$ | 0.04413 | 0.46802 | 0.18051 | 0.11464 | 0.04323 | 0.17167 |
| Within $R^2$ | 0.00480 | 0.00223 | 0.00447 | 0.00419 | 0.00265 | 0.00396 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table represents the correlation between firm characteristics and total foreign exposure through several channels. It is computed from a firm-by-country panel of average firm characteristics and exposure shares in each country in 2019. I exclude exposures to the headquarters country. Clustered (country) standard errors in parenthesis.

Table 5 shows the $\beta$ coefficients estimated from equation (5). Size, proxied by market cap and employees, correlates highly with average foreign exposure. Market capitalization better explains foreign exposure to capital markets (equity investing, equity, and debt financing). Number of employees correlates more with foreign trade exposure. Growth variables such as CAPEX and sales growth correlate negatively with foreign exposure. This may be a result of growth stocks being related to younger firms. Leverage is positively related to higher foreign debt financing and negatively related to other kinds of exposure.

## 4.6 Gravity Model of Exposure

Table 6: Gravity Model of Exposure Shares

| Dependent Variables: | Subsid | Investors | Bonds | Loans | Revenue | Cost |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| Distance | -0.3680*** | -0.3035** | -0.3444 | -0.2971** | -0.7065*** | -0.2580** |
| | (0.0869) | (0.1363) | (0.3079) | (0.1411) | (0.1755) | (0.1092) |
| Dipl. Agreement | -0.1932 | -0.2927* | 0.1167 | -0.2343 | -0.1965 | -0.1417 |
| | (0.1288) | (0.1664) | (0.2660) | (0.1894) | (0.1727) | (0.1057) |
| Comm. Language | 0.8412** | 0.8365** | 1.832** | 0.8768** | 1.341 | 0.7517*** |
| | (0.3138) | (0.3309) | (0.7719) | (0.3480) | (0.8142) | (0.2659) |
| Comm. Legal | -0.0394 | -0.1068 | -0.7014* | 0.0085 | -0.2293 | 0.0505 |
| | (0.1196) | (0.1909) | (0.4091) | (0.2904) | (0.2981) | (0.1260) |
| Comm. Religion | -0.1270 | -0.1948 | -0.4308 | -0.1857 | -0.4683** | -0.1669** |
| | (0.1274) | (0.1277) | (0.3123) | (0.1414) | (0.1891) | (0.0723) |
| *Fixed-effects* | | | | | | |
| factset_entity_id | Yes | Yes | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 162,646 | 162,646 | 162,646 | 162,646 | 162,646 | 162,646 |
| $R^2$ | 0.24201 | 0.28635 | 0.23939 | 0.54993 | 0.36186 | 0.32337 |
| Within $R^2$ | 0.00855 | 0.00913 | 0.01916 | 0.00701 | 0.01994 | 0.01052 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, BIS, Coppola et al. (2021), and Conte, Cotterlaz and Mayer (2022)
*Notes*: This table represents the estimation of a gravity model on 2019 foreign exposure shares for several channels of exposure. The bilateral distance variables are computed from the Gravity database of Conte, Cotterlaz and Mayer (2022), and between country of headquarters and exposure country. Clustered (company and country) standard errors are in parentheses.

To conclude the analysis of the determinants of exposure shares, I analyze a cross-sectional gravity model of foreign exposure:

$$S_{il}^{c} = \beta' G_{il} + \delta_i + \delta_l + \epsilon_{ir}, \tag{6}$$

where $S_{il}^{c}$ is the average exposure of firm $i$ to foreign location $l$ through channel $c$, and $G_{il}$ is a vector of standard gravity factors defined to reflect the bilateral distance between the headquarters of firm $i$ and location $l$: log of geographic distance, UN diplomatic disagreement, common language, common legal framework, and common religion. All bilateral distances are taken from Conte, Cotterlaz and Mayer (2022). I include firm and country fixed effects to control for size and other unilateral effects predicted by a gravity model and observed in Sections 5 and 4.4. The foreign exposure share refers to 2019, the year for which the database includes the most firms. I collapse the time dimension to simplify the interpretation and because shares are stable over time (see section 4.3).

Table 6 shows the estimated coefficients $\beta$ of equation (6). Distance and common language have high and significant coefficients with expected signs for all channels. All other measures of distance are mostly not significant. Revenues present a robust and negative relation with geographic distance.

Section 4.4 showed how multinationals tend to be exposed to the same foreign market through multiple channels at the same time. To reflect this finding, I augment the gravity model with each firm exposure to region $l$ through all channels except $c$, represented by the object $S_{il}^{g \neq c}$:

$$S_{il}^{c} = \beta' G_{il} + \sum_{g \neq c} \gamma^{g} S_{il}^{g} + + \delta_i + \delta_l + \epsilon_{il}. \tag{7}$$

Table 7 shows the estimates of the augmented gravity model in equation (7). Adding other channels of foreign exposure at the firm level increases the model's explanatory power from an average $R^2$ of 30 percent to an average $R^2$ of 40 percent. The within-$R^2$ of a gravity model goes from 1 to 2 percent, while including other exposure channels in the model can explain 10 to 20 percent additional variation in country of exposure. Notably, all exposure channels are a complement to each other. There is no case in which a firm's exposure to a country through a particular channel implies that the firm wants to divest from that country through other channels. For example, this could be the case for a firm that already has costs related to having suppliers in Country A and, therefore, might want to diversify or hedge on their country of financing. Another example would be a company's wanting to have equity financing and debt financing from different countries, and so on. Note that exposure to the headquarters country is not included.

Table 7: Augmented Gravity Model of Exposure Shares

| Dependent Variables: | Subsid | Investors | Bonds | Loans | Revenue | Cost |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| Distance | -0.0967* | -0.1375* | -0.1819 | -0.0580 | -0.4235*** | -0.1314* |
| | (0.0478) | (0.0787) | (0.2427) | (0.0387) | (0.0920) | (0.0660) |
| Dipl. Agreement | -0.1178 | -0.2271* | 0.2012 | -0.1726 | -0.0643 | -0.0911 |
| | (0.0691) | (0.1110) | (0.2473) | (0.1253) | (0.0793) | (0.0680) |
| Comm. Language | 0.1505** | 0.3950** | 1.448** | 0.1134 | 0.4716 | 0.4437*** |
| | (0.0707) | (0.1565) | (0.6442) | (0.1012) | (0.4734) | (0.1321) |
| Comm. Legal | 0.0966 | -0.0550 | -0.6750* | 0.1970 | -0.1156 | 0.1024 |
| | (0.0687) | (0.1111) | (0.3657) | (0.2381) | (0.1947) | (0.0778) |
| Comm. Religion | 0.0735 | -0.0826 | -0.3348 | 0.0078 | -0.2896** | -0.0833 |
| | (0.0968) | (0.1152) | (0.2901) | (0.1154) | (0.1384) | (0.0506) |
| Investors | 0.0497*** | | 0.0378** | 0.1441** | 0.1177*** | 0.0591*** |
| | (0.0165) | | (0.0168) | (0.0646) | (0.0237) | (0.0117) |
| Bonds | 0.1078*** | 0.0473*** | | 0.2091*** | 0.1434*** | 0.0299*** |
| | (0.0214) | (0.0121) | | (0.0714) | (0.0460) | (0.0081) |
| Loans | 0.0438*** | 0.1184*** | 0.1374*** | | 0.1180*** | 0.0334*** |
| | (0.0098) | (0.0206) | (0.0419) | | (0.0314) | (0.0075) |
| Revenue | 0.2609*** | 0.0998*** | 0.0972*** | 0.1218*** | | 0.1003*** |
| | (0.0566) | (0.0183) | (0.0336) | (0.0373) | | (0.0248) |
| Cost | 0.0841*** | 0.1018*** | 0.0411*** | 0.0700*** | 0.2036*** | |
| | (0.0153) | (0.0215) | (0.0139) | (0.0137) | (0.0498) | |
| Subsid | | 0.0485** | 0.0840* | 0.0520** | 0.2999*** | 0.0476*** |
| | | (0.0181) | (0.0416) | (0.0211) | (0.0341) | (0.0093) |
| *Fixed-effects* | | | | | | |
| factset_entity_id | Yes | Yes | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 162,646 | 162,646 | 162,646 | 162,646 | 162,646 | 162,646 |
| $R^2$ | 0.34456 | 0.33433 | 0.30729 | 0.59497 | 0.48057 | 0.36425 |
| Within $R^2$ | 0.14269 | 0.07575 | 0.10672 | 0.10638 | 0.20226 | 0.07029 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, BIS, Coppola et al. (2021), and Conte, Cotterlaz and Mayer (2022)

*Notes*: This table represents the estimation of a gravity model on 2019 foreign exposure shares for several channels of exposure. The bilateral distance variables are computed from the CEPII gravity database of Conte, Cotterlaz and Mayer (2022) and between country of headquarters and exposure country. I augment the gravity model with all channels of exposure information between each firm and the corresponding country of exposure. Clustered (company and country) standard errors are in parentheses.

# 5 Analysis

## 5.1 Covariance Decomposition

In this section, I present the decomposition of the unconditional correlation of returns across exposure channels. I start from the fact that the covariance between two excess stock returns can always be decomposed as:

$$\mathrm{Cov}[R_{it}, R_{jt}] = \mathrm{Cov}[R_{it}^{\text{model}}, R_{jt}^{\text{model}}] + \mathrm{Cov}[\epsilon_{it}, \epsilon_{jt}]. \tag{8}$$

The first component represents the covariances between returns with common factors under a specific model, and the second represents residual or idiosyncratic comovements.

The advantage of disposing a microlevel share of exposure to several regions is that it enables an estimation of the following nonparametric regional factor model:

$$\begin{aligned} R_{it} =& \alpha_i + \sum_l \delta_{lt}^{\text{Subsid.}} S_{il}^{\text{Subsid.}} + \delta_{lt}^{\text{Invest.}} S_{il}^{\text{Invest.}} + \delta_{lt}^{\text{Debt}} S_{il}^{\text{Debt}} + \delta_{lt}^{\text{Rev.}} S_{il}^{\text{Rev.}} + \delta_{lt}^{\text{Cost}} S_{il}^{\text{Cost}} + \epsilon_{it} && (9) \\ =& \alpha_i + \sum_c \delta_t S_i + \epsilon_{it}, && (10) \end{aligned}$$

where $R_{it}$ is the return of company $i$ at quarter $t$ in excess of the US risk-free rate, $S_{il}^c$ is the channel-$c$ exposure share of company $i$ to location $l$ at a specific time,[16] $\delta_{lt}^c$ is a time-by-location-by-channel fixed effect, $\delta_t$ is a one-by-$L$ size vector of location fixed effect for time $t$, and $S_i$ is a $L$-by-one size vector of location exposure shares to each channel $c$ for firm $i$.

From the model in equation (9) I can decompose the covariance between two stock returns, $i$ and $j$, implied by the model:

$$\begin{aligned} \mathrm{Cov}[R_{it}^{\text{model}}, R_{jt}^{\text{model}}] &= \sum_c \mathrm{Cov}[\delta_t^c S_i^c, \delta_t^c S_j^c] + \sum_c \sum_{g \neq c} \mathrm{Cov}[\delta_t^c S_i^c, \delta_t^g S_j^g] && (11) \\ &= \sum_c S_i^c \mathrm{Cov}[\delta_t^c, \delta_t^c] S_j^c + \sum_c \sum_{g \neq c} S_i^c \mathrm{Cov}[\delta_t^c, \delta_t^g] S_j^g && (12) \\ &= \sum_c S_i^c \Omega^{cc} S_j^c + \sum_c \sum_{g \neq c} S_i^c \Omega^{cg} S_j^g && (13) \end{aligned}$$

The first component of equation (11) represents the covariance between the model-implied

[16] The shares refer to 2019 because it is the sample year with the best data quality, but results are robust to using 2009 data or the average exposure across the whole sample.

returns due to exposure to a foreign country through the same channel $c$. The second component in equation (11) represents the covariance between the model-implied returns due to exposure to a foreign country but through two distinct channels, $c$ and $g$. For instance, suppose the model allowed for only revenue and cost exposure. Two stocks can comove either because they both have revenue, both have cost, or either one of them has cost and revenue originating from the same country.

Equation (13) contributes to a further interpretation of the covariance decomposition as being the product between a firm-specific exposure to different channel-location pairs $S_i^c$ and an estimated variance-covariance matrix $\Omega_t^{cg}$ of country-level shocks. Thanks to the nonparametric nature of the model, no structure is imposed on this matrix.

Finally, total in-sample covariance and model fit can be aggregated and summarized using the following metric, as in Bekaert, Hodrick and Xiaoyan (2009):

$$\gamma^{\text{cov}} = \frac{1}{W}\sum_{i=1}\sum_{j>i}\omega_i\omega_j\text{Cov}\left(R_{it}, R_{jt}\right) = \frac{1}{W}\sum_{i=1}\sum_{j>i}\omega_i\omega_j\left[\text{Cov}\left(\sum_c \hat{\delta}_t S_i, \sum_c \hat{\delta}_t S_j\right) + \text{Cov}\left(\epsilon_{it}, \epsilon_{jt}\right)\right], \tag{14}$$

where $W = \sum_i \sum_{j>i} \omega_i\omega_j$. The weights $\omega_i$ are either always equal to 1 or equal to the market capitalization of company $i$. A conceptually similar metric can be built for the decomposition of return variances:

$$\gamma^{\text{var}} = \frac{1}{W}\sum_{i=1}\omega_i^2\text{Var}\left(R_{it}\right) = \frac{1}{W}\sum_{i=1}\omega_i^2\left[\text{Var}\left(\sum_c \hat{\delta}_t S_i\right) + \text{Var}\left(\epsilon_{it}\right)\right]. \tag{15}$$

Table 8: Decomposition of In-sample Covariance to Common Exposure Channel Factors

| Cov $(X, Y)$ | | Covariance | | Variance | | Correlation | |
|---|---|---|---|---|---|---|---|
| X | Y | Unw. | Weight. | Unw. | Weight. | Unw. | Weight. |
| $R_{it}$ | $R_{jt}$ | 0.012 | 0.011 | 0.012 | 0.014 | 0.238 | 0.318 |
| $\hat{R}_{it}$ | $\hat{R}_{jt}$ | 0.012 | 0.012 | 0.012 | 0.013 | 0.235 | 0.362 |
| Investors | Investors | 0.023 | 0.025 | 0.023 | 0.022 | 0.464 | 0.736 |
| Subsid. | Subsid. | 0.001 | 0.001 | 0.001 | 0.001 | 0.013 | 0.024 |
| Debt | Debt | 0.031 | 0.035 | 0.033 | 0.028 | 0.630 | 1.037 |
| Revenue | Revenue | 0.010 | 0.011 | 0.010 | 0.009 | 0.197 | 0.320 |
| Cost | Cost | 0.003 | 0.003 | 0.004 | 0.003 | 0.069 | 0.100 |
| Investors | Subsid. | -0.003 | -0.004 | -0.003 | -0.002 | -0.058 | -0.118 |
| Investors | Debt | -0.047 | -0.051 | -0.049 | -0.045 | -0.961 | -1.513 |
| Investors | Revenue | 0.019 | 0.021 | 0.021 | 0.020 | 0.396 | 0.619 |
| Investors | Cost | 0.008 | 0.007 | 0.008 | 0.008 | 0.154 | 0.210 |
| Subsid. | Debt | 0.004 | 0.005 | 0.004 | 0.003 | 0.072 | 0.150 |
| Subsid. | Revenue | -0.002 | -0.002 | -0.002 | -0.001 | -0.032 | -0.065 |
| Subsid. | Cost | -0.000 | -0.001 | -0.000 | -0.000 | -0.010 | -0.019 |
| Debt | Revenue | -0.026 | -0.030 | -0.028 | -0.024 | -0.530 | -0.876 |
| Debt | Cost | -0.010 | -0.010 | -0.011 | -0.010 | -0.208 | -0.306 |
| Revenue | Cost | 0.002 | 0.002 | 0.002 | 0.003 | 0.046 | 0.071 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table represents the in-sample decomposition of the in-sample return covariance, according to a nonparametric model of country-channel exposure shares multiplied by country-time fixed effects. The first row represents the in-sample covariance. The second row represents the covariance according to the estimated model. All other rows represent the decomposition of the estimated model covariance.

Table 8 shows the decomposition of the variance and covariance of returns as represented by the model in equation (9) and computed from quarterly returns. I show covariance, variance, and correlation statistics unweighted and weighted by lagged company market capitalization. The first two lines of Table 8 show the in-sample and model fit covariance statistics.

A clear pattern emerges from the variance-covariance decomposition. All exposure channels contribute positively as comovement factors of returns. Two companies' returns are more likely to comove when both are exposed to the same (or correlated) country either through affiliate, revenue, cost, debt, or equity financing linkages.[17] At the same time, two companies' returns will tend to diverge when they are exposed to the same country through different channels of exposure. For instance, the returns of a company gaining revenues from a specific country and a company financed by that country are more likely to diverge. The latter is in line with positive gains from an operational hedging strategy and may be driving the strong correlation across channels of exposure observed in Section 4.4.

The most important channels of comovement are equity and debt financing, followed by trade revenue and costs. Exposure through affiliates presents lower covariance estimates. The exposure channels are data driven and do not allow for distinguishing between foreign exposures driven by arm's-length trade, intra-firm trade, and horizontal and vertical integration. Affiliate exposure may be capturing both horizontal and vertical integration, even though weighting this exposure by the employment size of the affiliate is more likely to capture production cost rather than sales. Revenue exposure aggregates revenues from horizontal integration and arm's-length trade.

The most important channels of divergence are equity versus debt financing, debt financing and revenues, and debt financing and costs. Not all cross-channels exposures imply return divergence. Having similar country exposure through investor and revenue, investor and cost, or subsidiary and debt is associated with higher comovement.

## 5.2 Cross-sectional Betas

An alternative way to evaluate return correlations and what explains them is through the lenses of a multifactor capital asset pricing model (CAPM). I can build $L$ country portfolio returns $R_{lt}$ as the relevant factors in:

$$R_{it} = \alpha_i + \sum_{l}^{L} \beta_{il} R_{lt} + \epsilon_{it}, \tag{16}$$

where $R_{it}$ is the excess return of company $i$ at quarter $t$, and $R_{lt}$ is the excess return of market $l$ at quarter $t$. The location's market returns are built as market cap-weighted portfolios of all companies whose main investor resides in location $l$, as defined by the Full Investor exposure variable. Contrary to previous studies that assign one country to each company (Forbes and Chinn, 2004; Bekaert, Hodrick and Xiaoyan, 2009), I include

[17] In the current iteration of the paper, I do not decompose between comovements due to exposure to the same country (the diagonal elements of $\Omega_t^{cc}$) or to countries with correlated macro shocks (the off-diagonal elements of $\Omega_t^{cc}$).

all 27 markets in the regression. Including so many factors may affect predictive performance, but the aim of this section is only to understand which international channels can explain in-sample return correlation. The $\beta_{il}$ coefficients represent the object of interest. Each $\beta_{il}$ is the in-sample conditional correlation between each company and investor returns residing in different countries. Note that in this first-stage regression, I do not use any exposure share information except to define the country portfolios. For simplicity, I do not include industry-time fixed effects in this benchmark estimate. Table 21 in the appendix replicates the benchmark estimates when I add four-digit Nomenclature of Economic Activities (NACE) industry-by-time fixed effects in equation (16). The results are virtually unchanged.

The second-stage regression then studies how different channels of country exposure can explain the cross section of country loadings $\hat{\beta}_{il}$:

$$\hat{\beta}_{il} = \sum_{c} \gamma^{c} S_{il}^{c} + \sum_{c} \sum_{c \neq g} \gamma^{cg} S_{il}^{c} S_{il}^{g} + \delta_i + \delta_l + \upsilon_{il}, \tag{17}$$

where $S_{il}^{c}$ represents the channel-$c$ exposure share of company $i$ to country $l$. The shares refer to 2019, the sample year with the best data quality, but results are robust to using 2009 or the average exposure across the whole sample. I do not include the country of investor share among the channels $c$ in this benchmark specification. This is because each investor country portfolio of returns $R_{lt}$ represents the benchmark channel against which I compute the return comovements $\beta_{il}$.

Table 9: How Channels of Exposure Explain Cross-sectional Country Return $\beta_{il}$'s

| Dependent Variable: | | | Betas | | | |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| Subsid | 0.5724*** | | | | 0.1217*** | 0.2059*** |
| | (0.0051) | | | | (0.0141) | (0.0237) |
| Debt | | 0.5708*** | | | 0.2193*** | 0.2507*** |
| | | (0.0050) | | | (0.0140) | (0.0284) |
| Revenue | | | 0.6257*** | | 0.1199*** | 0.1604*** |
| | | | (0.0060) | | (0.0125) | (0.0194) |
| Cost | | | | 0.6869*** | 0.2251*** | 0.2121*** |
| | | | | (0.0061) | (0.0159) | (0.0256) |
| Subsid × Debt | | | | | | 0.0094 |
| | | | | | | (0.0398) |
| Subsid × Revenue | | | | | | -0.1211*** |
| | | | | | | (0.0430) |
| Subsid × Cost | | | | | | -0.1290** |
| | | | | | | (0.0512) |
| Debt × Revenue | | | | | | -0.1057** |
| | | | | | | (0.0440) |
| Debt × Cost | | | | | | 0.0060 |
| | | | | | | (0.0444) |
| Revenue × Cost | | | | | | 0.1891*** |
| | | | | | | (0.0555) |
| *Fixed-effects* | | | | | | |
| companyid | Yes | Yes | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 221,281 | 221,281 | 221,281 | 221,281 | 221,281 | 221,281 |
| $R^2$ | 0.11477 | 0.11727 | 0.10760 | 0.11599 | 0.12345 | 0.12376 |
| Within $R^2$ | 0.07799 | 0.08059 | 0.07052 | 0.07925 | 0.08703 | 0.08735 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows how different country-channel exposure shares explain the cross section of returns beta loadings on country-specific portfolios. In the first stage, I estimate firm-specific betas on all country-specific portfolio returns. The country-specific portfolio returns of a location $l$ includes all firms whose main investor share is in $l$. In the second stage, I estimates how each firm's country-channel exposure share explains the beta loadings in a firm-by-country panel with firm and country fixed effects. Clustered (company) standard errors are in parentheses.

Table 9 shows the coefficients $\gamma^c$ from equation (17). Columns (1) through (4) include each channel in isolation, while columns (5) and (6) include all channel exposures with their interaction terms. The estimates generally confirm what is shown in Table 8, with a few minor differences. All channels are confirmed to positively explain comovement between returns of companies sharing exposure to the same country. No clear ranking across channels emerges from these estimates. Affiliates, debt financing, revenues, and costs country exposure are equally important channels in explaining $\beta$'s country loadings. Three interaction coefficients are negative and significant: the interaction between affiliates and revenues, the interaction between affiliates and costs, and the interaction between revenue and debt. These signs are the same as in Table 8. One interaction term is positive and significant in column (6): the interaction between revenue and costs. This interaction was virtually zero in Table 8. While it is theoretically possible that revenue and cost exposure to the same country amplify each other, the significance of this coefficient is not stable in some robustness specifications.

# 6 Robustness and Extensions

## 6.1 Cross-sectional Cash Flow Betas

Campbell-Shiller decompositions often show returns driven by discount rates rather than cash flows. Baele and Soriano (2010) shows how European stock comovements are due to increased covariance in discount rates, not cash flows. To verify whether the results in Table 9 may be driven by discount rates, I re-estimate the two-step equations (16) and (17), substituting quarter $t$ cash flows for returns. Table 10 confirms all the findings in Table 9. All coefficient signs coincide, and if anything, the magnitude of most coefficients increases. Table 10 shows less significant results compared with Table 9 because cash flows are noisier variables than returns.

Table 10: How Channels of Exposure Explain Cross-sectional Cash Flow $\beta$'s

| Dependent Variable: | Betas | | | | | |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| Subsid | 0.5238*** | | | | 0.0648 | 0.1080 |
| | (0.0313) | | | | (0.0842) | (0.1342) |
| Debt | | 0.5367*** | | | 0.2599*** | 0.4652*** |
| | | (0.0309) | | | (0.0863) | (0.1658) |
| Revenue | | | 0.5624*** | | 0.0289 | 0.2697** |
| | | | (0.0357) | | (0.0752) | (0.1249) |
| Cost | | | | 0.6478*** | 0.2802*** | 0.3520** |
| | | | | (0.0374) | (0.0985) | (0.1536) |
| Subsid × Debt | | | | | | 0.2854 |
| | | | | | | (0.2426) |
| Subsid × Revenue | | | | | | -0.4229 |
| | | | | | | (0.2757) |
| Subsid × Cost | | | | | | -0.0876 |
| | | | | | | (0.3104) |
| Debt × Revenue | | | | | | -0.4449 |
| | | | | | | (0.2839) |
| Debt × Cost | | | | | | -0.4480 |
| | | | | | | (0.2748) |
| Revenue × Cost | | | | | | 0.4882 |
| | | | | | | (0.3527) |
| *Fixed-effects* | | | | | | |
| companyid | Yes | Yes | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 207,365 | 207,365 | 207,365 | 207,365 | 207,365 | 207,365 |
| $R^2$ | 0.03086 | 0.03107 | 0.03054 | 0.03104 | 0.03123 | 0.03138 |
| Within $R^2$ | 0.00229 | 0.00250 | 0.00195 | 0.00247 | 0.00266 | 0.00282 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows how different country-channel exposure shares explain the cross section of cash flows beta loadings on country-specific portfolios. In the first stage, I estimate firm-specific betas on all country-specific cash flows portfolios. The country-specific cash flows portfolios of a location $l$ include the cash flows of all firms whose main investor share is in $l$. In the second stage, I estimates how each firm's country-channel exposure share explains the beta loadings in a firm-by-country panel with firm and country fixed effects. Clustered (company) standard errors are in parentheses.

## 6.2 Sample Sensitivity

Table 11: Testing Sample Sensitivity on Exposure Channel Correlation with Return $\beta$'s

| Dependent Variable: | Betas | | | |
|---|---|---|---|---|
| | All | Foreign | non-US | non-US Fgn |
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Subsid | 0.1217*** | 0.1309** | 0.1201*** | 0.1066** |
| | (0.0352) | (0.0621) | (0.0343) | (0.0497) |
| Debt | 0.2193*** | 0.1302** | 0.2315*** | 0.0578 |
| | (0.0702) | (0.0494) | (0.0765) | (0.0367) |
| Revenue | 0.1199** | 0.1778* | 0.0992** | 0.1803** |
| | (0.0566) | (0.0955) | (0.0463) | (0.0716) |
| Cost | 0.2251*** | 0.1890** | 0.2131*** | 0.1754** |
| | (0.0568) | (0.0913) | (0.0458) | (0.0790) |
| *Fixed-effects* | | | | |
| companyid | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 221,281 | 212,482 | 164,829 | 158,499 |
| $R^2$ | 0.12345 | 0.03125 | 0.12781 | 0.03513 |
| Within $R^2$ | 0.08703 | 0.00309 | 0.08334 | 0.00226 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows how different country-channel exposure shares explain the cross section of beta loadings on country-specific portfolios for different samples of exposures. In the first stage, I estimate firm-specific betas on all country-specific portfolios. The country-specific portfolios of a location $l$ include all firms whose main investor share is in $l$. In the second stage, I estimate how each firm's country-channel exposure share explains the beta loadings in a firm-by-country panel with firm and country fixed effects. Column (1) represents the estimates including all countries and all firms. Column (2) represents the estimates when I exclude beta loadings to the headquarters country. Column (3) represents the estimates when I exclude companies headquartered in the United States. Column (4) represents estimates when I exclude beta loadings to the headquarters country and companies headquartered in the United States. Clustered (company) standard errors are in parentheses.

Are the main results robust to changes in the sample and exposure type? Tables 11 and 12 focus on two main exercises. First, I exclude from the sample exposure to the country in which the firm is headquartered. On the one hand, it is important to include exposure to the headquarters country because it is often the largest exposure share in most channels. On the other hand, since the paper focuses on multinationals, the results should not be driven exclusively by exposure to the domestic market. The second exercise excludes companies headquartered in the United States. Of the roughly 14,000 companies in the sample, 6,442 are headquartered in the United States. Because the United States embodies a unique role at the center of global capital flows, I verify whether the results are driven by companies in this sample.

Tables 11 and 12 confirm the importance of all channels, regardless of the sample of interest. However, the cost exposure loses significance when I exclude headquarters shares. The interaction coefficients are the most sensitive to sample change. The signs generally remain constant, but the loss of power and magnitude demands further investigation.

Table 12: Testing Sample Sensitivity on Exposure Channel Correlation with Return $\beta$'s

| Dependent Variable: | Betas | | | |
|---|---|---|---|---|
| | All | Foreign | non-US | non-US Fgn |
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Subsid | 0.2059*** | 0.1133*** | 0.1950*** | 0.0998*** |
| | (0.0237) | (0.0287) | (0.0271) | (0.0337) |
| Debt | 0.2507*** | 0.1379*** | 0.1860*** | 0.0955** |
| | (0.0284) | (0.0388) | (0.0343) | (0.0474) |
| Revenue | 0.1604*** | 0.1399*** | 0.1575*** | 0.1571*** |
| | (0.0194) | (0.0219) | (0.0213) | (0.0238) |
| Cost | 0.2121*** | 0.1480*** | 0.2137*** | 0.1371*** |
| | (0.0256) | (0.0300) | (0.0293) | (0.0340) |
| Subsid × Debt | 0.0094 | 0.0954 | 0.0626 | -0.0864 |
| | (0.0398) | (0.1258) | (0.0443) | (0.1530) |
| Subsid × Revenue | -0.1211*** | 0.0026 | -0.1415*** | -0.0746 |
| | (0.0430) | (0.0874) | (0.0457) | (0.0957) |
| Subsid × Cost | -0.1290** | 0.0903 | -0.1437** | 0.4230* |
| | (0.0512) | (0.2058) | (0.0565) | (0.2406) |
| Debt × Revenue | -0.1057** | -0.0117 | -0.0370 | -0.0018 |
| | (0.0440) | (0.0960) | (0.0491) | (0.1024) |
| Debt × Cost | 0.0060 | -0.2817 | 0.0741 | -0.3750 |
| | (0.0444) | (0.2013) | (0.0513) | (0.2365) |
| Revenue × Cost | 0.1891*** | 0.4214*** | 0.0848 | 0.3306** |
| | (0.0555) | (0.1321) | (0.0601) | (0.1392) |
| *Fixed-effects* | | | | |
| companyid | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 221,281 | 212,482 | 164,829 | 158,499 |
| $R^2$ | 0.12376 | 0.03138 | 0.12809 | 0.03526 |
| Within $R^2$ | 0.08735 | 0.00322 | 0.08363 | 0.00240 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows how different country-channel exposure shares explain the cross section of beta loadings on country-specific portfolios for different samples of exposures. In the first stage, I estimate firm-specific betas on all country-specific portfolios. The country-specific portfolios of a location $l$ include all firms whose main investor share is in $l$. In the second stage, I estimate how each firm's country-channel exposure share explains the beta loadings in a firm-by-country panel with firm and country fixed effects. Column (1) represents the estimates including all countries and all firms. Column (2) represents the estimates when I exclude beta loadings to the headquarters country. Column (3) represents the estimates when I exclude companies headquartered in the United States. Column (4) represents estimates when I exclude beta loadings to the headquarters country and companies headquartered in the United States. Clustered (company) standard errors are in parentheses.

## 7 Conclusion

A company can be exposed to foreign markets by owning subsidiaries abroad or by being owned by foreign investors. A company can be exposed to direct lending by foreign banks or through the purchase of its bonds by foreign investors. Finally, a company can have customers located in foreign markets or can purchase intermediate inputs from different locations. To my knowledge, this is the first paper that gathers all these simultaneous channels of exposure to foreign markets of a sample of large international companies.

Among the findings from this paper are that most companies have simultaneous exposure to several of these channels and that often companies are exposed to the very same market in several different ways at the same time. While the importance of the United States and the eurozone in global capital markets and of China in trade is shared across many companies, having some specific exposure in a single channel for a certain country performs better than a gravity model in predicting any other exposure.

Companies that are exposed to the same country through the same channel have returns and cash flows that will comove. Companies that have exposure to the same country through different channels will comove less. Not all combinations of exposure lead to lower comovement, necessarily.

In future iterations of this paper, I will further explore the extent to which different companies try to match a country exposure through different channels. I will test the predictive power of a model that takes into consideration the full structure of exposure. And I will verify in more detail how and whether simultaneous different exposures to the same country provide operational hedging, conditional on specific country events.

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# A Data Sets

- **Factset Data Management Tool**: Factset Data Management Tool contains Factset's entity master file and links to the Symbology Master. The entity master file contains time-permanent entity identifiers, headquarters country, country of incorporation, and industry/sector classification. Factset also contains historical ownership linkages between parents and subsidiaries of the covered entities. The Symbology Master provides FactSet's comprehensive security-level symbology and its reference data. Data are available for both equity and fixed income securities.

- **Factset Geographic Revenue**: Factset Geographic Revenue (GeoRev) is a data set capturing revenue exposures of global entities to different countries/regions over time. Factset exploits annual reports and regulatory filings to achieve a consistent record. GeoRev covered 20,292 companies in 2009 and 72,606 companies in 2019. Most of these companies are publicly listed, but some are private companies and government institutions.

- **Factset Debt Capital Structure**: Factset Debt Capital Structure (DCS) provides both summary and detailed information about the debt structure of nearly 40,000 reporting entities globally. The data capture revolving credit (balances and availability), term loans, notes/bonds, and other borrowings as of a specific fiscal date. Debt coverage starts in 2006. The data are collected from annual reports, credit agreements, and indentures. The frequency of the raw data can be annual, semi-annual, or quarterly.

- **Factset Supply Chain Relationships**: The Factset Supply Chain Relationships package covers business relationship among companies globally. Factset gathers relationship information from public sources such as SEC 10-K annual filings, investor presentations, and press releases. Factset then classifies the following relationship types: customer, supplier, competitor, in-licensing, manufacturing, marketing, distribution, out-licensing, equity-investment, investor, joint-venture, integrated-product offering, and research collaboration. I use only customer-supplier relationships in this paper. The database covers 31,000 publicly traded companies around the world, comprising more than 450,000 business relationships from 2003 onward, on a point-in-time basis.

- **S&P Capital-IQ**: S&P Capital-IQ contains balance sheet information on global public companies and some private companies. The Capital-IQ Xpress-Feed contains cross-referenced company identifiers that enable the merging of entities in Capital-IQ with external sources such as Factset, Dealscan, and others. The identifiers used to match entities across sources are CUSIP numbers, Legal Entity IDs, company addresses, and names.

- **Dealscan**: The Loan Pricing Corporation's (LPC) Dealscan database contains detailed data on the global syndicated loan market. The Dealscan data included in this paper comprise all borrowers matched with Factset entities from 2009 through 2019. Appendix C.5 shows the number of matched borrowers and loans by borrowing and lender country. Syndicated loans are organized in the form of packages and facilities in which multiple lenders generally participate. Approximately one-third of total cross-border lending is in the form of syndicated loans (Cerutti, Hale and Minoiu, 2015). Moreover, syndicated loans represent the most common way large public companies receive loans (Caglio, Darst and Kalemli-Özcan, 2021).

# B Sample

Factset contained 59,149 public entities as of 2021.[18] Entities are defined in Factset as public/private companies, subsidiaries and joint ventures, government institutions, individuals, and various types of funds that are linked to a permanent identifier across time. When a merger and acquisition (M&A) occurs, one or both entity IDs may be discontinued and registered as extinct subsidiaries of a new entity.

I match 52,787 public Factset entities to Capital IQ entities through CUSIP, Exchange ID, Legal Entitiy ID, address and/or name. Of the 52,787 matched Factset-Capital IQ entities, 37,958 contain actively covered information about their ownership structure, debt capital structure, and geographic revenue. Finally, 19,250 of the preceding companies

[18]This statistic includes companies that are not currently active

were actively exchanged from 2009 through 2021. As a comparison with official data, the World Federation of Exchanges (WFE) database reports a total of 43,248 listed companies in the world in 2019. The total number of listed companies in the world has remained stable at about 43,000 since 2005. Stable trends are prominent in advanced economies, whereas emerging markets typically have an increasing trend of listed companies. The number of companies by country of headquarters presented in this paper may differ from other sources because, for the World Bank and the WFE, a company is considered domestic when it is incorporated in the same country where the exchange is located. The only exception is the case of foreign companies that are listed exclusively on one exchange.

Even though my final sample contains less than half of all public entities in the world in 2021, their market capitalization represents 77 percent of the world's total market capitalization. Moreover, these 19,250 public companies now control 1 million different entities and controlled 2 million entities over the course of the sample period. Their global revenues amount to $37 trillion, or 38 percent of the World GDP.

# C Exposure Methodology

## C.1 Subsidiaries Exposure

In its simplest form, the ownership structure of the companies in Factset can be represented as a directed graph with weight 1 associated with each edge. The ownership graph is represented by its adjacency matrix $O$ with dimensions $M \times M$, where rows represent the subsidiary and columns represent the parent entity. One example could be:

$$O = \begin{bmatrix} O_{11} & \cdots & O_{1M} \\ \vdots & \ddots & \vdots \\ O_{M1} & \cdots & O_{MM} \end{bmatrix} \qquad \text{e.g.} \qquad O_0 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

There are different ways a parent company can be considered to have a stake in a subsidiary. The straightforward interpretation is that a parent puts equity into the subsidiary. Another interpretation is that a parent decides where to allocate employment or machinery across its subsidiaries for production. For flexibility, define a vector $W_{M\times 1}$ to represent either total equity, capital, or employment at the consolidated level of all $M$

entities. Define $Z^O = Diag(W) \cdot O$, the matrix showing the flows of variable $W$ going from the column parent to the row subsidiary. Then I can establish the following accounting identity:

$$W = Z^O e + W^{\text{Ultimate}} \qquad W = (Z^O)' e + W^P,$$

where $W^{\text{Ultimate}}$ represents the consolidated value of $W$ for ultimate parents only, $W^{\text{Ultimate}}$ contains the consolidated financial value of $W$ for the entities that are ultimate parents and zero for all subsidiaries, $W^{\text{P}}$ represents the $W$-size of each entity net of all its subsidiaries, and $e$ is a vector of ones.

Define now the Ownership Leontief matrix as:

$$L^O = (I - Z^O \cdot \text{diag}(W)^{-1}) = (I - A^O)^{-1}.$$

Suppose $W$ represents equity, then each column of $L^O$ represents how many dollars in value each entity would increase if a parent company gains a dollar and allocates it proportionally to its subsidiary network. The column of $L^O$ can be seen as upward exposure to parents. The main issue with $L^O$ is that it is expressed in the unit of the variable $W$, which may not be comparable with the units of other channels of exposure studied in this paper. To solve this, I define the following relative measure of exposure:

$$S^{\text{Subs.}} = \text{Diag}(W^P) \cdot \text{Diag}(W)^{-1} \cdot L^O. \tag{18}$$

Each element $S_{ij}^{\text{Subs.}}$ of $S^{\text{Subs.}}$ represents the column entity $j$'s share of $W$ allocated in row entity $i$. The rows of $S^{\text{Subs.}}$ represent how important the column parent entity $j$ is for the row entity $i$. To aggregate up to the country level, I multiply $S^{\text{Subs.}}$ by the matrix $H_{M\times C}$, assigning each entity to its headquarters country.

The quality of the underlying data depends on the financial variable used to weight subsidiaries' size. Table 13 shows the number of entities with non-missing data when choosing different financial weighting variables.

Table 13: Number of Entities with Populated Information in the Whole Subsidiary Network

| Year | Factset | Final Sample | | | | |
|---|---|---|---|---|---|---|
| | All | All | Employment Weight | Sales Weight | Assets Weight | Revenues Weight |
| 2009 | 3131044 | 376259 | 66067 | 32263 | 29995 | 27124 |
| 2010 | 3543354 | 436311 | 78968 | 39444 | 34540 | 31623 |
| 2011 | 3956882 | 515282 | 93976 | 46815 | 41201 | 38188 |
| 2012 | 4275431 | 595721 | 109381 | 53500 | 49991 | 46225 |
| 2013 | 4629300 | 694266 | 128395 | 60464 | 64005 | 58935 |
| 2014 | 4971356 | 766318 | 138031 | 65230 | 69297 | 63079 |
| 2015 | 5572851 | 850304 | 149047 | 71040 | 73755 | 66776 |
| 2016 | 5941019 | 931962 | 161259 | 77419 | 78423 | 70474 |
| 2017 | 6566583 | 1052450 | 174573 | 84299 | 83282 | 74678 |
| 2018 | 7361023 | 1159414 | 187073 | 90903 | 87082 | 77950 |
| 2019 | 8002484 | 1250163 | 194419 | 94576 | 61424 | 55127 |

*Source*: Author's calculations from Factset and Capital IQ
*Notes*: This table shows the number of unique entities in the network covered by Factset from 2009 through 2019 under different sample requirements. The second column of the table shows the total number of entities covered by Factset. All the "Final Sample" columns consider only the entities that are in any way connected to the ownership network of the companies in the main sample. The "Final Sample - All" column considers all entities in the network. The remaining columns consider the network of companies in the sample for which there is information on the weight variable.

In 2019, Factset covered 8 million different entities. Of these, 1.25 million were a direct or indirect subsidiary of some entity in this paper's sample of 19,250 listed companies. If I restrict the network of subsidiaries to include only subsidiaries that have employment information, the network size drops to 194,419 entities. The network size drops further if I choose to use sales, assets, or revenues as a weight. This sharp drop in data coverage means that if I want to weight each subsidiary by size, I lose information on 80 percent of declared subsidiaries. While subsidiaries with poor information are likely to be small, the sheer amount of information lost in this case raises important concerns. For this reason, I generate alternative subsidiary exposure measures. Two of these alternative measures include the full network of subsidiaries, as in column (3) of Table 13, but not weighted by subsidiary size. I compare these measures, and I replicate the main results in the paper to show that the choice of weighting versus not weighting, or using the full versus limited network, does not change the main results qualitatively.

I define the following alternative measures of subsidiary shares:

| $S^{\text{Subs.}}$ | Weight Variable | Interpretation |
|---|---|---|
| Count | $W = e$ | Share of subsidiaries' number |
| Discount | $W = \delta e$ | Share of discounted subsidiaries' number |
| Employment | $W = \overline{\text{Number of employees}}$ | Share of employees |
| Sales | $W = \overline{\text{Sales}}$ | Share of sales |
| Assets | $W = \text{Assests in Dollars}_t$ | Share of assets |

The employment-weighted measure is the one used in all benchmark results. The count measure is computed by substituting an all-ones vector to the weight variable $W$ in equation (18). By my doing so, $S^{\text{Subs.}}$ represents the share of subsidiaries of each entity, not including intermediary subsisiaries, that is, those entities that are parents and subsidiaries at the same time. To also give some weight to intermediary subsidiaries, I define a *discount* measure of the subdiary count, $\delta = 0.8$, in which a greater weight is given to subsidiaries higher in the hierarchy. All other measures use financial variables as weights. Notably, employment and sales are kept fixed over time to increase coverage. The assets variable changes over time because it has the best time coverage and is computed to verify whether changes in the weights of subsidiaries, rather than changes in the network structure, may include important time trends. Tables 14 and 15 summarize the differences in total foreign exposure under different weighting assumptions.

Table 14: Foreign Subsidiary Exposure Summary Statistics for Different Weighting

| Weight Variable | Average | SD | W. Average | HHI Average |
|---|---|---|---|---|
| Count | 0.24 | 0.32 | 0.43 | 0.77 |
| Discount | 0.18 | 0.25 | 0.34 | 0.77 |
| Employees | 0.08 | 0.21 | 0.25 | 0.92 |
| Sales | 0.33 | 0.42 | 0.53 | 0.85 |
| Assets | 0.03 | 0.12 | 0.15 | 0.96 |

*Source*: Author's calculations from Factset and Capital IQ
*Notes*: This table shows summary statistics of total exposure to non-headquarters countries under alternative measures of subsidiary shares. All statistics are computed from a company-by-year panel. The average and SD columns represents the simple average and standard deviation of the measure. The W. Average column represent the average weighted by a company's lagged market capitalization. HHI Average is the Herfindal index of exposure to different countries, computed for each company-year and then averaged in the panel.

Table 15: Average Subsidiary Foreign Exposure for Different Weighting by Country

| HQ Country | # Companies | Count | Discount | Assets | Sales | Employees |
|---|---|---|---|---|---|---|
| United States | 6442 | 0.21 | 0.17 | 0.05 | 0.17 | 0.07 |
| China | 4104 | 0.11 | 0.08 | 0.01 | 0.05 | 0.01 |
| Japan | 3409 | 0.25 | 0.20 | 0.02 | 0.14 | 0.06 |
| Eurozone | 2766 | 0.28 | 0.22 | 0.04 | 0.19 | 0.12 |
| India | 2617 | 0.13 | 0.10 | 0.01 | 0.09 | 0.03 |
| Canada | 2075 | 0.35 | 0.27 | 0.02 | 0.15 | 0.10 |
| South Korea | 1976 | 0.14 | 0.11 | 0.00 | 0.09 | 0.05 |
| Taiwan | 1401 | 0.42 | 0.31 | 0.01 | 0.15 | 0.08 |
| Hong Kong SAR China | 1327 | 0.52 | 0.40 | 0.04 | 0.16 | 0.10 |
| Australia | 1323 | 0.25 | 0.19 | 0.03 | 0.07 | 0.05 |
| United Kingdom | 1210 | 0.33 | 0.26 | 0.05 | 0.22 | 0.16 |
| Singapore | 553 | 0.43 | 0.33 | 0.03 | 0.15 | 0.14 |
| Sweden | 549 | 0.41 | 0.32 | 0.09 | 0.29 | 0.19 |
| Thailand | 545 | 0.11 | 0.08 | 0.01 | 0.04 | 0.02 |
| Others | 482 | 0.14 | 0.11 | 0.02 | 0.07 | 0.05 |
| Indonesia | 459 | 0.09 | 0.07 | 0.00 | 0.03 | 0.00 |
| Israel | 389 | 0.26 | 0.21 | 0.03 | 0.17 | 0.09 |
| Poland | 343 | 0.15 | 0.12 | 0.02 | 0.08 | 0.03 |
| Brazil | 301 | 0.15 | 0.12 | 0.02 | 0.12 | 0.04 |
| Switzerland | 273 | 0.60 | 0.47 | 0.17 | 0.50 | 0.27 |
| Russia | 263 | 0.11 | 0.08 | 0.01 | 0.09 | 0.04 |
| Turkey | 258 | 0.12 | 0.10 | 0.00 | 0.04 | 0.01 |
| Norway | 216 | 0.34 | 0.27 | 0.08 | 0.28 | 0.14 |
| Denmark | 162 | 0.45 | 0.36 | 0.08 | 0.30 | 0.18 |
| Philippines | 150 | 0.12 | 0.09 | 0.01 | 0.06 | 0.03 |
| Mexico | 126 | 0.19 | 0.15 | 0.05 | 0.15 | 0.07 |
| Saudi Arabia | 122 | 0.22 | 0.18 | 0.01 | 0.08 | 0.04 |

*Source*: Author's calculations from Factset and Capital IQ.
*Notes*: This table shows the number of companies in the sample and the average foreign-country exposure by headquarters country under alternative measures of subsidiary shares. Foreign exposure is the sum exposure to all non-headquarters countries. The average is over a year-by-company sample.

## C.2 Investor Exposure

In mid-2020, I pulled from Capital IQ the following variables for all the ultimate parents of the sample: IQ_HOLDER_CIQID, IQ_HOLDER_PERCENT, IQ_HOLDING_SECURITY_TYPE, IQ_HOLDING_PERCENT, IQ_HOLDING_CIQID, IQ_INVESTMENTS_ALL_STAKE, IQ_INVESTMENTS_ALL_REL, IQ_INVESTMENTS_ALL_ID, IQ_INVESTORS_ALL_STAKE, IQ_INVESTORS_ALL_REL, and IQ_INVESTORS_ALL_ID. The first five variables contain information on who holds the common equity of the ultimate parents, with the associated stake. The last six variables represent the same kind of information for private stocks. The data sources are typically companies' annual reports, 10Ks, news, and event scripts. There are 590,534 holders of common equity in one of the 19,000 companies in the sample, forming 4.5 million linkages. There are 37,804 private investors linked to 19,089 companies in the sample, forming 80,005 private investment linkages.

Capital IQ does not record a history of these investor linkages. However, the Wholesale Credit Risk Center at the Federal Reserve Bank of Chicago contains backups of the private investment variables whenever it requires a new data pull. From a series of several backups, a yearly history of investment linkages can be built. I use the history of the private investor-investment linkages from 2020 to 2023 to test the persistence level of investment country exposure. I find that the persistence coefficient of investor country exposure was 0.9944 for the period of 2000 to 2023, which is not significantly different from 1. However, I also find that about 4 percent of exposure shares changed by more than 5 percent from 2020 to 2023, which can potentially imply large changes if extrapolated in decades. For this reason, the country of investor is mostly considered as a cross-sectional control, and in the beta analysis, it is used only to assign the main country of investor. In the period of 2020 to 2023, the country of main investor virtually never changes.

The algorithm to translate the firm-to-firm investor linkages to firm-to-country investor exposure is as follows:

1. Check whether both a holding company and holder company have declared, respectively, the same relationship and discard all duplicate data. Keep the record with the least missing ownership percentage information. Do the same for private investor-investment linkages.

2. Merge common equity investors and private investors in a unique data set. Verify whether there is any inconsistency or duplication.

3. Thirty percent of linkages have some information on the ownership percentage. There is often a mix of ownership stakes that are populated and missing for the same holding company. The missing ownership data often represent the smallest stakes because companies tend to declare only their major investors. For this reason, I assign to all holders with missing stake information the same ownership percentage as the smallest investor for which there are data. If, after the assignment, the sum of all ownership shares for a company is greater than 100 percent, I do not run any assignment. After this procedure, 60 percent of linkages has information on the ownership percentage. The remaining 40 percent of missing ownership shares is predicted from a lasso regression estimated on the populated part of the data set that contains as predictors the assets and country of the investment company, headquarters country, industry, age, number of other investors, and country of investor.

4. Each investor in the firm-to-firm data built above can now be linked to a country according to its Factset headquarters when available or Capital IQ country ID. However, even after I have assigned a share stake for every firm-to-firm investor linkage, the total ownership shares do not sum to 1. In other words, there is typically some "missing" ownership. I take two different approaches to assigning the residual unclaimed ownership to a country that result in two different investor measures:

   (a) **Direct Investor**: Assign any missing ownership to the country where most of the equity shares are exchanged. This information is obtained from the country associated with the exchange of the "main equity" security identifier associated with the company by the Factset Data Management package. In most cases, the main country of security exchange corresponds to the headquarters country.

   (b) **Full Investor**: Assign any missing ownership shares to the investor country shares in the restated equity flow matrices by Coppola et al. (2021) (cleaned as specified in Appendix C.2.1) and associated with the nationality of the issuer.

### C.2.1 Issuer-investor Matrices by Coppola et al. (2022)

Coppola et al. (2021) merges micro-level securities information with Morningstar funds holdings to restate bilateral investment positions according to the nationality of the ultimate parent of the issuer. Coppola et al. (2021) shows how the official residency-based statement of bilateral capital flows overstates the importance of tax havens and understates the importance of large emerging markets as destinations of capital flows. The restated capital flows by Coppola et al. (2021) are well suited to merging with the companies in my sample because the authors also assign investors exposures to the headquarters nationality of the ultimate parent. Moreover, the main source of my information on the headquarters country of the ultimate parent is the same as the source preferred in Coppola et al. (2021): Factset. Therefore, while this paper does not possess firm-to-firm-level decomposition of the country of investors in the ultimate parent, it applies a proxy for it by combining minority shareholders data when available and integrating that information by country with the restated country-level funds holding of ultimate parents.

One data limitation in Coppola et al. (2021) is that funds and ETF investor data are available for only nine large investor geographies: the United States, the European Monetary Union (EMU), Great Britain, Canada, Switzerland, Australia, Sweden, Denmark, and Norway. To obtain the full matrix linking investors to issuer countries, I use the following methodology:

- Aggregate bilateral external position in Coppola et al. (2021) according to the countries and regions of interest. This entails aggregating the eurozone as one area and aggregating all countries not listed in Table 1 into the "Other" category.

- Populate the equity and bond flow investor-issuer matrix with "Funds Holding" methodology bilateral position, full restatement variable, when available. All flows are available for the following investor countries: Australia, Canada, Switzerland, Denmark, eurozone, Great Britain, Norway, Sweden, and United States.

- Domestic investments are not available for countries not included in the preceding list. In this case, use the total market capitalization value of a country, computed according to the headquarters of the equity issuer, to infer each year's domestic equity investment. Using the headquarters nationality of the issuer better matches the methodology of Coppola et al. (2021). As for bond flows, infer domestic investment from the total debt security claims outstanding, on a nationality base, from the Banks of International Settlements (BIS) Debt Securities Statistics.

## C.3 Revenue Exposure

Factset Geographic Revenue (GeoRev) is a data set capturing revenue exposures of global entities to different countries and regions over time. Factset gathers companies' annual reports and regulatory filings to achieve a consistent record. GeoRev covered 20,292 companies in 2009 and 72,606 companies in 2019. Most of these companies are publicly listed, but some are private companies and government institutions.

Not all companies declare their revenue segments at the country level. For this reason, according to the Factset manual, "GeoRev captures data through a proprietary four-level geographic classification structure. An estimation algorithm based on GDP weighting and accounting logic is then applied to solve for non-explicit disclosures." Factset harmonizes heterogeneous declarations of sales distribution across geographies at different levels of aggregation and attaches a "certainty rank" to each value according to whether it was declared directly by the firm, imputed from previous values, or estimated by more aggregate firm-level data.

The main factors used by Factset to assign a certainty rank to each record are:

- Reporting standards of the country where the source annual report/filing was filed
- A company's previous years' country-level reporting
- Reliability of country GDP data
- Proportion of total report value that must be estimated

The exact process for assigning the certainty index is confidential. Nevertheless, the certainty measure enables one to distinguish with varying degrees of confidence between exposures that have been directly declared by the firm and exposures that were imputed. This allows for robustness checks on only highly certain information or the weighting of estimates by certainty level. Table 16 shows the distribution of all the companies covered by GeoRev and the distribution of country-level exposures across different degrees of certainty.

Table 16: Summary Statistics on Coverage and Certainty Index of Factset GeoRev

| Year | # Companies | High | Medium-High | Medium | Medium-Low | Low |
|---|---|---|---|---|---|---|
| *A. All Companies in Georev* | | | | | | |
| 2009 | 20292 | 33% | 20% | 22% | 17% | 7% |
| 2010 | 20305 | 32% | 20% | 23% | 18% | 8% |
| 2011 | 26018 | 32% | 20% | 23% | 18% | 8% |
| 2012 | 35503 | 33% | 19% | 22% | 17% | 8% |
| 2013 | 48441 | 34% | 19% | 23% | 17% | 8% |
| 2014 | 63136 | 34% | 19% | 23% | 17% | 8% |
| 2015 | 67809 | 34% | 18% | 23% | 18% | 8% |
| 2016 | 71328 | 34% | 18% | 23% | 18% | 8% |
| 2017 | 73151 | 33% | 18% | 24% | 18% | 8% |
| 2018 | 74851 | 31% | 18% | 24% | 18% | 8% |
| 2019 | 74527 | 31% | 18% | 24% | 18% | 8% |
| *B. Companies in the Main Sample* | | | | | | |
| 2009 | 12515 | 31% | 21% | 23% | 18% | 7% |
| 2010 | 13437 | 30% | 21% | 23% | 18% | 8% |
| 2011 | 16412 | 30% | 21% | 23% | 18% | 8% |
| 2012 | 18055 | 30% | 21% | 23% | 18% | 8% |
| 2013 | 20054 | 30% | 20% | 23% | 18% | 8% |
| 2014 | 20434 | 30% | 20% | 23% | 18% | 8% |
| 2015 | 20550 | 29% | 20% | 24% | 19% | 8% |
| 2016 | 20509 | 30% | 19% | 24% | 19% | 9% |
| 2017 | 20249 | 28% | 20% | 25% | 19% | 9% |
| 2018 | 19887 | 27% | 20% | 25% | 19% | 9% |
| 2019 | 19372 | 27% | 20% | 25% | 19% | 9% |

*Source*: Author's calculations from Factset GeoRev
*Notes*: This table shows the number of companies in the Factset Geographic Revenue package, with associated percentage of country exposure records with different certainty index (variable *certainty_class*). A high certainty index corresponds to a country-year exposure with certainty class "A," essentially equivalent to a direct report by the company. A medium-high certainty index corresponds to certainty class "B," a record where Factset imputed some missing information with some medium-high confidence. Medium, medium-low, and low certainty correspond to certainty classes "C," "D," and "E." The table is split into certainty statistics in the full Geographic Revenue package and in the sample of companies of this paper.

This measure has two main limitations. First, as mentioned earlier, a large volume of data is imputed, albeit with a medium-high degree of certainty, by the data provider. Together with a measurement-error issue, this imputation does not allow for a serious investigation of the external margin of this channel. Second, this measure does not distinguish between arm's-length foreign sales, sales from subsidiaries, and indirect sales from a region. This limitation further complicates the interpretation of the interaction effect between sales exposure and subsidiary exposure.

## C.4 Cost Exposure

Assume that the matrix $Z_{N\times N}$ contains the global $N$ firms to $N$ firms sales flows. Assume that the vector $S$ with dimensions $N\times 1$ contains the total sales of each company, including sales to final customers. And assume that the matrix $F$ contains each company's sales to final customers only.

$$Z = \begin{bmatrix} Z_{11} & \cdots & Z_{1N} \\ \vdots & \ddots & \vdots \\ Z_{N1} & \cdots & Z_{NN} \end{bmatrix} \qquad S = \begin{bmatrix} S_1 \\ \vdots \\ S_N \end{bmatrix} \qquad F = \begin{bmatrix} F_1 \\ \vdots \\ F_N \end{bmatrix}$$

Then, the following accounting identity holds: $S = Ze + F$, where $e$ is a vector of ones. The *Direct Requirement Matrix* $A$ is defined as $A = Z \cdot \text{Diag}(S)^{-1}$. This is equivalent to dividing each flow $Z_{sc}$ by the total sales of the buying sector, aka customer $c$. $A$ represents the intensity of the buying sector, meaning how much the customer is buying from each firm, as a share of the customer sales/costs.[19]

$$A = \begin{bmatrix} Z_{11}/S_1 & \cdots & Z_{1N}/S_N \\ \vdots & \ddots & \vdots \\ Z_{N1}/S_1 & \cdots & Z_{NN}/S_N \end{bmatrix}$$

$A$ represents the value share of the supplier's $s$ input that goes into \$1 of production of customer $c$.

$$S = A\,S + F \qquad \Rightarrow \qquad S = (I - A)^{-1}F = LF$$

Each *column* $c$ of the Leontief Matrix $L$ in this context represents the complete list of how many sales each firm in the global economy must produce to make possible \$1 of sales of the customer $c$.

As in the subsidiary exposure case, the issue with $L$ is that it is expressed in dollar

[19] Note that for now, we assume that total costs = total sales; that is, the markets are perfectly competitive.

flow nominal terms, which makes it hard to compare to other exposure shares studied in this paper. For this reason, I modify the matrix $L$ to represent the share of value added of the subsidary that is contained in the sales of the customers. Define $V$ as the $N \times 1$ vector of value added of each firm. In this context, I define value added as including all costs different from the purchase of raw materials from other companies (employment, operational, financial costs, etc.) in addition to profits. Then:

$$VA = \text{Diag}(V) \cdot \text{Diag}(S)^{-1} \cdot L.$$

Each column of $VA$ shows the firm-source of value added that is embodied in the sales of the customer (taking into account both direct and indirect sales). Assigning each subsidiary its headquarters country, I can then use $VA$ to obtain the foreign country share of value added embedded in the sales of each company.

Having established the accounting foundation of the value added share matrix, the main issue is that I cannot observe it. I make two main assumptions to argue that I can use the Factset supply chain data set to estimate $VA$. First, the full network of supplier-customer relationship available in Factset is representative of all the main global connections among the firms in the sample. Second, each supplier relationship is equally important to each customer. The latter assumption can be relaxed by weighting each supplier by its total sales or by imputing sales flows across companies (roughly 10 percent of the records do have sales flow information). The latter imputation is currently a work in progress.

Under such assumptions, I can compute from Factset an estimate to the allocation matrix $A$ in the following steps:

- Populate the supply chain directed graph for all $N$ firms included in Factset supply chain $Z^S_{N\times N}$ with 1 when a customer-supplier relation is active, and 0 otherwise.
- Divide each column of $Z^S$ by the total number of suppliers $C^S = Z^S * \text{Diag}(Z^S e)^{-1}$.
- Further rescale each column by the customer's raw-material-to-revenue ratio $R$, proxied by the customer's industry raw-material-to-revenue ratio $A^S = R * C^S = R * Z^S * \text{Diag}(Z^S e)^{-1}$.

The last rescaling implies that total sales $S$ for all companies in Factset are normalized to 1, and therefore we can compute the value added vector $V^S = e - A^S e$. Therefore, $S^{\text{cost}} = VA^S = V^S(I - A^S)^{-1}$. Finally, I multiply $S^{\text{cost}}$ by $H$, a matrix associating each supplier company with its headquarters country.

### C.5 Loan Exposure

I compute loan exposure as follows:

- I use information on 176,027 origination deals signed during the 1994–2019 period and contained in Dealscan. I match the borrower entity identifier of each deal (variable *borrower_rpt_stc_id* ) with a Factset entity identifier. I match the parent of the borrower in each deal (variable *parent_rpt_stc_id*) with a Factset entity identifier. I am able to match 81 percent of the ultimate parents of the borrowers in Dealscan with a Factset entity ID. The matching is achieved while giving the following order of priority to the entity information:

  Legal Entity ID > Ticker > CUSIP number > Fuzzy Name + HQ Country match > Fuzzy Name from CapitalIQ + HQ Country match

  Forty percent of the companies in the sample have at least one syndicated loan that I can match to Dealscan.

- Each deal contains information on the credit line at issuance but not the amount outstanding at any given time. I translate the credit line information to an amount outstanding using the following method:

  1. I assume that all loans have an amortized payment schedule, as most corporate loans do. I apply the following formula:

  $$\text{amount outstanding}_t = \text{amount outstanding}_{t-1}\left(1 - \frac{r_t(r_t+1)^{n_t}}{(1+r_t)^{n_t}-1}\right),$$

     where the original amount outstanding is the dollar amount of the credit line, $n_t$ is the remaining yearly maturity of the line, and $r_t$ is the LIBOR rate plus the spread agreed in the deal. If no information on the spread is available, I assign the spread with a lasso regression estimated on the sample of deals containing the information.

  2. I link the total amount outstanding computed above to the precisely estimated amount outstanding of loans of the ultimate borrowers contained in Factset Debt Capital Structure. Factset does not specify whether outstanding loans are syndicated. However, I use information on the issuance currency of all loans to better match the two sources. If I find that the total amount outstanding computed from Dealscan for a certain currency is higher than the amount outstanding in DCS, I adjust the amount outstanding to align with the DCS

estimates. I do so because I assume that in this case the company must not be using the full syndicated credit line. If I find that the total amount outstanding computed from Dealscan is lower than in DCS, then I assign the residual unaccounted loans in DCS as an exposure to the country of loan currency issuance. Information on syndicated loans takes precedence over information on issuance currency for two reasons. First, Dealscan observes the nationality of the lender directly. Second, syndicated loans represent most of the cross-border borrowing of large public companies. Syndicated loans are highly representative of how large public companies obtain loans (Caglio, Darst and Kalemli-Özcan, 2021).

- Once I have computed and adjusted the amount outstanding to line up with the DCS estimates, I assign the syndicated portion of the loan to the nationality of the ultimate parent of the syndicated lender, according to the credit proportion specified in each deal. Forty percent of the deals do not have information on the exact proportion of credit within the syndicate. For such deals, I use a lasso regression to estimate the percentage of proportion each dealer typically has. Note how I am assuming that borrowers draw proportionally across syndicate lenders. Cerutti, Hale and Minoiu (2015) applies the same assumption and finds correspondence between official Bank for International Settlements (BIS) credit statistics and aggregate syndicated loan data.
- Finally, for any loan amount outstanding that is not linkable to a syndicated loan, I assign the amount outstanding to the country of currency issuance.

# D Additional Tables

Table 17: Summary Financials of Sample Companies in a Balanced and Unbalanced Sample

| Variable | Trim Mean | Trim SD | W. Mean | W. SD | 5% | 25% | 50% | 75% | 95% |
|---|---|---|---|---|---|---|---|---|---|
| | Unbalanced Sample | | | | | | | | |
| EBITDA / Assets | 0.03 | 0.28 | 0.08 | 23.79 | -0.40 | 0.02 | 0.07 | 0.13 | 0.24 |
| Oper. Income / Assets | -0.04 | 0.42 | -0.05 | 77.16 | -0.55 | -0.00 | 0.04 | 0.08 | 0.19 |
| CAPEX / Assets | -0.05 | 0.06 | -0.05 | 4.17 | -0.19 | -0.06 | -0.03 | -0.01 | -0.00 |
| Sales / Assets | 0.80 | 0.65 | 0.64 | 0.93 | 0.03 | 0.29 | 0.69 | 1.14 | 2.20 |
| Debt over Assets | 0.30 | 0.31 | 0.26 | 34.90 | 0.00 | 0.07 | 0.22 | 0.39 | 0.73 |
| Profitability | 0.23 | 0.21 | 0.24 | 5.34 | 0.00 | 0.07 | 0.17 | 0.32 | 0.70 |
| Leverage Ratio | 0.73 | 1.31 | 0.62 | 3703.31 | -0.24 | 0.07 | 0.40 | 0.99 | 3.35 |
| Common Equity Share | 0.97 | 0.08 | 0.97 | 152.69 | 0.77 | 0.98 | 1.00 | 1.00 | 1.00 |
| Excess Return | -0.70 | 51.77 | 13.15 | 35.48 | -103.66 | -27.36 | 2.31 | 29.51 | 88.46 |
| Book to Market | 0.89 | 0.90 | 0.58 | 195.79 | 0.01 | 0.32 | 0.65 | 1.20 | 2.88 |
| Total Assets | 2080.43 | 7109.89 | 176017.32 | 449922.01 | 2.06 | 42.33 | 195.55 | 913.61 | 12399.93 |
| Employees | 3487.00 | 8797.00 | | | 6.00 | 121.00 | 594.00 | 2600.00 | 20000.00 |
| | Balanced Sample | | | | | | | | |
| EBITDA / Assets | 0.08 | 0.10 | 0.07 | 27.47 | -0.08 | 0.04 | 0.08 | 0.13 | 0.23 |
| Oper. Income / Assets | 0.04 | 0.09 | 0.03 | 25.61 | -0.11 | 0.01 | 0.04 | 0.09 | 0.18 |
| CAPEX / Assets | -0.04 | 0.04 | -0.04 | 0.04 | -0.12 | -0.05 | -0.03 | -0.01 | -0.00 |
| Sales / Assets | 0.81 | 0.61 | 0.66 | 0.58 | 0.03 | 0.32 | 0.75 | 1.16 | 2.07 |
| Debt over Assets | 0.24 | 0.18 | 0.25 | 0.86 | 0.00 | 0.07 | 0.20 | 0.35 | 0.59 |
| Profitability | 0.23 | 0.19 | 0.25 | 0.20 | 0.01 | 0.08 | 0.18 | 0.33 | 0.66 |
| Leverage Ratio | 0.78 | 1.14 | 1.37 | 42.10 | 0.00 | 0.12 | 0.45 | 0.99 | 3.19 |
| Common Equity Share | 0.96 | 0.08 | 0.96 | 7.11 | 0.77 | 0.97 | 1.00 | 1.00 | 1.00 |
| Excess Return | 3.88 | 41.85 | 11.23 | 30.21 | -78.01 | -18.25 | 5.67 | 28.57 | 75.76 |
| Book to Market | 1.01 | 0.88 | 0.52 | 237.39 | 0.11 | 0.41 | 0.76 | 1.33 | 3.02 |
| Total Assets | 5430.42 | 17746.72 | 192800.23 | 422623.43 | 21.22 | 145.25 | 540.99 | 2623.02 | 32660.49 |
| Employees | 8026.00 | 19020.00 | | | 31.00 | 336.00 | 1380.00 | 5893.00 | 49310.00 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)

*Notes*: This table shows financial summary statistics of all companies in the sample. I split the sample between balanced and unbalanced. The unbalanced sample is the benchmark sample. The balanced sample is used for robustness tests. The financial information is gathered from Capital IQ. All statistics are computed from a quarter-by-firm panel. Trim Mean and Trim SD drop the top and bottom percentiles of the sample. W. Mean and W. SD stand for weighted mean and weighted standard deviation, respectively, where the weight is the lagged market capitalization of the company. The last five columns of the sample represent different quantiles of the distribution.

Table 18

| # Active Channels | # Firms | Percent Firm | Percent Subsid. | Percent Investor | Percent Debt | Percent Revenue | Percent Cost |
|---|---|---|---|---|---|---|---|
| *A. Foreign Exposure Channel Active if* > 5% | | | | | | | |
| 5.00 | 1021 | 6.5% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% |
| 4.00 | 3123 | 19.9% | 81.1% | 91.9% | 33.5% | 98.6% | 94.9% |
| 3.00 | 6167 | 39.3% | 36.4% | 74.7% | 19.5% | 86.6% | 82.8% |
| 2.00 | 10387 | 66.2% | 8.3% | 54.9% | 6.5% | 58.0% | 72.4% |
| 1.00 | 14165 | 90.3% | 1.2% | 20.7% | 1.5% | 31.7% | 44.9% |
| 0.00 | 15694 | 100.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| *A. Foreign Exposure Channel Active if* > 0% | | | | | | | |
| 5.00 | 1535 | 9.8% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% |
| 4.00 | 4533 | 28.9% | 86.4% | 93.9% | 28.9% | 96.4% | 94.4% |
| 3.00 | 8651 | 55.1% | 32.9% | 89.0% | 12.6% | 87.4% | 78.1% |
| 2.00 | 13029 | 83.0% | 6.1% | 79.4% | 4.5% | 54.0% | 56.1% |
| 1.00 | 15230 | 97.0% | 1.1% | 50.5% | 1.7% | 21.9% | 24.9% |
| 0.00 | 15694 | 100.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows the number and percentage of active foreign exposures for all companies in the main sample. Panel A considers a company to have foreign exposure if the exposure is higher than 5 percent. Panel A considers a company to have foreign exposure if the exposure is higher than 0. Row 5, with the number of active channels being one, reads as follows. There are 14,165 companies in the sample, (equivalent to 90.3 percent) with at least 5% foreign exposure in one of the six channels. Of the companies that have foreign exposure in one channel only, 1.2 percent are exposed through foreign subsidiaries, 20.7 percent are exposed through a foreign investor, 1.5 percent are exposed through debt, 31.7 percent are exposed through foreign revenue, and 44.9 percent are exposed through foreign cost.

Table 19: Importance Coefficients (Shapley Value) of Fixed Effects in Explaining Exposures

| **Fixed Effects** | **Subsidiary** | | **Investors** | | **Revenues** | **Costs** | **Bonds** | **Loans** |
|---|---|---|---|---|---|---|---|---|
| | Empl. W. | Sales W. | Direct | Full | | | | |
| | | | | Balanced Sample | | | | |
| Exp. Country | 0.38 | 0.40 | 0.48 | 0.41 | 0.48 | 0.29 | 0.46 | 0.37 |
| Company ID | 0.35 | 0.35 | 0.17 | 0.33 | 0.19 | 0.33 | 0.28 | 0.19 |
| USA | 0.07 | 0.05 | 0.20 | 0.10 | 0.01 | 0.15 | 0.07 | 0.18 |
| Industry | 0.07 | 0.06 | 0.03 | 0.06 | 0.04 | 0.08 | 0.06 | 0.04 |
| Year | 0.04 | 0.05 | 0.02 | 0.00 | 0.08 | 0.05 | 0.06 | 0.16 |
| Eurozone | 0.04 | 0.06 | 0.04 | 0.04 | 0.13 | 0.03 | 0.03 | 0.02 |
| HQ Country | 0.04 | 0.03 | 0.05 | 0.06 | 0.07 | 0.06 | 0.05 | 0.03 |
| | | | | Unbalanced Sample | | | | |
| Company ID | 0.44 | 0.40 | 0.25 | 0.44 | 0.30 | 0.43 | 0.36 | 0.33 |
| Exp. Country | 0.37 | 0.38 | 0.45 | 0.39 | 0.41 | 0.27 | 0.45 | 0.34 |
| USA | 0.05 | 0.05 | 0.18 | 0.06 | 0.01 | 0.13 | 0.04 | 0.10 |
| Industry | 0.04 | 0.04 | 0.02 | 0.03 | 0.04 | 0.05 | 0.04 | 0.03 |
| Year | 0.04 | 0.03 | 0.01 | 0.01 | 0.07 | 0.04 | 0.05 | 0.15 |
| HQ Country | 0.04 | 0.03 | 0.05 | 0.04 | 0.07 | 0.05 | 0.04 | 0.03 |
| Eurozone | 0.03 | 0.05 | 0.04 | 0.03 | 0.09 | 0.02 | 0.02 | 0.02 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows the relative importance coefficients of various fixed effects combinations computed from Shapley value regressions (Lipovetsky and Conklin, 2001). In contrast to Table 2, this table separates the effects of the US and eurozone fixed effects from the country of exposure fixed effetcs.

Table 20: How Exposures Explain Beta Loadings on Investor Country Portfolios, Including Investor Exposure in the Model

| Dependent Variable: | | | | Betas | | | |
|---|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Variables* | | | | | | | |
| Subsid | 0.5724*** | | | | | 0.0732*** | 0.1599*** |
| | (0.0051) | | | | | (0.0140) | (0.0238) |
| Investors | | 0.9189*** | | | | 0.4066*** | 0.2346*** |
| | | (0.0078) | | | | (0.0182) | (0.0267) |
| Debt | | | 0.5708*** | | | 0.1386*** | 0.2012*** |
| | | | (0.0050) | | | (0.0143) | (0.0293) |
| Revenue | | | | 0.6257*** | | 0.0752*** | 0.1251*** |
| | | | | (0.0060) | | (0.0123) | (0.0198) |
| Cost | | | | | 0.6869*** | 0.1410*** | 0.1019*** |
| | | | | | (0.0061) | (0.0158) | (0.0261) |
| Subsid × Investors | | | | | | | 0.0514 |
| | | | | | | | (0.0728) |
| Subsid × Debt | | | | | | | 0.0393 |
| | | | | | | | (0.0467) |
| Subsid × Revenue | | | | | | | -0.1230*** |
| | | | | | | | (0.0436) |
| Subsid × Cost | | | | | | | -0.2050*** |
| | | | | | | | (0.0593) |
| Investors × Debt | | | | | | | -0.0652 |
| | | | | | | | (0.0656) |
| Investors × Revenue | | | | | | | 0.0725 |
| | | | | | | | (0.0607) |
| Investors × Cost | | | | | | | 0.4123*** |
| | | | | | | | (0.0785) |
| Debt × Revenue | | | | | | | -0.0908* |
| | | | | | | | (0.0470) |
| Debt × Cost | | | | | | | -0.0658 |
| | | | | | | | (0.0558) |
| Revenue × Cost | | | | | | | 0.0767 |
| | | | | | | | (0.0572) |
| *Fixed-effects* | | | | | | | |
| companyid | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | |
| Observations | 221,281 | 221,281 | 221,281 | 221,281 | 221,281 | 221,281 | 221,281 |
| $R^2$ | 0.11477 | 0.11937 | 0.11727 | 0.10760 | 0.11599 | 0.12719 | 0.12808 |
| Within $R^2$ | 0.07799 | 0.08278 | 0.08059 | 0.07052 | 0.07925 | 0.09092 | 0.09185 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows how different country-channel exposure shares explain the cross section of returns beta loadings on country-specific portfolios. In the first stage, I estimate firm-specific betas on all country-specific portfolio returns. The country-specific portfolio returns of a location $l$ include all firms whose main investor share is in $l$. In the second stage, I estimates how each firm's country-channel exposure share explains the beta loadings in a firm-by-country panel with firm and country fixed effects. In contrast to Table 9, this table includes investor exposure as an explanatory variable, for robustness purposes.

Table 21: How Channels of Exposure Explain Cross-sectional Country Return $\beta_{il}$'s
$\beta_{il}$ Computed with Firm and Industry-Time Fixed Effects

| Dependent Variable: | Betas | | | | | |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| Subsid | 0.5218*** | | | | 0.0766 | 0.2187*** |
| | (0.0249) | | | | (0.0525) | (0.0644) |
| Debt | | 0.5256*** | | | 0.1683*** | 0.2017*** |
| | | (0.0243) | | | (0.0390) | (0.0731) |
| Revenue | | | 0.6095*** | | 0.1038** | 0.0973 |
| | | | (0.0228) | | (0.0487) | (0.0817) |
| Cost | | | | 0.7279*** | 0.3650*** | 0.2181*** |
| | | | | (0.0250) | (0.0592) | (0.0810) |
| Subsid × Debt | | | | | | -0.2185 |
| | | | | | | (0.1330) |
| Subsid × Revenue | | | | | | -0.0043 |
| | | | | | | (0.1308) |
| Subsid × Cost | | | | | | -0.1940 |
| | | | | | | (0.1782) |
| Debt × Revenue | | | | | | -0.2083* |
| | | | | | | (0.1123) |
| Debt × Cost | | | | | | 0.3493** |
| | | | | | | (0.1567) |
| Revenue × Cost | | | | | | 0.2787 |
| | | | | | | (0.2028) |
| *Fixed-effects* | | | | | | |
| companyid | Yes | Yes | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 219,113 | 219,113 | 219,113 | 219,113 | 219,113 | 219,113 |
| $R^2$ | 0.12628 | 0.13126 | 0.12381 | 0.13953 | 0.14401 | 0.14559 |
| Within $R^2$ | 0.07567 | 0.08094 | 0.07306 | 0.08969 | 0.09443 | 0.09610 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows how different country-channel exposure shares explain the cross section of returns beta loadings on country-specific portfolios. In the first stage, I estimate firm-specific betas on all country-specific portfolio returns. The country-specific portfolio returns of a location $l$ include all firms whose main investor share is in $l$. In the second stage, I estimate how each firm's country-channel exposure share explains the beta loadings in a firm-by-country panel with firm and country fixed effects. In contrast to Table 9, this table includes industry-time fixed effects in the first stage.

Table 22: Robustness to Alternative Exposure Channel Measures in Explaining Cross-sectional $\beta_{il}$'s

| Dependent Variable: | Betas | | | |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Subsid | 0.2059*** | | | 0.2051*** |
| | (0.0237) | | | (0.0374) |
| Debt | 0.2507*** | 0.2434*** | 0.3071*** | 0.1585*** |
| | (0.0284) | (0.0281) | (0.0299) | (0.0417) |
| Revenue | 0.1604*** | 0.1801*** | 0.2479*** | |
| | (0.0194) | (0.0205) | (0.0253) | |
| Cost | 0.2121*** | 0.2187*** | 0.2762*** | 0.1943*** |
| | (0.0256) | (0.0249) | (0.0288) | (0.0370) |
| Subsid × Debt | 0.0094 | | | 0.0439 |
| | (0.0398) | | | (0.0594) |
| Subsid × Revenue | -0.1211*** | | | |
| | (0.0430) | | | |
| Subsid × Cost | -0.1290** | | | -0.1157 |
| | (0.0512) | | | (0.0737) |
| Debt × Revenue | -0.1057** | -0.0578 | -0.0796 | |
| | (0.0440) | (0.0494) | (0.0533) | |
| Debt × Cost | 0.0060 | -0.0193 | -0.0504 | -0.0113 |
| | (0.0444) | (0.0459) | (0.0451) | (0.0658) |
| Revenue × Cost | 0.1891*** | 0.2518*** | 0.0546 | |
| | (0.0555) | (0.0647) | (0.0687) | |
| Subsid_Count | | 0.2475*** | | |
| | | (0.0259) | | |
| Subsid_Count × Debt | | 0.0263 | | |
| | | (0.0571) | | |
| Subsid_Count × Revenue | | -0.2717*** | | |
| | | (0.0523) | | |
| Subsid_Count × Cost | | -0.1524** | | |
| | | (0.0689) | | |
| Subsid_Sales_Weight | | | 0.0441*** | |
| | | | (0.0152) | |
| Subsid_Sales_Weight × Debt | | | -0.0218 | |
| | | | (0.0455) | |
| Subsid_Sales_Weight × Revenue | | | -0.0969** | |
| | | | (0.0394) | |
| Subsid_Sales_Weight × Cost | | | 0.0080 | |
| | | | (0.0581) | |
| Revenue_no_impute | | | | 0.1244*** |
| | | | | (0.0251) |
| Revenue_no_impute × Subsid | | | | -0.1025* |
| | | | | (0.0576) |
| Revenue_no_impute × Debt | | | | -0.0579 |
| | | | | (0.0584) |
| Revenue_no_impute × Cost | | | | 0.2110*** |
| | | | | (0.0763) |
| *Fixed-effects* | | | | |
| companyid | Yes | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 221,281 | 227,734 | 146,784 | 124,949 |
| $R^2$ | 0.12376 | 0.12095 | 0.13811 | 0.11949 |
| Within $R^2$ | 0.08735 | 0.08492 | 0.09397 | 0.08358 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows how different country-channel exposure shares explain the cross section of returns beta loadings on country-specific portfolios. In the first stage, I estimate firm-specific betas on all country-specific portfolio returns. The country-specific portfolio returns of a location $l$ include all firms whose main investor share is in $l$. In the second stage, I estimates how each firm's country-channel exposure share explains the betas loadings in a firm-by-country panel with firm and country fixed effects. In contrast to Table 9, this table includes several specifications in which alternative measures of exposure presented in Appendix C are used instead of the benchmark measures.

## Table 23: Robustness to Alternative Exposure Channel Measures in Explaining Cross-sectional $\beta_{il}$'s

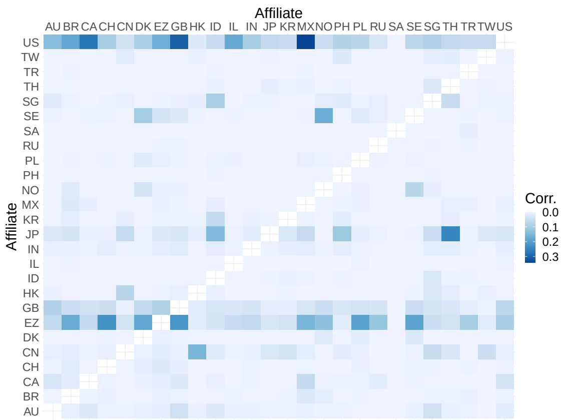
| Dependent Variable: | | Betas | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| Cost_count | 0.0586*** | | |
| | (0.0136) | | |
| Subsid | 0.2586*** | 0.1915*** | 0.2074*** |
| | (0.0227) | (0.0225) | (0.0234) |
| Debt | 0.3187*** | 0.1394*** | |
| | (0.0260) | (0.0302) | |
| Revenue | 0.1823*** | 0.1652*** | 0.1459*** |
| | (0.0225) | (0.0154) | (0.0194) |
| Cost_count × Subsid | 0.0355 | | |
| | (0.0523) | | |
| Cost_count × Debt | -0.0071 | | |
| | (0.0457) | | |
| Cost_count × Revenue | 0.0901** | | |
| | (0.0379) | | |
| Subsid × Debt | -0.0791** | 0.1985*** | |
| | (0.0355) | (0.0452) | |
| Subsid × Revenue | -0.1498*** | -0.2127*** | -0.2288*** |
| | (0.0473) | (0.0429) | (0.0439) |
| Debt × Revenue | -0.0197 | -0.1371*** | |
| | (0.0469) | (0.0422) | |
| IO_cost | | 0.4039*** | |
| | | (0.0390) | |
| IO_cost × Subsid | | -0.3349*** | |
| | | (0.0513) | |
| IO_cost × Debt | | -0.1017** | |
| | | (0.0448) | |
| IO_cost × Revenue | | 0.2776*** | |
| | | (0.0587) | |
| Debt_DCS_Curr | | | 0.1326*** |
| | | | (0.0256) |
| Cost | | | 0.2128*** |
| | | | (0.0248) |
| Debt_DCS_Curr × Subsid | | | 0.1184*** |
| | | | (0.0386) |
| Debt_DCS_Curr × Revenue | | | 0.0831* |
| | | | (0.0435) |
| Debt_DCS_Curr × Cost | | | 0.1620*** |
| | | | (0.0445) |
| Subsid × Cost | | | -0.2053*** |
| | | | (0.0471) |
| Revenue × Cost | | | 0.0422 |
| | | | (0.0575) |
| *Fixed-effects* | | | |
| companyid | Yes | Yes | Yes |
| iso_country | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 176,691 | 285,247 | 223,757 |
| $R^2$ | 0.12312 | 0.10915 | 0.12383 |
| Within $R^2$ | 0.08884 | 0.07234 | 0.08821 |

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: This table shows how different country-channel exposure shares explain the cross section of returns beta loadings on country-specific portfolios. In the first stage, I estimate firm-specific betas on all country-specific portfolio returns. The country-specific portfolio returns of a location $l$ include all firms whose main investor share is in $l$. In the second stage, I estimates how each firm's country-channel exposure share explains the betas loadings in a firm-by-country panel with firm and country fixed effects. In contrast to Table 9, this table includes several specifications in which alternative measures of exposure presented in Appendix C are used instead of the benchmark measures.

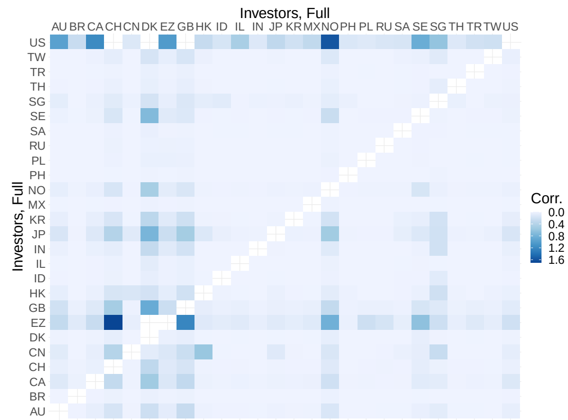
# E Additional Figures

Figure 3: Cross-country Correlations within Channel

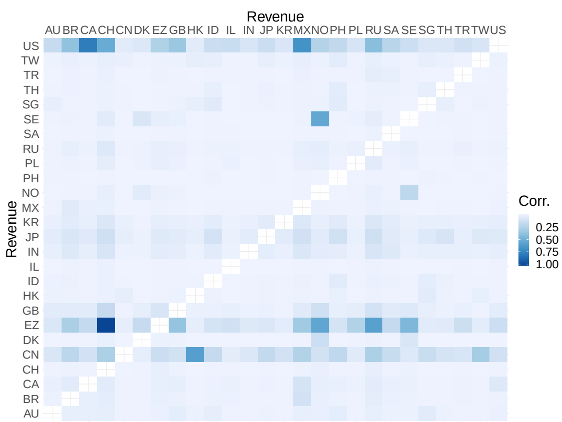
(a) Subsidiaries



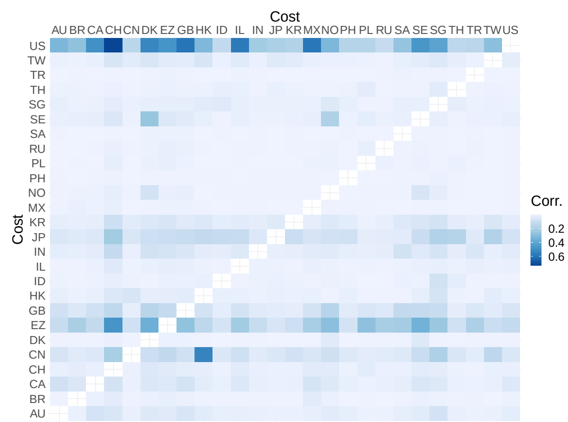

(b) Investors



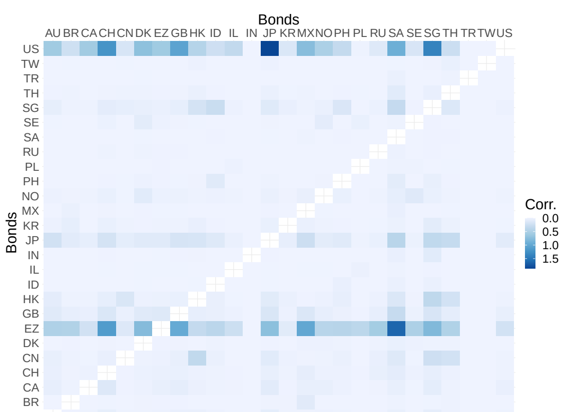

(c) Revenues



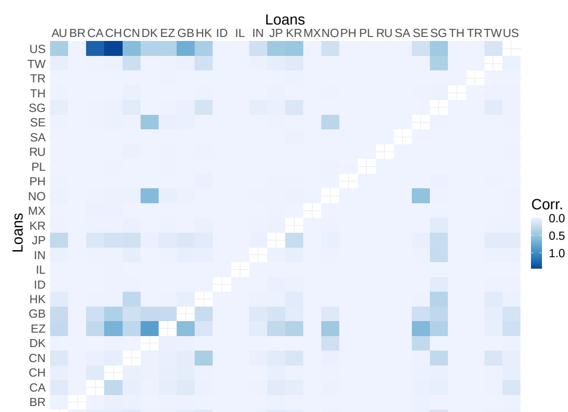

(d) Costs




(e) Bonds



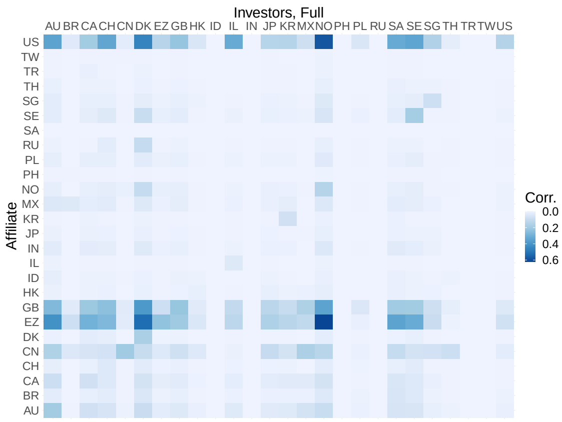

(f) Loans



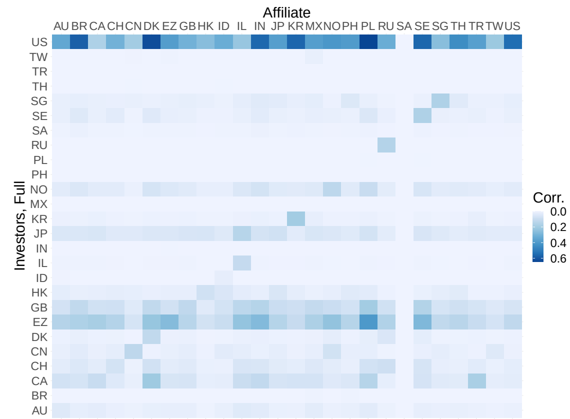

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: Each cell of these panels represents the correlation between a foreign exposure in the x-axis country-channel combination and the y-axis country-channel combination, conditional on the x-axis exposure being nonzero.

Figure 4: Cross-country Correlation across Channels

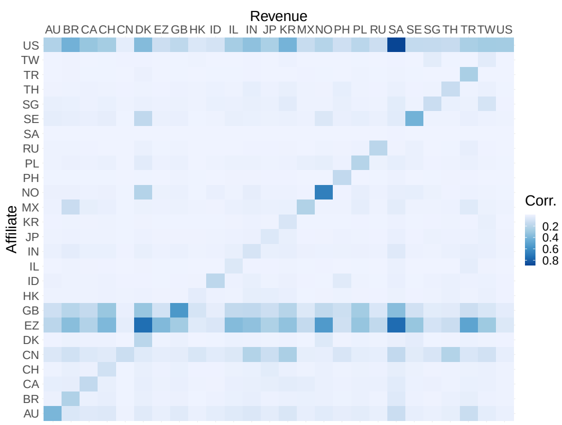
(a) Subsidiaries on Investors



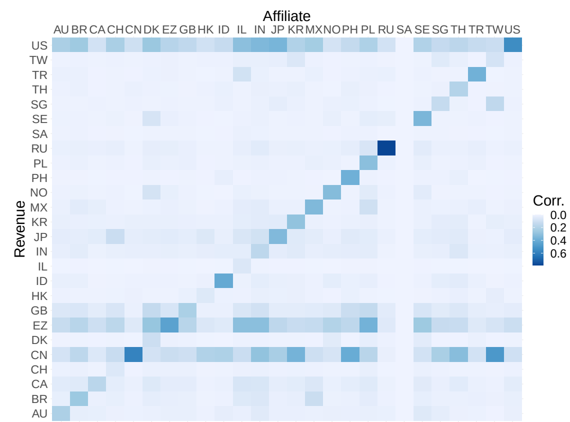

(b) Investors on Subsidiaries



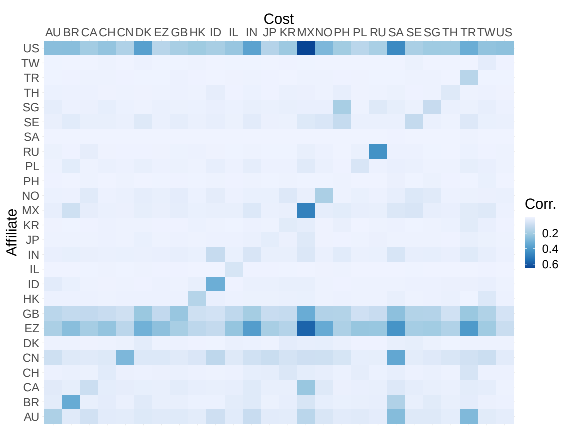

(c) Subsidiaries on Revenue



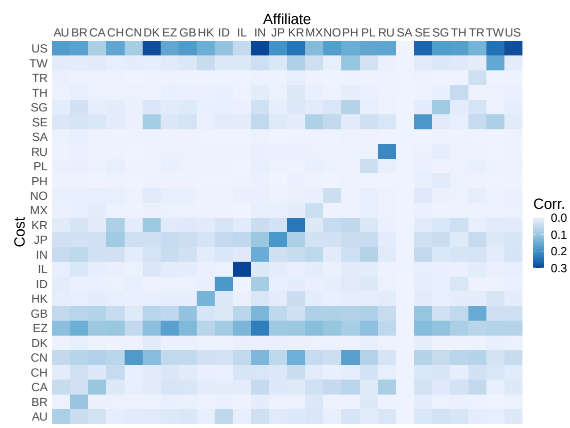

(d) Revenue on Subsidiaries




(e) Subsidiaries on Costs



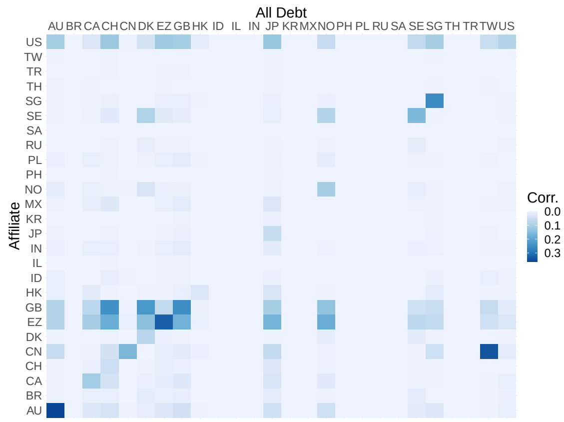

(f) Costs on Subsidiaries



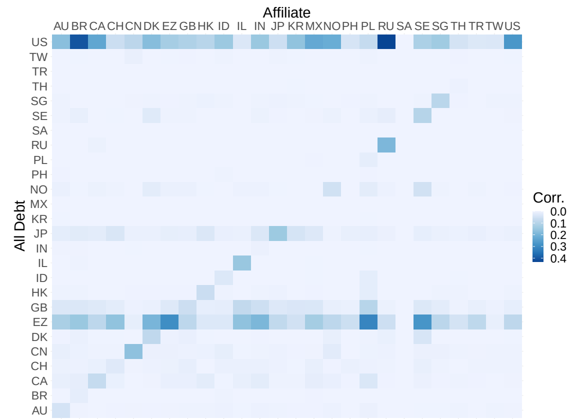

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: Each cell of these panels represents the correlation between a foreign exposure in the x-axis country-channel combination and the y-axis country-channel combination, conditional on the x-axis exposure being nonzero.

Figure 5: Cross-country Correlation across Channels

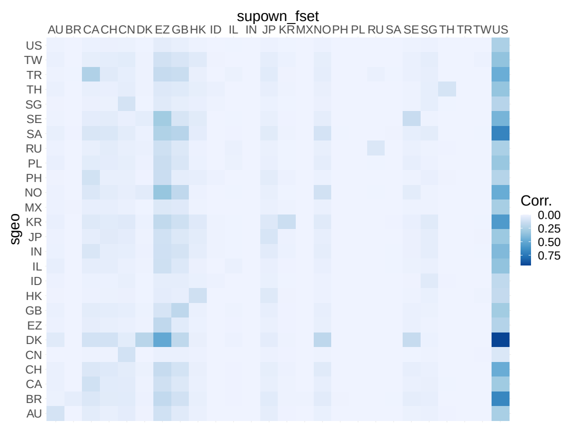
(a) Subsidiaries on Debt



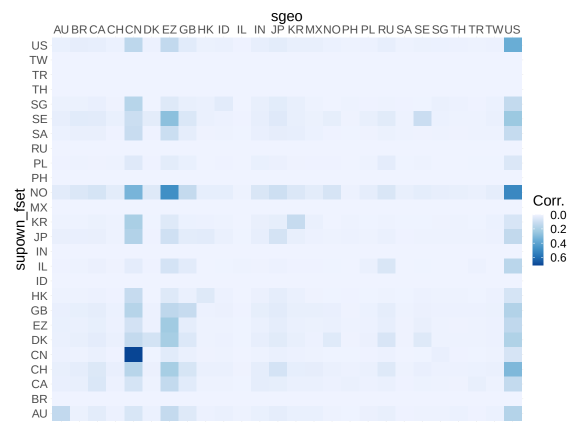

(b) Debt on Subsidiaries



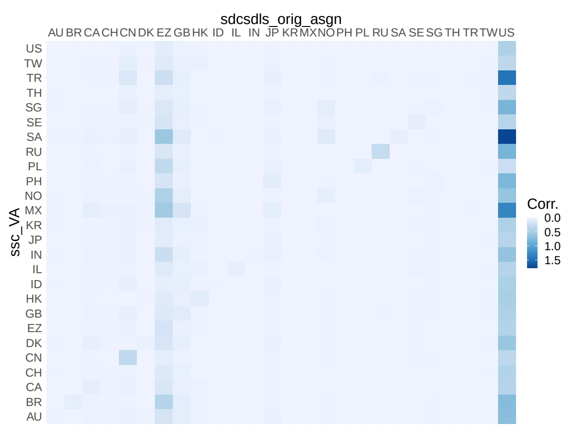

(c) Investor on Revenue



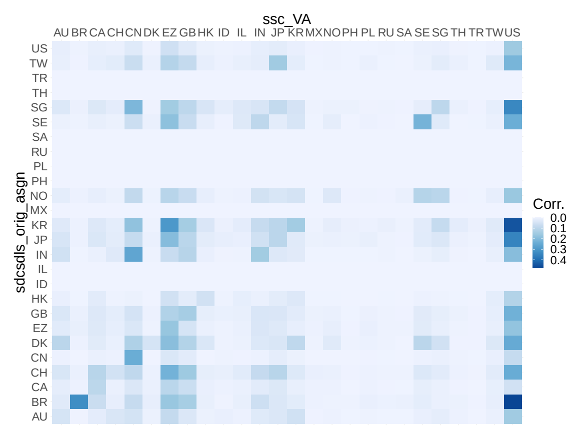

(d) Revenue on Investor




(e) Debt on Costs



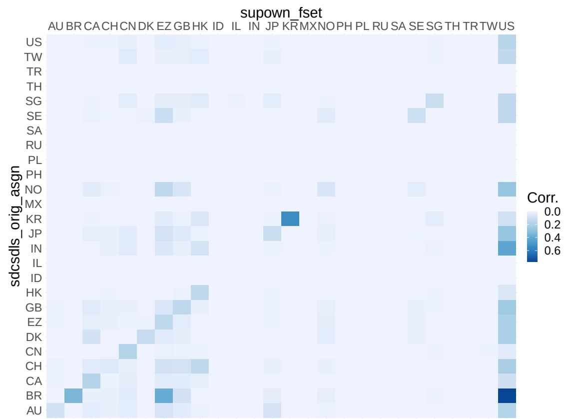

(f) Costs on Debt



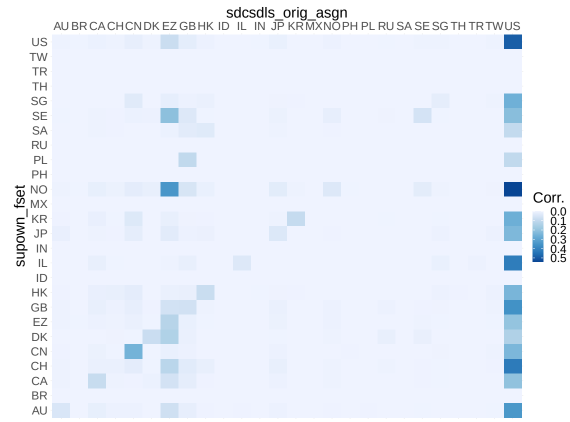

*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: Each cell of these panels represents the correlation between a foreign exposure in the x-axis country-channel combination and the y-axis country-channel combination, conditional on the x-axis exposure being nonzero.

Figure 6: Cross-country Correlation across Channels

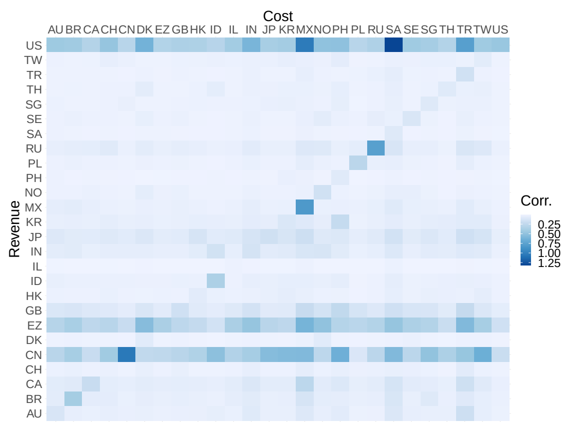
(a) Investors on Debt



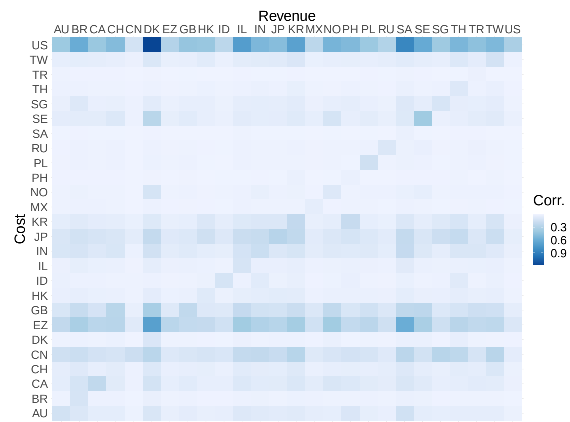

(b) Debt on Investors



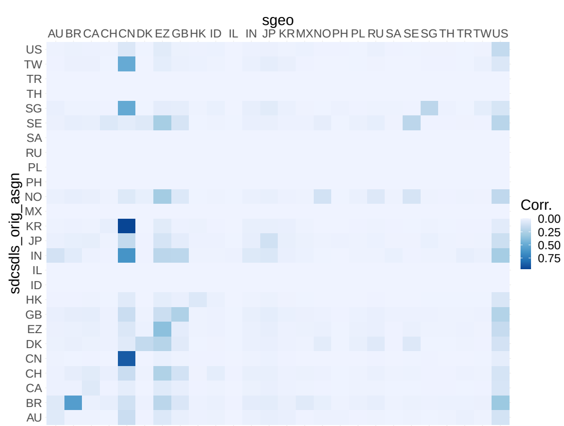

(c) Revenue on Costs



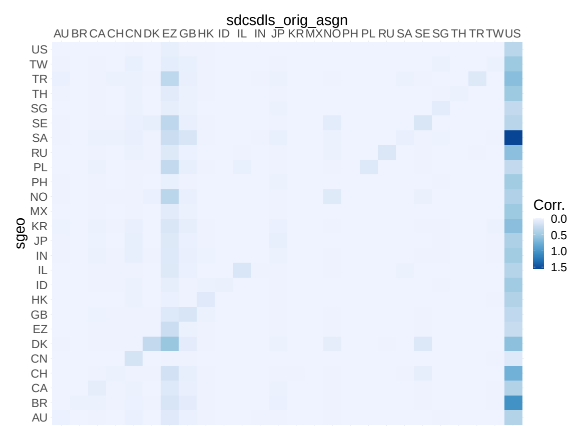

(d) Costs on Revenues




(e) Revenue on Debt




(f) Debt on Revenue




*Source*: Author's calculations from Factset, Capital IQ, OECD, IMF, BIS, and Coppola et al. (2021)
*Notes*: Each cell of these panels represents the correlation between a foreign exposure in the x-axis country-channel combination and the y-axis country-channel combination, conditional on the x-axis exposure being nonzero.