The Channels of International Comovement

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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 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 stock 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 affect foreign subsidiaries. However, financing and trade connections form a complex and correlated network. This complicates efforts to establish causality and the relative importance of transmission mechanisms using aggregate data. 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 their activities to international markets. I use detailed firm-to-firm and firm-to-market data sets to explore the average relative importance of trade, debt financing, and equity linkages in determining cash flows and return comovement. I gather novel facts about how these exposures are determined across firms and how they interact to dampen excess dependence on foreign countries.

I study simultaneous connections through foreign investors, subsidiaries, debt financing, costs, and revenues. Fifthy-eight percent of listed companies are exposed to foreign markets through at least three of these channels at the same time. A company with an active exposure towards a particular country is likely to have several other kinds of exposures in the very same country. In other words, companies match equity, debt, and operations to be related to the same market. 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.

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. (2020). 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 affiliates, investors, revenue, cost, bond, 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.

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 minimize ad-hoc assumptions. But this also means that the measured exposures do not always allow a disaggregation into detailed economic channels. For example, geographic revenues aggregate arm's length and affiliates trade, as this is how official company's reports segment revenue estimates. Outstanding bond obligations issued in foreign currency are assumed to be held by the nationals of the currency's country (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 each subsidiary. Nevertheless, several emerging patterns align with economic theory and aggregate macroeconomic flows.

I provide a battery of stylized facts related to the exposure patterns of multinationals in my sample. The average degree of home bias is high across all channels. Nevertheless, only 8 percent of large listed companies have no strong ties with some foreign market through at least one exposure channel. Forty percent have strong ties with foreign markets through at least three channels, and 20 percent through at least four. The most globally integrated flows are equity investment and revenues. 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 predicting other kinds of exposure.

In the last part of the paper, I study return and cash flow comovement. Based on evidence drawn from the harmonized micro-level data and aggregate patterns, I make the crucial 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 multi-factor CAPM model, including loadings on the market returns of all countries in the sample. Besides enabling a study of all channels, this CAPM method improves on previous studies because the market portfolio returns are computed according to my new measure of investor exposure rather than referring only to the country of headquarters, exchange, or incorporation. I verify that returns 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 countries in many ways 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 single 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. All these findings are unconditional and may change depending on any particular shock.

The contributions of this paper are three. First, it measures and harmonizes six different channels of foreign-country exposure at the firm level: investors, affiliates, bond and loan holders, revenue, and cost. I provide careful details on the methodology and data harmonization assumptions. Second, I provide evidence on novel stylized facts, including how the exposure channels positively correlate to each other, predict 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 identification. I can study the contribution of any single channel, controlling for all others, conditional on firm- and industry-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 for robustness tests. Section **??** concludes.

2 Literature

This paper relates to several branches of macro-finance research. One branch looks at the consequences of globalization on stock return comovements. The main scope of this literature is to measure how stock market comovement evolves as goods markets become more integrated over time (Forbes and Rigobon, 2002; Bekaert et al., 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." Auer et al. (2022) emphasizes how accounting for the contribution to the value added in global input-output structures shows a strong link between equity markets and global value chain integration. While my paper also studies returns comovements, it focuses on the impact of several exposure channels, on both the real and financial side. 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 et al. (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 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 et al. (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 an active literature studying the transmission of specific country shocks to foreign and domestic companies. Hassan et al. (2021) focuses on the importance of foreign country shocks in explaining returns and real effects on multinational firms. The focus of Hassan et al. (2021) 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, but the mechanism depends on the nature of the event. di Giovanni and Hale (2020) use a spatial regression model to quantify the foreign spillovers of United States monetary policy through the trade network. Boehm et al. (2019) shows how the supply disruption due to the 2011 Tōhoku earthquake in Japan spilled over through firm-to-firm production linkages. Miranda-Agrippino and Rey (2020) show how monetary contractions in the United States lead to significant deleveraging of global financial intermediaries and tightening of foreign financial conditions. Kalemli-Ozcan et al. (2013) show that legislative-regulatory harmonization in financial services is associated with less synchronized output cycles. Ivashina et al. (2015) shows that shocks in credit conditions of eurozone banks affect lending conditions in the US. Cravino and Levchenko (2016) shows that a 10% growth in the sales of the headquarter is associated with a 2% growth in the sales of the affiliate. Bena et al. (2022) shows that investment is 18% lower in subsidiaries of parents experiencing a downturn.

Many papers find evidence of operational hedges implemented by multinational companies (Alfaro et al., 2021; Hoberg and Moon, 2017; Colacito et al., 2021). However, these papers typically study a hedge between only two channels of exposure, and they focus primarily on nominal hedging through FX derivatives markets.

Finally, Lane and Milesi-Ferretti (2008), Coppola et al. (2020), and Maggiori et al. (2020) are examples of recent papers in the international macroeconomic literature that have significant 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 within the boundaries of the firm.

3 Data Sources and Harmonization of Country Exposures

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 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.[1] 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

[1] When an M&A occurs, one or both entity IDs may be discontinued and registered as extinct subsidiaries of a new entity.

country of incorporation or legal offices.[2]

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).[3]

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.[4] 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:

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

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 mid-term 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.

[2] Multinationals sometimes register their companies in tax haven countries for purposes of tax advantage (Coppola et al., 2020; Wier and Zucman, 2022).

[3] The entity coverage changes substantially in relation to the financial variable used as weight. This is because the full network of entities contains mostly private companies with poorer reporting standards. The Capital IQ data set contains information on private companies too, but it has no information on the size of a large number of subsidiaries in the network. 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.

[4] M varies from 3.1 millions in 2009 to 8 millions in 2019.

3.2 Investors 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 assign to each entity in the sample the equity holders and investors of each company's ultimate parent. The country of each investor corresponds to the headquarters country designated by Factset when available, otherwise the country is designated by Capital IQ.

There are several data limitations to this variable that require careful evaluation.[5] 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, when a time series of investor data is available, the share of investors by nationality remained persistent. Second, the exact percentage of ownership of all minority shareholders is not always available or fully accountable. For this reason I build two alternative measures of investor exposure. There are two main versions of investor exposure.

- **Direct Investor Exposure**: The unclaimed ownership share is assigned to the main country of exchange of the equity security. In most cases, the main investor share corresponds to the country of exchange of the equity issuance, which in turn corresponds to the headquarters country.

- **Full Investor Exposure**: The unclaimed ownership share is assigned to the headquarters country and then multiplied by the corresponding share of investors in the aggregate equity flows matrices created by Coppola et al. (2020). The disadvantage of this approach is that the latter restated matrices are at only the country-by-country level. However, since Coppola et al. (2020) links micro-level 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. Coppola et al. (2020) improves official IMF CPIS statistics, which, by construction, over-represent exposure to tax-haven countries.

3.3 Revenue Exposure

The Factset Geographic Revenue (GeoRev) data set captures revenue exposures of global entities to different countries/regions over time. Factset exploits annual reports and reg-

[5] Appendix C.2 explains in detail the methodology, limitations, and robustness tests.

ulatory 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, 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. I use the country-level disaggregation as benchmark, and I use the certainty index information to test the estimates’ robustness. The appendix shows the sensitivity tests to geographic revenue uncertainty.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 dataset is not well-suited to study the extensive margin of foreign-revenue exposure as 70% of the country-level records has some degree of imputation, even though most of them are associated with a high-to-medium degree of certainty.

3.4 Cost Exposure

I use two complementary data sets to proxy for cost exposure across countries. I use the Factset Supply Chain package and the OECD ICIO input-output tables.

3.4.1 Supply Chain Costs

Factset Supply Chain, also called FactSet Revere, collects and verifies supply chain relationship information using various sources: 10-K filings, conference call transcripts, presentations to investors, 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 of customer-supplier relationships, competitors, joint ventures, creditors, and other factors that were in effect on any given date from 2003 to 2023.

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. 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. Each cell of A^S represents the raw materials to revenue ratio divided by each customer’s total number of suppliers. Similarly to the formula for the affiliate shares, the cost exposure, accounting for both direct and indirect exposure, is then computed as:

$$S^{\text{cost}} = S^C (I - A^S)^{-1} \cdot H,$$

where $S^C = e - A^S e$ represents the value added and other costs over the revenue share of each customer. I also compute simpler, more direct measures of cost exposure by counting the number of unique entities with which the customer has a relation or by weighting each association by the size of the supplier's sales. 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.

3.4.2 IO Industry Costs

To account for direct and indirect cost exposures common to an entire industry, I combine information from the OECD input-output 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 input-output tables. Each column of the value-added matrix represents the decomposition of a specific country-industry pair output by the country-industry origin of value added. Therefore, I can evaluate each country's relative importance in determining an entity's costs by assigning each share of value-added source 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 country-industry pair.

3.5 Debt Exposure

Debt exposure is split between bond and loan exposure. Later in the paper, I aggregate the two into total debt exposure whenever the estimation requires more parsimonious measures of exposure. Total debt exposure weights bond and loans exposure by their relative weights in total debt outstanding from Factset Debt Capital Structure.

3.5.1 Bond Exposure

To compute bond exposures, I use Factset Debt Capital Structure (DCS) and aggregate information on bond holdings from Coppola et al. (2020) and Maggiori et al. (2020). Factset DCS provides summary and detailed information on the debt structure of nearly 40,000 reporting entities. 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 et al. (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 account for issuance currency, they find that "knowledge of the issuer's nationality offers very little additional information for predicting the investor's nationality" page(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 issued in dollars by the holder countries' shares in the restated bond holdings capital flows matrix of Coppola et al. (2020) corresponding 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 the robustness and appendix section, 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 Debt Capital Structure (DCS) and Dealscan to compute loan exposure. The Loan Pricing Corporation's (LPC) Dealscan database 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 by borrowing and lender country.

Approximately one-third of total cross-border lending is in the form of a syndicated loan (Cerutti et al., 2015). Moreover, syndicated loans represent the most common way large public companies receive loans (Caglio et al., 2021). 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. If not available, I impute the credit proportion of each lender according to an estimation available in appendix C.5. I use the loan issuance currency to link the outstanding syndicated credit to the total loans outstanding amount from Factset DCS. I do so because the information on the credit line of each syndicated loan does not necessarily reflect usage rates. The value of loans outstanding from DCS help to discipline cases in which the usage rate is low. I assign any residual outstanding credit not accounted by syndicated loans to the country of the issuance currency, following the same methodology to compute bond exposure. I assign the estimated syndicated loans outstanding as an exposure to the country of the ultimate parent of the lender.

4 Descriptive Statistics

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 non-financial entities for which data are available in all Factset, Capital IQ, and Dealscan data sets 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. Therefore, all companies are at the "top" of their ownership hierarchy but are not necessarily ultimate parents. The sample covers, on average, 33 percent of all currently active non-financial public companies worldwide and 77 percent of the corresponding global market value. Table 17 in the appendix shows the financial characteristics of the firms in the sample. As in other papers focusing on listed companies (Bekaert et al., 2009; di Giovanni and Hale, 2020), listed companies generally have sound financials and high liquidity buffers. They also tend to have higher levels of investment and profitability. The large majority purchase and sell goods in international markets.

Table 1 shows the number of companies covered by headquarters country and each channel's average foreign country of exposure. This is an average over a year-by-company sample. Foreign exposure is defined as 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.[6]

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

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

HQ Country	# Companies	Affiliates Empl.	Affiliates Sales W.	Investors Direct	Investors Full	Revenues	Costs	IO Costs	Bonds	Loans
United States	6442	0.07	0.17	0.11	0.31	0.25	0.11	0.06	0.20	0.04
China	4104	0.01	0.05	0.08	0.33	0.16	0.07	0.01	0.02	0.06
Japan	3409	0.06	0.14	0.09	0.31	0.15	0.10	0.08	0.00	0.00
Euro Zone	2766	0.12	0.19	0.18	0.57	0.36	0.16	0.11	0.03	0.10
India	2617	0.03	0.09	0.08	0.29	0.17	0.05	0.10	0.01	0.02
Canada	2075	0.10	0.15	0.21	0.55	0.60	0.12	0.15	0.07	0.22
South Korea	1976	0.05	0.09	0.05	0.30	0.24	0.09	0.17	0.01	0.01
Taiwan	1401	0.08	0.15	0.07	0.46	0.53	0.12	0.24	0.02	0.02
Hong Kong SAR China	1327	0.10	0.16	0.27	0.47	0.70	0.12	0.16	0.09	0.25
Australia	1323	0.05	0.07	0.25	0.80	0.43	0.11	0.08	0.08	0.09
United Kingdom	1210	0.16	0.22	0.41	0.77	0.49	0.19	0.13	0.11	0.22
Singapore	553	0.14	0.15	0.20	0.52	0.55	0.11	0.28	0.06	0.25
Sweden	549	0.19	0.29	0.21	0.59	0.49	0.15	0.16	0.05	0.07
Thailand	545	0.02	0.04	0.13	0.32	0.15	0.08	0.20	0.01	0.03
Others	482	0.05	0.07	0.19	0.60	0.15	0.12	0.06	0.16	0.22
Indonesia	459	0.00	0.03	0.18	0.44	0.11	0.14	0.08	0.09	0.19
Israel	389	0.09	0.17	0.17	0.47	0.41	0.16	0.13	0.03	0.30
Poland	343	0.03	0.08	0.26	0.42	0.22	0.09	0.20	0.04	0.03
Brazil	301	0.04	0.12	0.22	0.43	0.13	0.17	0.07	0.05	0.09
Switzerland	273	0.27	0.50	0.26	0.71	0.63	0.23	0.21	0.12	0.22
Russia	263	0.04	0.09	0.13	0.38	0.12	0.15	0.09	0.05	0.16
Turkey	258	0.01	0.04	0.13	0.38	0.18	0.09	0.11	0.06	0.08
Norway	216	0.14	0.28	0.27	0.49	0.51	0.19	0.16	0.06	0.23
Denmark	162	0.18	0.30	0.19	0.87	0.53	0.17	0.18	0.12	0.20
Philippines	150	0.03	0.06	0.14	0.30	0.11	0.14	0.11	0.04	0.11
Mexico	126	0.07	0.15	0.19	0.40	0.19	0.24	0.01	0.23	0.18
Saudi Arabia	122	0.04	0.08	0.05	0.07	0.17	0.18	0.10	0.02	0.03

Source: Author's calculations from Factset, Capital IQ, OECD, BIS, and Coppola et al. (2020)
Notes: This table shows the number of companies in the sample and the average foreign-country exposure, by headquarters country. The headquarters country is assigned by Factset according to the location of senior managers. Foreign exposure is the sum of all non-headquarters exposure country. The average is over a year-by-company sample. The details on the construction of each exposure channel measure are in section 3

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. (2020).

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 the 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? There answer is because 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 only includes 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

What determines exposure to different countries for any given channel? Are firms highly heterogeneous in their exposure levels? Or are there some countries in which most firms are consistently active? 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 exposure-shares variation. All such factors are highly correlated to each other. I estimate Shapley value regressions to tackle the multi-colinearity and evaluate the relative importance of these characteristics.

The importance coefficient in Shapley value regressions is computed by recording the R^2 of all possible combinations of fixed effects that can be included in the model. One mix will include only the firm fixed effect, another only the country fixed effect, another the year fixed, another year-country, 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:

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

where S_{ilt}^{channel} represents the channel exposure of company i to location c 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 fixes effects represents a concept similar to an analysis of variance (ANOVA) decomposition.

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,

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

Fixed Effect	Subsid. Empl.	Subsid. Sales	Investors Direct	Investors Full	Revenues	Costs	Bonds	Loans
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, BIS, and Coppola et al. (2020)

Notes: This table shows the relative importance coefficients computed from Shapley value regressions of various 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 to each type of fixed effects, using the R^2 of the fixed effect coalition as gain in the Shapley value formula. 3

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 a country is the best predictor of multinational exposures in any given channel, regardless of the identity of the firm, its industry, or the year. Table 18 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 most crucial impact 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 (2) 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. This is a testament to how stable the country of exposure is, on average, in the sample.

4.3 Shares over Time

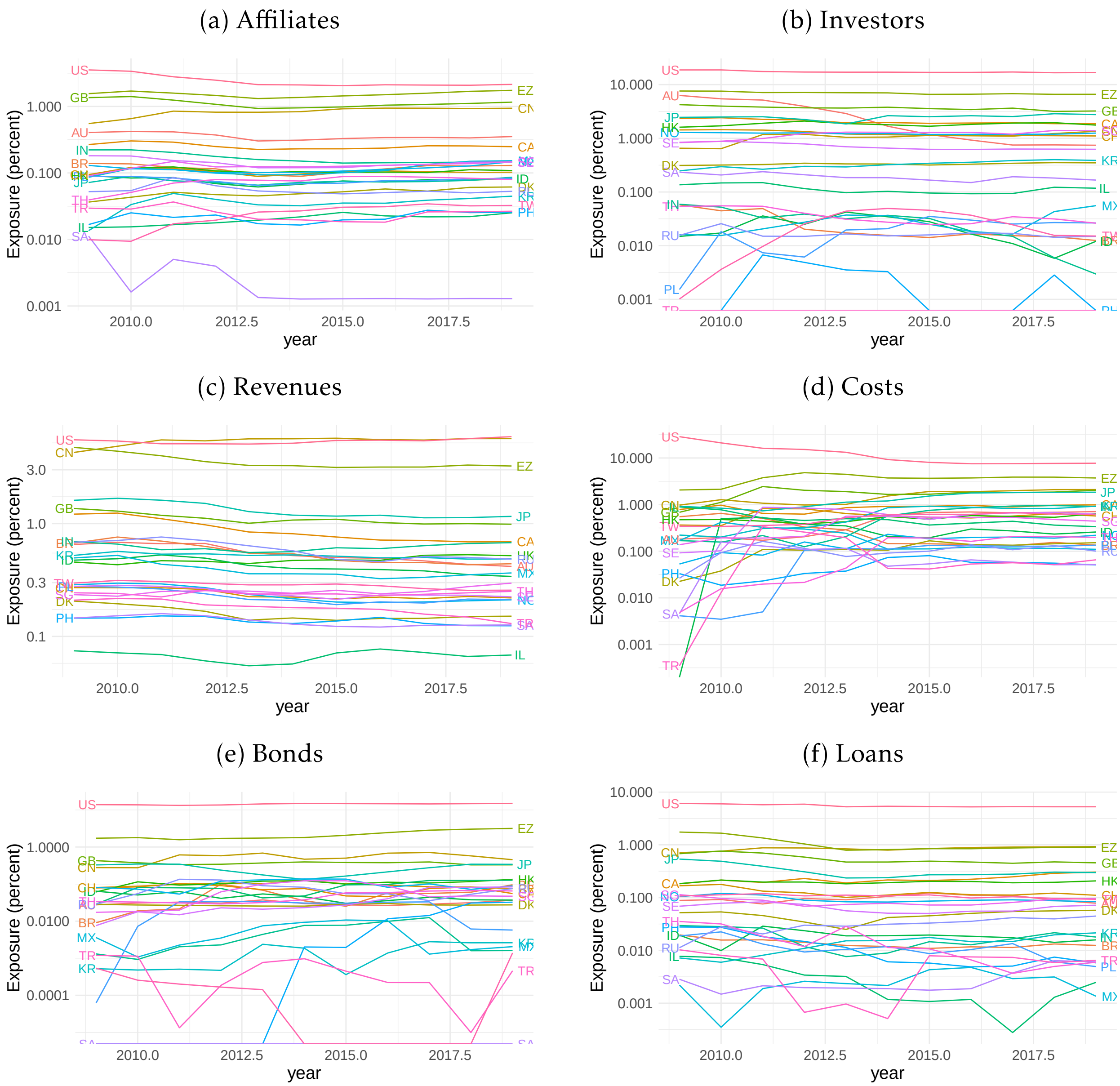
This section explores time trends in foreign exposure channels. Figure 1 shows the average exposure to all countries and channels from 2009 through 2019. I consider only foreign exposures, defined as exposures to countries different from the headquarters country. The shares are plotted on a logarithmic 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 certain kinds of global capital flows. Second, affiliates and cost exposures displayed some exposure trends before 2013, but those trends flattened after 2013. 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 exploit the entire network of private and public company linkages. A smaller network before 2012 implies different shares, a problem that cannot be solved by balancing on the panel of listed ultimate parents. Finally, bond exposures have a mild decrease in the percentage of US exposure, while revenues have a mild reduction in revenue shares to small countries and an increase towards China. Both of these trends, while soft, are visible in aggregate data.

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. Table 4 shows the persistence coefficient of each channel of exposure, conditional on exposure being positive at time $t-1$. 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 lower persistence is observed when including firms that started being covered or that terminate operations in the middle of the sample.[7] Due to the high persistence of exposure shares, I will henceforth focus mostly on studying 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.

[7] 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.

Figure 1: Mean Shares of Foreign Exposure across Companies



Source: Author's calculations from Factset, Capital IQ, OECD, BIS, and Coppola et al. (2020)

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 δ^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.

4.4 Country Determinants of Exposure

This section investigate 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 in-

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

Clustered (factset_entity_id & iso_country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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

Clustered (factset_entity_id & iso_country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Source: Author's calculations from Factset, Capital IQ, OECD, BIS, and Coppola et al. (2020)

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 ρ^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 exposure country between 2009 and 2019. The balanced panel only includes firms that have information available in all years between 2009 and 2019.

cludes the most firms.

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

$$S^c_{il} = \gamma^{cg}_{lr}\ S^g_{ir}|_{S^g_{ir}>0} + \epsilon_{il}, \tag{3}$$

where γ^{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. We focus on the correlation conditional on $S_{ir}^{g} > 0$ to capture how the exposure intensity of one channel correlates with another.The coefficient γ_{lr}^{cg} 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. Sections 4.6 will study conditional correlations in regression form.

Figure 2 shows a graphic representation of the correlation matrices obtained from estimating equation 3 for all country-channel combinations. The estimates consider only foreign exposures i.e. I do not include observations where either country g or l coincide with the headquarters country. The coefficients in every matrix cell read as 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.

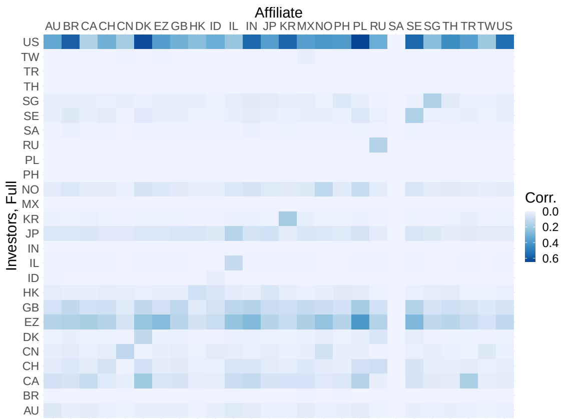
Figure 2 shows the six combinations of exposure channels for which there is the highest degree of within-country cross-channels correlation. All other cases are presented in the appendix. The most striking pattern illustrates that most multinationals in the sample are exposed to the United States and 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 only through a revenue and cost channel. Great Britain, Japan, and Norway have a widespread footprint in 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.

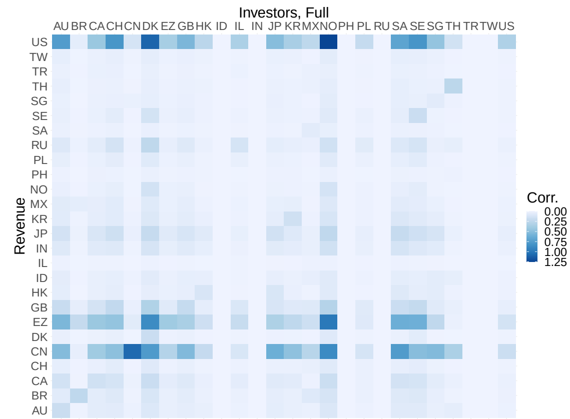
The high within-country cross-channel correlation is not mechanically built into the exposure measures. One concern may be that subsidiary's liabilities are classified as foreign debt in the debt measure. Or that cost exposure included interest payments. But each exposure channel does not contain another in its definition and measurement. For

Figure 2: Unconditional Exposure Country Correlations, across Channels

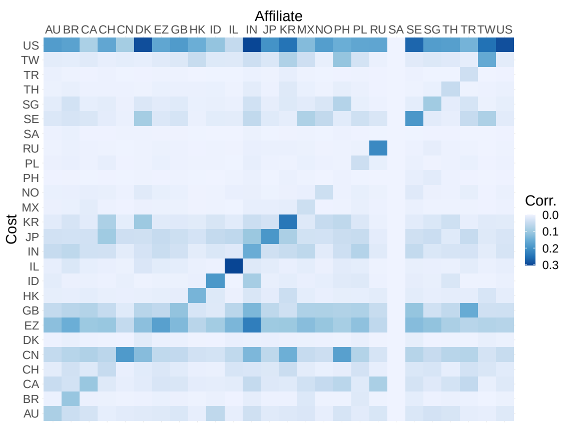
(a) Investors over Affiliates



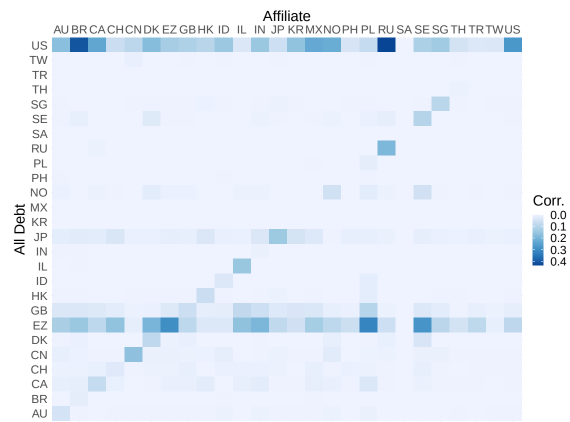
(b) Revenues over Investors



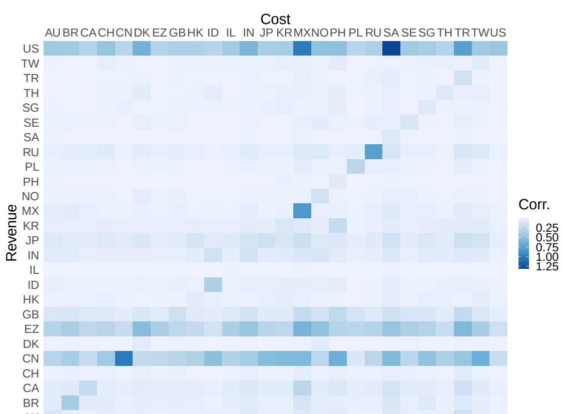
(c) Costs over Affiliates



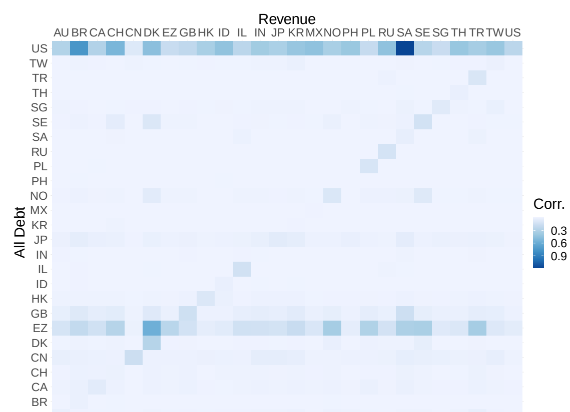
(d) Debt over Affiliates



(e) Revenues over Costs



(f) Debt over Revenue



Source: Author's calculations from Factset, Capital IQ, OECD, BIS, and Coppola et al. (2020)

Notes: Each cell of these panels represent 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.

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 demand that this debt is consolidated and translated into the currency of the ultimate parent[8]. 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, intra-firm, 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 partner, or financial partners, so there cannot be overlapping between suppliers and subsidiaries, or suppliers and banks.

Disposing of all the international linkages of a company also helps to understand which channels are the most conducive to return comovement and how the interaction between exposures plays out. This can also show why multinationals are exposed the way they are.

4.5 Firms Determinants of Exposure

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

$$S^c_{ir} = \beta X_i + \delta_r + \epsilon_{ir}, \tag{4}$$

where S^c_{ir} is the average share of firm i's exposure to location r; 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 δ_r is a region fixed effects. The foreign exposure share refers to the year 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).

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

Table 5: Correlation between Firm Characteristic 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

Clustered (iso_country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Source: Author's calculations from Factset, Capital IQ, OECD, BIS, and Coppola et al. (2020)
Notes: This table represents the correlation between firms characteristics and total foreign exposure through several channels. It is computed from a firm-by-country panel of average firms characteristics and exposure shares in each country in 2019. I exclude exposures to the country of headquarters.

Table 5 shows the β coefficients estimated from equation 4. 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

To conclude the analysis of the determinants of exposure shares, I analyze an augmented gravity model of foreign exposure, keeping time, firm-specific, and country-specific ef-

Table 6: Gravity Model of Exposure Shares

Dependent Variables:	Affiliates	Investors	Bonds	Loans	Revenue	Cost
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Distance	-0.2994***	-0.2766**	-0.3604	-0.2482**	-0.7041***	-0.2415**
	(0.0750)	(0.1321)	(0.3123)	(0.1177)	(0.1730)	(0.0870)
Dipl. Agreement	-0.1518	-0.2963*	0.1166	-0.2461	-0.0958	-0.1428
	(0.1020)	(0.1583)	(0.2609)	(0.1930)	(0.1888)	(0.0960)
Comm. Language	0.6837**	0.7425***	1.798**	0.7967**	1.559	0.6554***
	(0.2782)	(0.2640)	(0.7576)	(0.3402)	(0.9654)	(0.2170)
Comm. Legal	0.0145	-0.0807	-0.6911	0.0292	-0.2092	0.0550
	(0.1026)	(0.1767)	(0.4059)	(0.2966)	(0.2845)	(0.1168)
Comm. Religion	-0.1220	-0.1784	-0.4142	-0.2251	-0.5800**	-0.1845**
	(0.0980)	(0.1186)	(0.3070)	(0.1476)	(0.2212)	(0.0775)
Fixed-effects						
factset_entity_id	Yes	Yes	Yes	Yes	Yes	Yes
iso_country	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	385,807	407,665	168,574	403,854	407,855	407,751
R^2	0.07813	0.11655	0.23636	0.09632	0.15543	0.18133
Within R^2	0.00728	0.00828	0.01911	0.00664	0.01738	0.00798

Clustered (factset_entity_id & iso_country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Source: Author's calculations from Factset, Capital IQ, OECD, BIS, Coppola et al. (2020), and Conte et al. (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 et al. (2022), and between country of headquarters and exposure country. I include firm and country fixed effects, and I collapsed the time dimension.

fects fixed:

$$S_{ir}^{c} = \beta' G_{ir} + \delta_i + \delta_r + \epsilon_{ir}, \tag{5}$$

where S_{ir}^{c} is the average exposure of firm i to foreign region r through channel c, and G_{ir} is a vector of standard gravity factors defined to reflect the bilateral distance between the headquarters of firm i and region r: log of geographic distance, UN diplomatic disagreement, common language, common legal framework, and common religion. All bilateral distances are taken from Conte et al. (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 4 and 4.4. The foreign exposure share refers to the year 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 β of equation 5. 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 international markets through multiple channels at the same time. To reflect this finding, I augment the gravity model with each firm exposure to region r through all channels except c, represented by the object $S_{ir}^{g \neq c}$:

$$S_{ir}^{c} = \beta' G_{ir} + \sum_{g \neq c} \gamma^{g} S_{ir}^{g} + + \delta_i + \delta_r + \epsilon_{ir}. \tag{6}$$

Table 7 shows the estimates of the augmented gravity model in equation 6. Adding other channels of the active exposure at the firm level increases the model's explanatory power from an average R^2 of 15 percent to an average R^2 of 40 percent. Notably, all exposure channels are a complement to each other. There is no case in which a firm's being exposed to a country through a particular channel implies that the firms 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.

Table 7: Augmented Gravity Model of Exposure Shares

Dependent Variables:	Affiliates	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)	
Affiliates		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

Clustered (factset_entity_id & iso_country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Source: Author's calculations from Factset, Capital IQ, OECD, BIS, Coppola et al. (2020), and Conte et al. (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 et al. (2022), and between country of headquarters and exposure country. I augment the gravity model with all channels of exposures information between each firm and the corresponding country of exposure. I include firm and country fixed effects, and I collapsed the time dimension.

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:

$$\text{Cov}[R_{it}, R_{jt}] = \text{Cov}[\hat{R}^{\text{model}}_{it}, \hat{R}^{\text{model}}_{jt}] + \text{Cov}[\epsilon_{it}, \epsilon_{jt}]. \tag{7}$$

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 micro-level share of exposure to several regions is that it enables an estimation of the following nonparametric regional factor model:

$$\begin{aligned} R^e_{it} =& \alpha_i + \sum_l \delta^{\text{Affiliate}}_{lt} s^{\text{Affiliate}}_{il} + \delta^{\text{Investor}}_{lt} s^{\text{Investor}}_{il} + \delta^{\text{Debt}}_{lt} s^{\text{Debt}}_{il} + \delta^{\text{Revenue}}_{lt} s^{\text{Revenue}}_{il} + \delta^{\text{Cost}}_{lt} s^{\text{Cost}}_{il} + \epsilon_{it} \qquad (8) \\ =& \alpha_i + \sum_c \delta_t S_i + \epsilon_{it}, \qquad (9) \end{aligned}$$

where R^e_{it} is the return of company i at quarter t in excess of the US risk-free rate, s^c_{il} is the channel-c exposure share of company i to location l at a specific time,[9] δ^c_{lt} is a time-by-location-by-channel fixed effect, δ_t is a L-by-one size vector of location fixed effects 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 (8) we can decompose the covariance between two stock returns, i and j, implied by the model:

$$\begin{aligned} \text{Cov}[\hat{R}^{\text{model}}_{it}, \hat{R}^{\text{model}}_{jt}] &= \sum_c \text{Cov}[\delta^c_t S^c_i, \delta^c_t S^c_j] + \sum_c \sum_{g \neq c} \text{Cov}[\delta^c_t S^c_i, \delta^g_t S^g_j] \qquad (10) \\ &= \sum_c S^c_i \text{Cov}[\delta^c_t, \delta^c_t] S^c_j + \sum_c \sum_{g \neq c} S^c_i \text{Cov}[\delta^c_t, \delta^g_t] S^g_j \qquad (11) \\ &= \sum_c S^c_i \Omega^{cc}_t S^c_j + \sum_c \sum_{g \neq c} S^c_i \Omega^{cg}_t S^g_j \qquad (12) \end{aligned}$$

[9] The shares refer to the year 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.

The first component of equation (10) represents the covariance between the model-implied returns due to exposure to foreign country shocks through the same channel c. The second component in equation (10) represents the model implied returns to exposure to foreign country shocks 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, cost, or cost and revenue, respectively, originating from the same country.

Equation (12) helps further interpret the covariance decomposition as being the product between a firm-specific micro exposure to different channel-location pairs and an estimated variance-covariance matrix Ω_t^{cg} of country-level shocks. Thanks to the non-parametric 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 et al. (2009):

$$\gamma^{\text{cov}} = \frac{1}{W}\sum_{i=1}\sum_{j>i}\omega_i\omega_j \text{Cov}\left(R_{it}, R_{jt}\right) = \frac{1}{W}\sum_{i=1}\sum_{j>i}\omega_i\omega_j\left[\text{Cov}\left(\sum_c \hat{\delta}_t S_i, \sum_c \hat{\delta}_t S_j\right) + \text{Cov}\left(\epsilon_{it}, \epsilon_{jt}\right)\right]. \tag{13}$$

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

$$\gamma^{\text{var}} = \frac{1}{W}\sum_{i=1}\omega_i^2 \text{Var}\left(R_{it}\right) = \frac{1}{W}\sum_{i=1}\omega_i^2\left[\text{Var}\left(\sum_c \hat{\delta}_t S_i\right) + \text{Var}\left(\epsilon_{it}\right)\right]. \tag{14}$$

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, BIS, and Coppola et al. (2020)
Notes: This table represents the in-sample decomposition of the in-sample return covariance, according to a non-parametric 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 (8). 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. The model does an excellent job of explaining the average covariance structure of returns.

A clear pattern emerges from the variance-covariance decomposition. All exposure channels positively contribute as comovement factors of returns. Two companies' returns are more likely to comove when both are exposed to the same (or similar) country either through affiliate, revenue, cost, debt, or equity financing linkages.[10] 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 is likely to 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 rather than sales costs. 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.

5.2 Cross-sectional Betas

An alternative way to evaluate return correlations and what explains them is through the lenses of a multi-factor capital asset pricing model (CAPM). I can build L country portfolio returns as the relevant factors:

$$R_{it} = \alpha_i + \sum_{l}^{L} \beta_{il} R_{lt} + \epsilon_{it}, \tag{15}$$

where R_{it} is the excess return of company i at quarter t, and R_{lt} is the excess return of country 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 et al., 2009), I include 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-

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

sample return correlation. The β_{il} coefficients represent the object of interest. Each β_{il} is the in-sample conditional correlation between each company and different country measure of returns. Note that in this first-stage regression, I do not use any exposure share information except to define the coutnry portfolios. I do not include industry-time fixed effects for simplicity in this benchmark estimate. Table 20 in the appendix replicates the benchmark estimates when I add 4-digit NACE industry-by-time fixed effects in equation 15.

The second-stage regression then studies how different channels of country exposure can explain the cross-section of country loadings β_{il}:

$$\hat{\beta}_{il}^{\text{returns}} = \sum_{c} \gamma^{c} w_{il}^{c} + \delta_{i} + \delta_{l} + v_{il}, \tag{16}$$

where w_{il}^{c} represents the channel-c exposure share of company i to country l. The shares refer to the year 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 I compute the return comovements β_{il}.

Table 9: How Channels of Exposure Explain Cross-sectional Country Return β_{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

Clustered (companyid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Source: Author's calculations from Factset, Capital IQ, OECD, BIS, and Coppola et al. (2020)
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 firms' country-channel exposure share explains the betas loadings in a firm-by-country panel with firm and country fixed effects.

Table 9 shows the coefficients γ^c from equation (16). 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 β'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 instead virtually 0 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 (15) and (16), 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 than Table 9 because cash flows are noisier variables than returns.

Table 10: How Channels of Exposure Explain Cross-sectional Cash Flow β'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

Clustered (companyid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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 includes all firms cash flows whose main investor share is in l. In the second stage, I estimates how each firms' country-channel exposure share explains the betas loadings in a firm-by-country panel with firm and country fixed effects.

6.2 Sample Sensitivity

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 some specific channels. On the other hand, since the paper's focus is 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 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.

Table 11: Testing Sample Sensitivity on Exposure Channel Correlation with Return β'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

Clustered (companyid & iso_country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Source: Author's calculations from Factset, Capital IQ, OECD, BIS, and Coppola et al. (2020)
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 includes all firms whose main investor share is in l. In the second stage, I estimates how each firms' country-channel exposure share explains the betas 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 headquarter country. Column (3) represents the estimates when I exclude companies headquartered in the US. Column (4) represents estimates when I exclude beta loadings to the headquarter country and companies headquartered in the US.

Tables 11 and 12 confirm the importance of all channels, regardless of the sample of interest. The interaction coefficients are the most sensitive to sample change. The signs generally remain constant but the loss of power and magnitude demand further investigation in a future iteration of this paper.

Table 12: Testing Sample Sensitivity on Exposure Channel Correlation with Return β'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

Clustered (companyid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Source: Author's calculations from Factset, Capital IQ, OECD, BIS, and Coppola et al. (2020)
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 includes all firms whose main investor share is in l. In the second stage, I estimates how each firms' country-channel exposure share explains the betas 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 headquarter country. Column (3) represents the estimates when I exclude companies headquartered in the US. Column (4) represents estimates when I exclude beta loadings to the headquarter country and companies headquartered in the US.

References

Alfaro, Laura, Mauricio Calani, and Liliana Varela, "Granular Corporate Hedging Under Dominant Currency," Working Paper 28910, National Bureau of Economic Research June 2021.

Auer, Raphael, Bruce Muneaki Iwadate, Andreas Schrimpf, and Alexander F. Wagner, "Global Production Linkages and Stock Market Comovement," Swiss Finance Institute Research Paper Series 22-18, Swiss Finance Institute February 2022.

Baele, Lieven and Pilar Soriano, "The determinants of increasing equity market comovement: economic or financial integration?," *Review of World Economics / Weltwirtschaftliches Archiv*, 2010, *146* (3), 573–589.

Barrot, Jean-Noel, Erik Loualiche, and Julien Sauvagnat, "The Globalization Risk Premium," *The Journal of Finance*, 2019, *74* (5), 2391–2439.

Bekaert, Geert, Campbell Harvey, Andrea Kiguel, and Xiaozheng Wang, "Globalization and Asset Returns," *Annual Review of Financial Economics*, 2016, *8* (1), 221–288.

_ , Robert J. Hodrick, and Zhang Xiaoyan, "International Stock Return Comovements," *The Journal of Finance*, 2009, *64* (6), 2591–2626.

Bena, Jan, Serdar Dinc, and Isil Erel, "The international propagation of economic downturns through multinational companies: The real economy channel," *Journal of Financial Economics*, 2022, *146* (1), 277–304.

Boehm, Christoph E., Aaron Flaaen, and Nitya Pandalai-Nayar, "Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tōhoku Earthquake," *The Review of Economics and Statistics*, 03 2019, *101* (1), 60–75.

Caglio, Cecilia R, R. Matthew Darst, and Şebnem Kalemli-Özcan, "Collateral Heterogeneity and Monetary Policy Transmission: Evidence from Loans to SMEs and Large Firms," Working Paper 28685, National Bureau of Economic Research April 2021.

Cerutti, Eugenio, Galina Hale, and Camelia Minoiu, "Financial crises and the composition of cross-border lending," *Journal of International Money and Finance*, 2015, *52*, 60–81. Adjustment in the Aftermath of the Global Crisis 2008-09: New Global Order?

Colacito, Ric, Yan Qian, and Andreas Stathopoulos, "Global Sales, International Currencies and the Currency Denomination of Debt," Technical Report, SSRN 2021.

Conte, M., P. Cotterlaz, and T. Mayer, "The CEPII Gravity database," Working Paper 2022-05, National Bureau of Economic Research July 2022.

Coppola, Antonio, Matteo Maggiori, Brent Neiman, and Jesse Schreger, "Redrawing the Map of Global Capital Flows: The Role of Cross-Border Financing and Tax Havens," NBER Working Papers 26855, National Bureau of Economic Research, Inc 2020.

Cravino, Javier and Andrei A. Levchenko, "Multinational Firms and International Business Cycle Transmission*," *The Quarterly Journal of Economics*, 11 2016, *132* (2), 921–962.

di Giovanni, Julian and Galina Hale, "Stock Market Spillovers Via the Global Production Network: Transmission of U.S. Monetary Policy," Working Papers 1213, Barcelona Graduate School of Economics October 2020.

Fillat, Jose, Stefania Garetto, and Lindsay Oldenski, "Diversification, cost structure, and the risk premium of multinational corporations," *Journal of International Economics*, 2015, *96* (1), 37–54.

Fillat, José L. and Stefania Garetto, " Risk, Returns, and Multinational Production *," *The Quarterly Journal of Economics*, 09 2015, *130* (4), 2027–2073.

Forbes, Kristin J. and Menzie D. Chinn, "A Decomposition of Global Linkages in Financial Markets over Time," *The Review of Economics and Statistics*, 2004, *86* (3), 705–722.

_ **and Roberto Rigobon**, "No Contagion, Only Interdependence: Measuring Stock Market Comovements," *The Journal of Finance*, 2002, *57* (5), 2223–2261.

Hassan, Tarek A., Jesse Schreger, Markus Schwedeler, and Ahmed Tahoun, "Sources and Transmission of Country Risk," Working Papers 2021.

Herskovic, Bernard, "Networks in Production: Asset Pricing Implications," *Journal of Finance*, 2018, *73* (4), 1785–1818.

Hoberg, Gerard and S. Katie Moon, "Offshore activities and financial vs operational hedging," *Journal of Financial Economics*, 2017, *125* (2), 217–244.

_ **and** _ , "The Offshoring Return Premium," *Management Science*, 2019, *67* (6), 2876–2899.

Ivashina, Victoria, David S. Scharfstein, and Jeremy C. Stein, "Dollar Funding and the Lending Behavior of Global Banks*," *The Quarterly Journal of Economics*, 04 2015, *130* (3), 1241–1281.

Kalemli-Ozcan, Sebnem, Elias Papaioannou, and Jose-Luis Peydro, "Financial Regulation, Financial Globalization, and the Synchronization of Economic Activity," *The Journal of Finance*, 2013, *68* (3), 1179–1228.

Lane, Philip and Gian Maria Milesi-Ferretti, "International Investment Patterns," *The Review of Economics and Statistics*, 2008, *90* (3), 538–549.

Maggiori, Matteo, Brent Neiman, and Jesse Schreger, "International Currencies and Capital Allocation," *Journal of Political Economy*, 2020, *128* (6), 2019–2066.

Miranda-Agrippino, Silvia and Hélène Rey, "U.S. Monetary Policy and the Global Financial Cycle," *The Review of Economic Studies*, 05 2020, *87* (6), 2754–2776.

Pukthuanthong, Kuntara and Richard Roll, "Global market integration: An alternative measure and its application," *Journal of Financial Economics*, 2009, *94* (2), 214–232.

Wier, Ludvig S and Gabriel Zucman, "Global Profit Shifting, 1975-2019," Working Paper 30673, National Bureau of Economic Research November 2022.

A Data Sets

- **Factset Data Management Tool**: Factset Data Management Tool contains Factset's entity master file and links to 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.

- **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-reference 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 address, 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. The appendix 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 a syndicated loan (Cerutti et al., 2015). Moreover, syndicated loans represent the most common way large public companies receive loans (Caglio et al., 2021).

B Sample

Factset contained 59,149 public entities, as of 2021.[11] 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. A Merging of entities typically discontinues the identifier. Acquisitions simply change the type and parent company of one of the two entities. Bankruptcy flags the entity as inactive.

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-CUSIP entities, 37,958 contain actively covered information about their ownership structure, debt capital structure, and geographic revenue. Of these companies, 33,848 are ultimate parents. Finally, 19,250 of the above companies 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.

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

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 to 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:

$$O = \begin{bmatrix} O_{11} & \cdots & O_{1N} \\ \vdots & \ddots & \vdots \\ O_{N1} & \cdots & O_{NN} \end{bmatrix} \qquad \text{e.g.} \qquad O_0 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

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

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

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

Define now the Ownership Leontief matrix, and the Ownership Ghosh matrix:

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

Suppose W represented 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. Each column of G^O represents the amount of increased W to expect in the entity row after the column subsidiary increases \$1 in value. The columns of G are either 1 or 0 since all accounts are at the consolidated level. The main issue with the matrices L^O and G^O is that they are 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:

$$S^{\text{Subs.}} = \text{Diag}(W^P) \cdot \text{Diag}(W)^{-1} \cdot L^O. \tag{17}$$

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, 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

In 2019, Factset covered 8 millions different entities. Of these, 1.25 millions 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 194,000 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 to subsidiary share:

$S^{\text{Subs.}}$	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 (17). 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 higher 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

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
Euro Zone	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

C.2 Investor Exposure

In mid-2020, I pulled the following variables from Capital IQ and for all the ultimate parents of the sample companies: IQ_HOLDER_CIQID, IQ_HOLDER_PERCENT, IQ_HOLDING_SECURIT
IQ_HOLDING_PERCENT, IQ_HOLDING_CIQID, IQ_INVESTMENTS_ALL_STAKE, IQ_INVESTMENTS

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, but only if the parent is private or if the investor did not buy public shares. The data sources are typically companies' annual reports, 10Ks, news, and event scripts. There are 37,804 private investors linked to 19,089 companies in the sample, forming 80,005 private investment linkages. There are 590,534 holders of common equity in one of the 19,000 companies in the sample, forming 4.5 million linkages.

Capital IQ does not record a history of these investor linkages. However, the Federal Reserve System 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. In this paper's sample of companies, 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, looking deeper into the data, we can 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 in this paper is mostly considered as a cross-sectional control, and in the beta analysis, it is mainly used to assign the main country of investor, which is very unlikely to shift even across long periods of time. 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 formed as follows:

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

- Merge common equity investors and private investors in a unique data set. Verify whether there are any duplicate data .

- Thirty percent of linkages have information on the percentage of ownership. There is often a mix of ownership stakes that are populated and missing within 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 of the smallest investor for which we have 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 percentage of ownership. The remaining 40 percent of missing ownership shares is predicted from a lasso regression on the populated part of the data set that contains assets of the investment company, headquarters country, industry, age, number of other investors, and country of investor.

- Each investor in the firm-to-firm data built above can now be linked to a country according to their 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, there is typically a large amount of ”unclaimed” ownership. I take two different approaches to assigning the residual unclaimed ownership to a country that result in two different investor measures:

  1. **Direct Investor**: Assign all the unclaimed ownership share to the country where most of the shares are exchanged. This information is obtained from the country associated to the exchange of the “main equity” security identifier associated to the company by the Factset Data Management package.
  2. **Full Investor**: Assign the unclaimed share to the headquarters country and then multiply the shares by the restated share of investors in that country represented by the restated equity flow matrices by Coppola et al. (2020) and cleaned as specified in Appendix C.2.1

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

Coppola et al. (2020) 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. (2020) 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. (2020) are well suited for 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. (2020): 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. (2020) 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. (2020) 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.
- I 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 list above. In this case, I 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 Coppola et al. (2020)’s methodology. As for bond flows, I infer domestic investment from the total debt security claims outstanding, on a nationality base, from the Organisation for Economic Co-operation and Development (OECD) 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%
A. 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%

This measure has two main limitations. First, as mentioned above, 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.

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

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. [12]

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

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 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,

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

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). If we assign to each subsidiary its headquarters country, we can then use VA to understand the foreign country share of value added embedded in the sales of each company.

Having established the theoretical foundation of the value added share matrix, the main issue is that I cannot observe the global matrix of sales flows across firms Z. I make two main assumptions to argue that I can use the Factset supply chain dataset 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.

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 M firms included in Factset supply chain $Z^S_{M\times M}$ with 1 when a customer-supplier relation is active, and 0 otherwise.
- Divide each column of Z^S by the total number of suppliers $ZZ^S = Z^S * \text{Diag}(Z^S e)^{-1}$
- 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. $A^S = R * ZZ^S = R * Z^S * \text{Diag}(Z^S e)^{-1}$

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 $S^{\text{cost}} = VA^S = V^S (I - A^S)^{-}1 \cdot H$, where H is a matrix associating each supplier company to its headquarter 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. I can match 76 percent of the direct borrowers 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 > Name Fuzzy 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. Note how I prefer using information on syndicated loans over issuance currency to assign the country of exposure, whenever the information is avail-

able. This is for two reasons. First, knowing the nationality of the bank is more line with the kind of exposure studeid in this paper. Second, syndicated loans represent most of the cross-border borrowing of large public companies. Syndicated loans are highly representative of how large public companies take loans (Caglio et al., 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. In the latter case, 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 et al. (2015) applies the same assumption and finds correspondence between official Bank for International Settlements (BIS) Lending 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 the 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

Table 18: Importance Coefficients (Shapley Value) of Fixed Effects in Explaining Exposures

	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

Table 19: Exposures Summary Statistics

	Average	SD	W. Average	HHI Average
Bonds	0.19	0.26	0.32	0.76
Debt	0.08	0.24	0.20	0.95
Loans	0.08	0.25	0.18	0.97
Revenue	0.30	0.37	0.40	0.75
IO Cost	0.12	0.11	0.09	0.73
Subsidiaries	0.08	0.21	0.25	0.92
Cost	0.24	0.23	0.33	0.68
Investors	0.14	0.24	0.23	0.86
Investors Full	0.42	0.21	0.47	0.46

Dependent Variable:				beta_win			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
own	0.5724***					0.0732***	0.1599***
	(0.0051)					(0.0140)	(0.0238)
inv		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)
geo				0.6257***		0.0752***	0.1251***
				(0.0060)		(0.0123)	(0.0198)
scc					0.6869***	0.1410***	0.1019***
					(0.0061)	(0.0158)	(0.0261)
own × inv							0.0514
							(0.0728)
own × debt							0.0393
							(0.0467)
own × geo							-0.1230***
							(0.0436)
own × scc							-0.2050***
							(0.0593)
inv × debt							-0.0652
							(0.0656)
inv × geo							0.0725
							(0.0607)
inv × scc							0.4123***
							(0.0785)
debt × geo							-0.0908*
							(0.0470)
debt × scc							-0.0658
							(0.0558)
geo × scc							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

Clustered (companyid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 20: How Channels of Exposure Explain Cross-sectional Country Return β_{il}'s
β_{il} computed with firm and industry-time fixed effects

Dependent Variable:	Betas					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subsid	0.5196***				0.1065***	0.1766***
	(0.0051)				(0.0139)	(0.0230)
Debt		0.5249***			0.2491***	0.3034***
		(0.0050)			(0.0136)	(0.0270)
Revenue			0.5661***		0.0978***	0.1343***
			(0.0060)		(0.0124)	(0.0188)
Cost				0.6189***	0.1598***	0.1206***
				(0.0062)	(0.0155)	(0.0244)
Subsid × Debt						-0.0239
						(0.0387)
Subsid × Revenue						-0.0858**
						(0.0420)
Subsid × Cost						-0.0840*
						(0.0499)
Debt × Revenue						-0.1347***
						(0.0431)
Debt × Cost						0.0164
						(0.0432)
Revenue × Cost						0.1876***
						(0.0548)
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	0.08368	0.08778	0.07681	0.08378	0.09195	0.09229
Within R^2	0.06874	0.07291	0.06176	0.06884	0.07714	0.07749

Clustered (companyid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

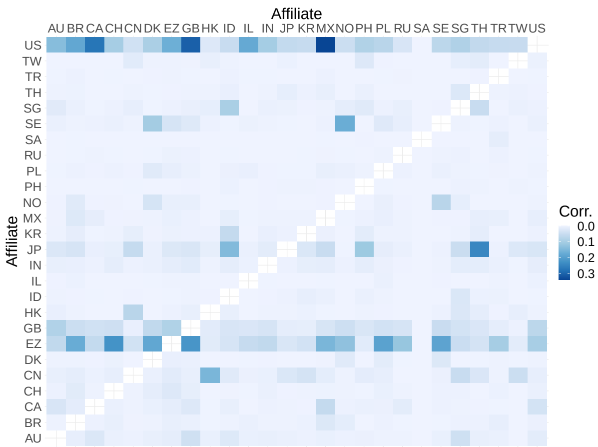
Dependent Variable:				Betas			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Subsid	0.2059***			0.2051***	0.2586***	0.1915***	0.2074***
	(0.0237)			(0.0374)	(0.0227)	(0.0225)	(0.0234)
Debt	0.2507***	0.2434***	0.3071***	0.1585***	0.3187***	0.1394***	
	(0.0284)	(0.0281)	(0.0299)	(0.0417)	(0.0260)	(0.0302)	
Revenue	0.1604***	0.1801***	0.2479***		0.1823***	0.1652***	0.1459***
	(0.0194)	(0.0205)	(0.0253)		(0.0225)	(0.0154)	(0.0194)
Cost	0.2121***	0.2187***	0.2762***	0.1943***			0.2128***
	(0.0256)	(0.0249)	(0.0288)	(0.0370)			(0.0248)
Subsid × Debt	0.0094			0.0439	-0.0791**	0.1985***	
	(0.0398)			(0.0594)	(0.0355)	(0.0452)	
Subsid × Revenue	-0.1211***				-0.1498***	-0.2127***	-0.2288***
	(0.0430)				(0.0473)	(0.0429)	(0.0439)
Subsid × Cost	-0.1290**			-0.1157			-0.2053***
	(0.0512)			(0.0737)			(0.0471)
Debt × Revenue	-0.1057**	-0.0578	-0.0796		-0.0197	-0.1371***	
	(0.0440)	(0.0494)	(0.0533)		(0.0469)	(0.0422)	
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				0.0422
	(0.0555)	(0.0647)	(0.0687)				(0.0575)
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)			
Cost_count					0.0586***		
					(0.0136)		
Cost_count × Subsid					0.0355		
					(0.0523)		
Cost_count × Debt					-0.0071		
					(0.0457)		
Cost_count × Revenue					0.0901**		
					(0.0379)		
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)
Debt_DCS_Curr × Subsid							0.1184***
							(0.0386)
Debt_DCS_Curr × Revenue							0.0831*
							(0.0435)
Debt_DCS_Curr × Cost							0.1620***
							(0.0445)
Fixed-effects							
companyid	Yes	Yes	Yes	Yes	Yes	Yes	Yes
iso_country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	221,281	227,734	146,784	124,949	176,691	285,247	223,757
R^2	0.12376	0.12095	0.13811	0.11949	0.12312	0.10915	0.12383
Within R^2	0.08735	0.08492	0.09397	0.08358	0.08884	0.07234	0.08821

Clustered (companyid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

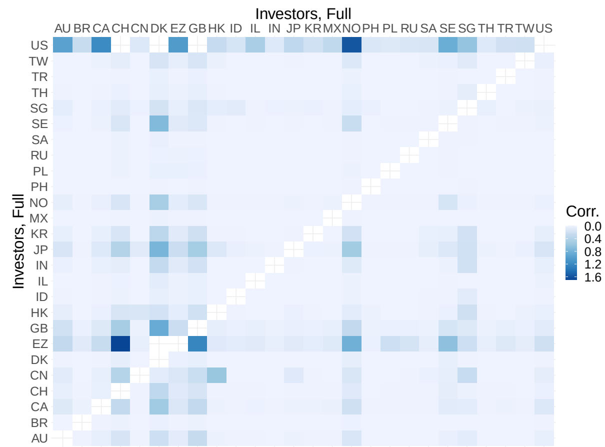
E Additional Figures

Figure 3: Cross-country Correlations, within Channel

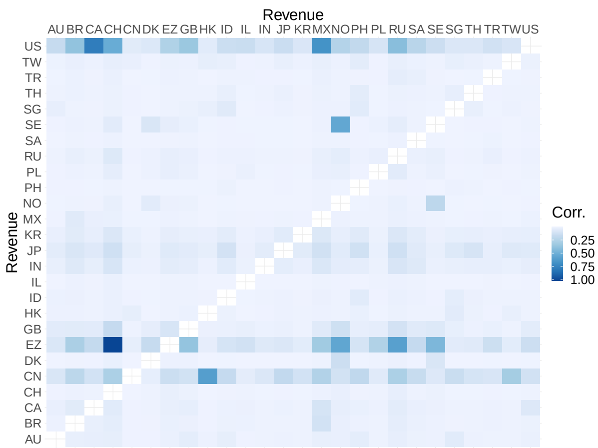
(a) Affiliates



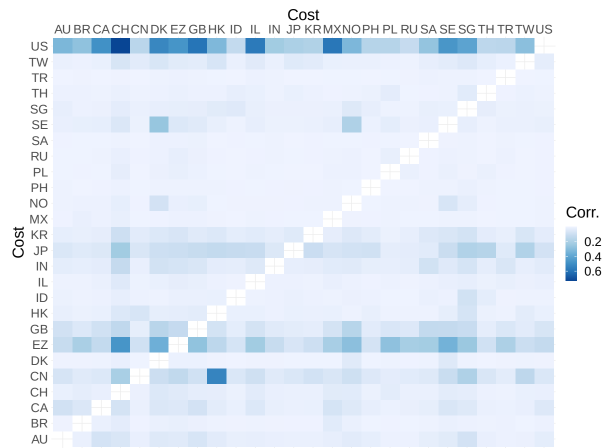
(b) Investors



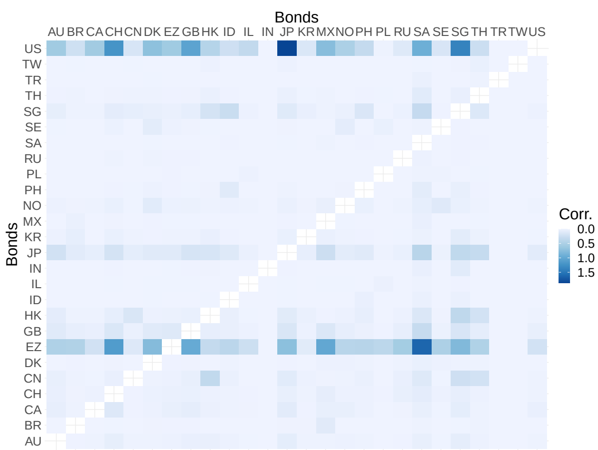
(c) Revenues



(d) Costs



(e) Bonds



(f) Loans

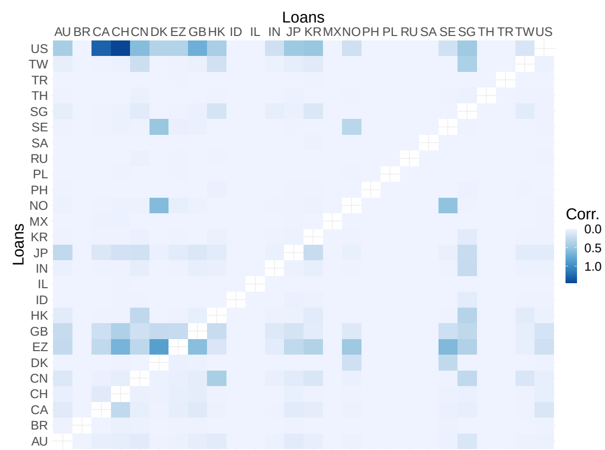
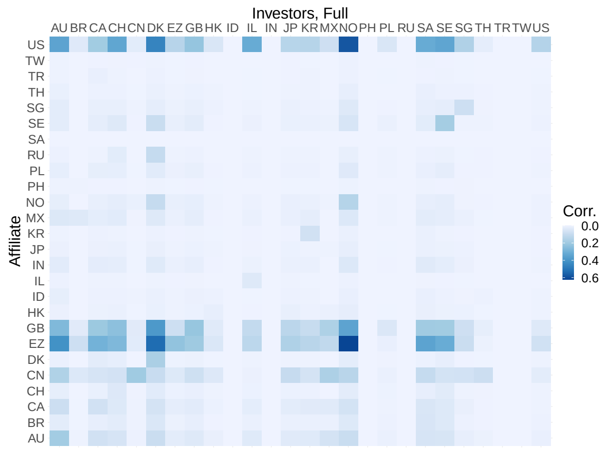
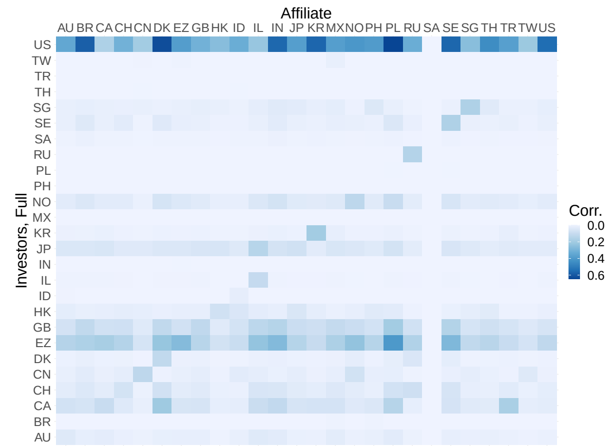


Figure 4: Intensive Margin Correlation, across Channels

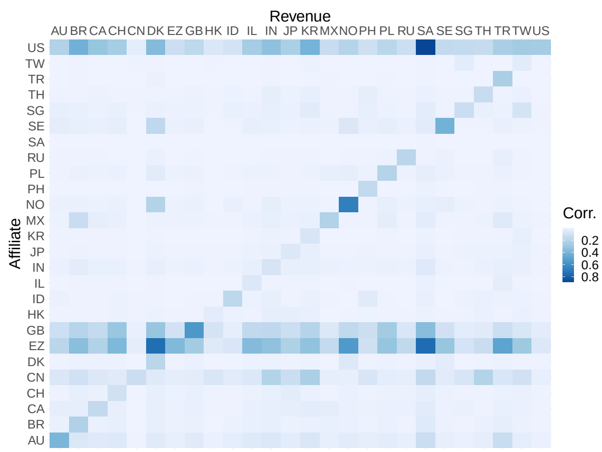
(a) Affiliates, Investors



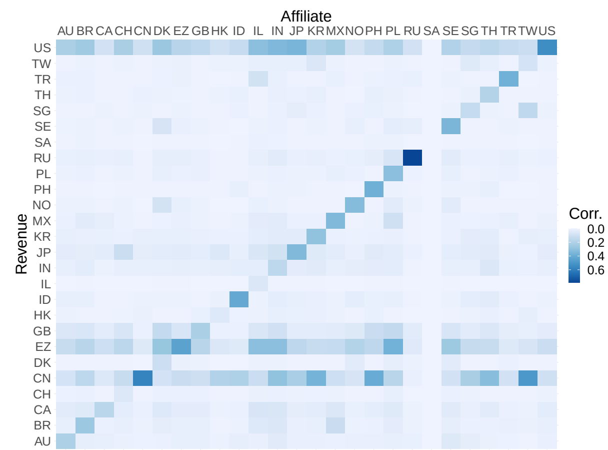
(b) Investors, Affiliates



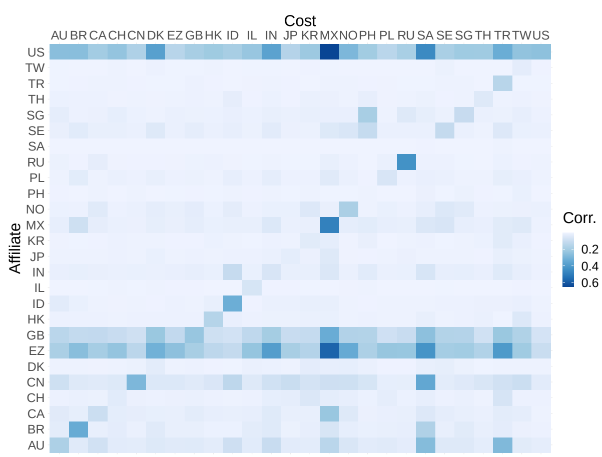
(c) Affiliates, Revenue



(d) Revenue, Affiliate



(e) Affiliate, Costs



(f) Costs, Affiliate

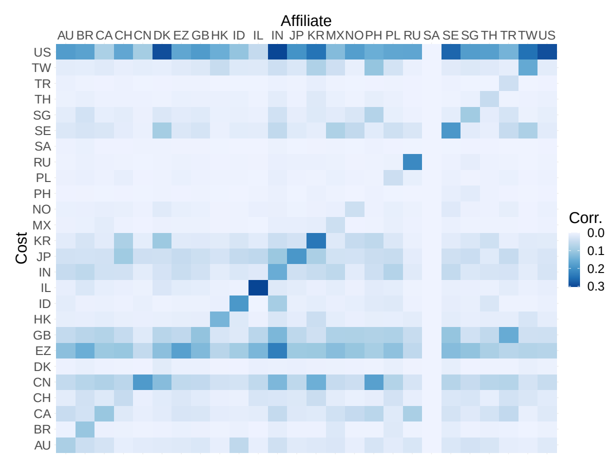
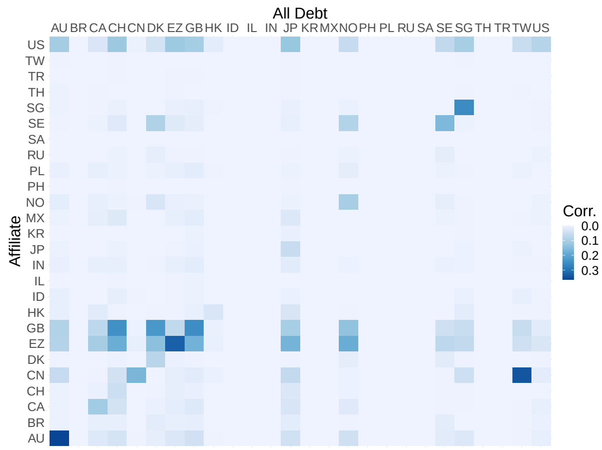
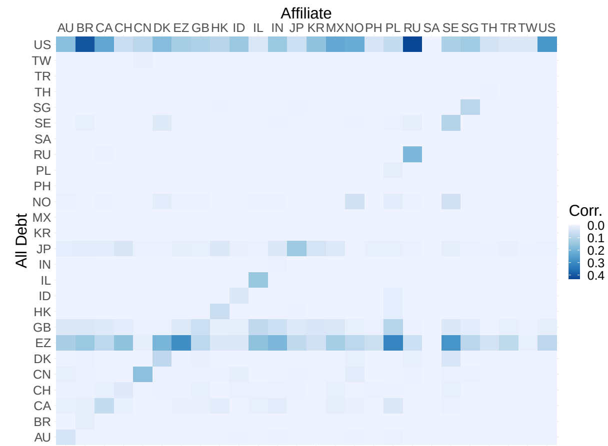


Figure 5: Intensive Margin Correlation, across Channels

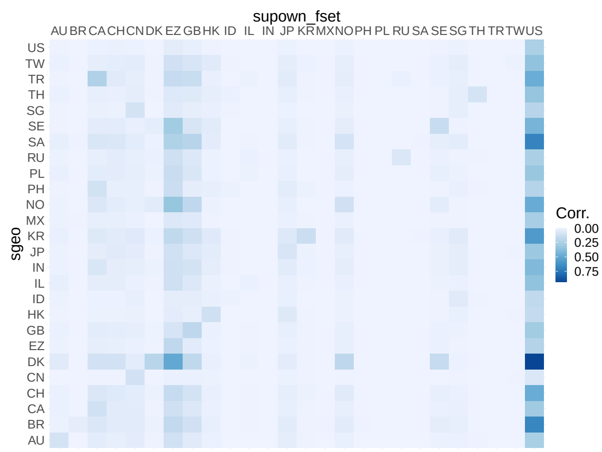
(a) Affiliate, Debt



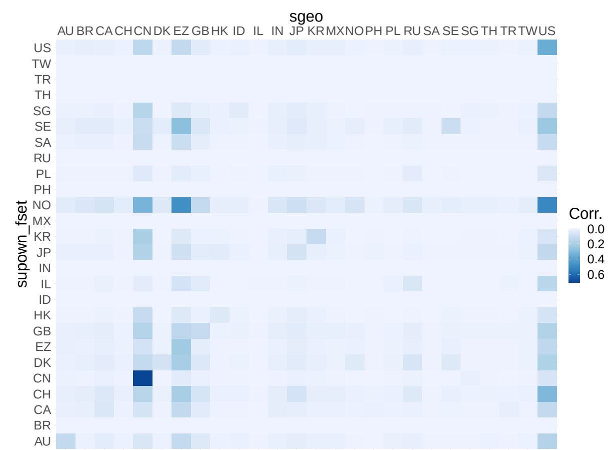
(b) Debt, Affiliate



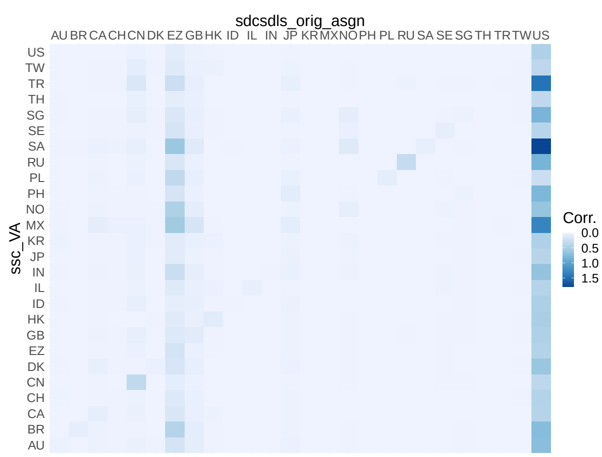
(c) Investor, Revenue



(d) Revenue, Investor



(e) Debt, Costs



(f) Costs, Debt

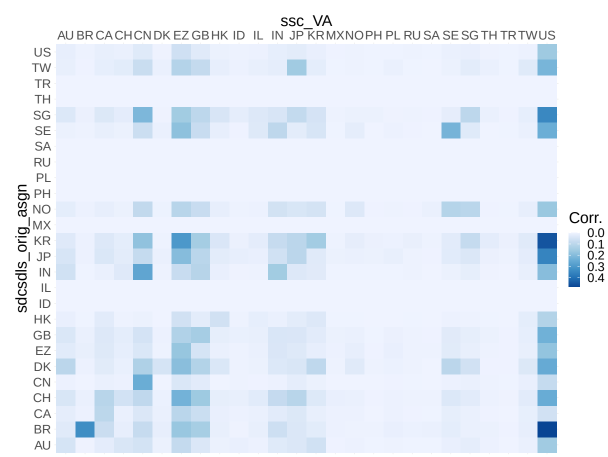
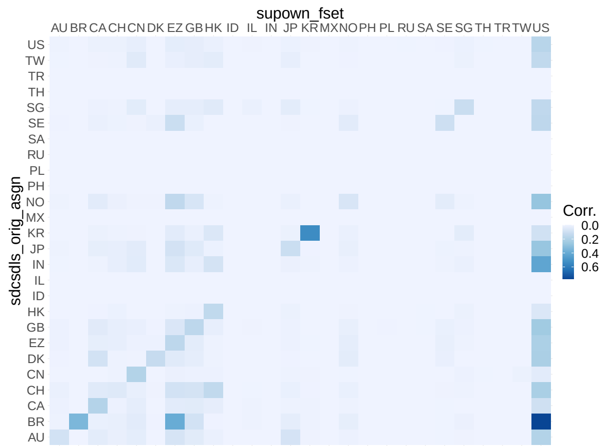
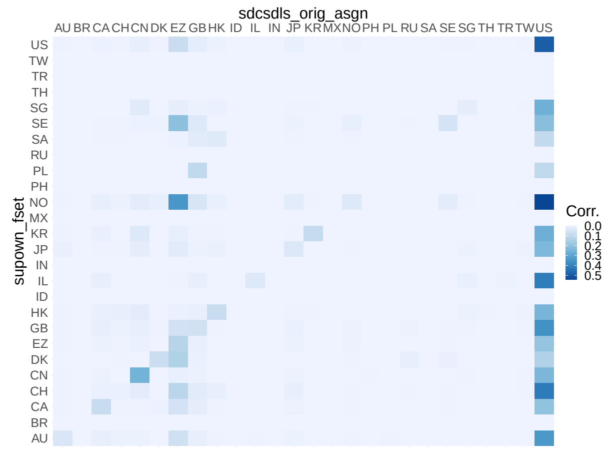


Figure 6: Intensive Margin Correlation, across Channels

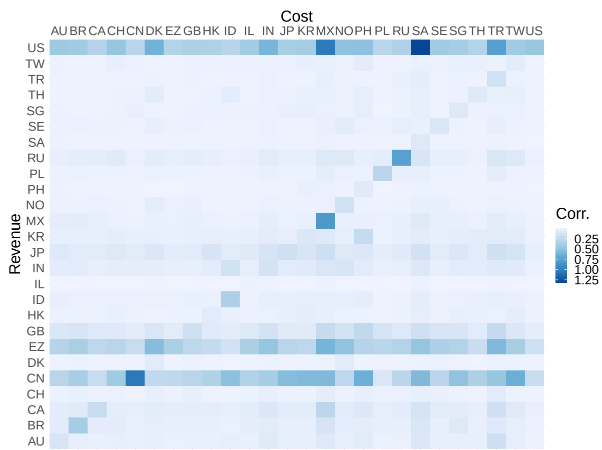
(a) Investors, Debt



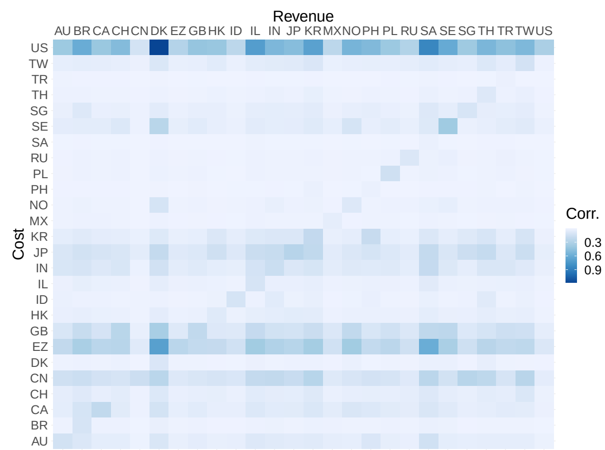
(b) Debt, Investors



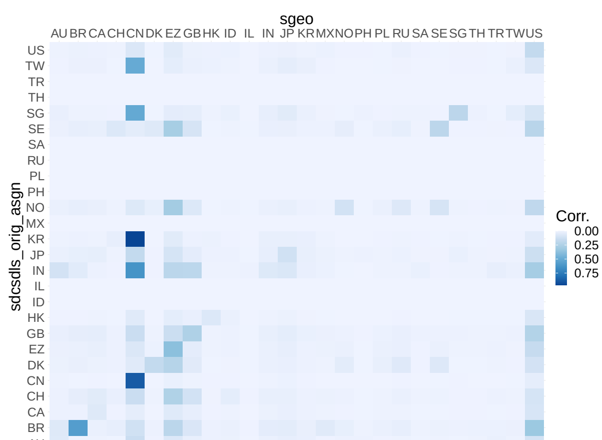
(c) Revenue, Costs



(d) Costs, Revenues



(e) Revenue, Debt



(f) Debt, Revenue