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FINANCIAL CRISES AND THE GLOBAL SUPPLY NETWORK: EVIDENCE FROM MULTINATIONAL ENTERPRISES

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ABSTRACT

This paper empirically examines the effects of financial crises on the organization of production of multinational enterprises. We construct a panel of European multinational networks from 2003 through 2015. We use as a financial shock the increase in risk premia between August 2007 and July 2012 and build a multinational-specific shock based on the network structure before the shock. Multinationals facing a larger financial shock perform worse in terms of revenue, employment, and growth in the number of affiliates. Lower growth in the number of affiliates operates through a negative effect on domestic and foreign affiliates, and is concentrated in affiliates in a vertical relationship with the parent. These effects built up slowly over time. Negative effects are driven by multinationals with initially more leveraged parents, who reduce relatively more the number of foreign affiliates. These findings lend support to the hypothesis of financial frictions shaping multinational activity.

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A data appendix is available at http://www.nber.org/data-appendix/w31216

1 Introduction

Financial crises have large, negative, and persistent effects on economic activity. Compared to normal recessions, they cause more significant declines in output, credit, and employment in the affected countries (see, among others, Schularick and Taylor, 2012 or Jordà et al., 2013). This paper examines the effect of financial crises on the organization of production and performance of multinational enterprises (MNEs). We also investigate whether the adjustment of MNEs to financial shocks operates through MNEs whose parents are financially constrained when the financial shock hits. To perform our exercises, we leverage a rich long panel dataset containing the evolution of MNEs affiliates' networks and MNEs' performance. Our data allow us to construct a firm-specific shock based on the initial exposure of MNEs affiliates to the financial shock,[1] so that the variation we use in our empirical setting compares MNEs in the same country and industry with differential exposure to the financial shock.[2]

We use the most recent financial crisis as our financial shock. The financial crisis had a global spread. However, it was particularly severe within the Eurozone. As an illustration of the financial disruption in the Eurozone, Figure 1 shows the monthly evolution of the 10-year government bond yields of Germany and Spain from 2001 through 2023. Both countries had almost identical borrowing costs during the early 2000s.[3] This pattern dramatically changed in August 2007 when BNP suspended subprime-related funds. At that moment, the difference between the borrowing costs of the Spanish and German governments—the risk premium—started to rise. It was not until the "whatever it takes" speech of ECB's president Mario Draghi in July 2012 that the risk premium stopped increasing and started to decline. Similar figures are obtained for other members of the so-called periphery (Portugal, Italy, Ireland, and Greece). By contrast, the changes in risk premium are much milder for the so-called core countries (e.g., France or Belgium).

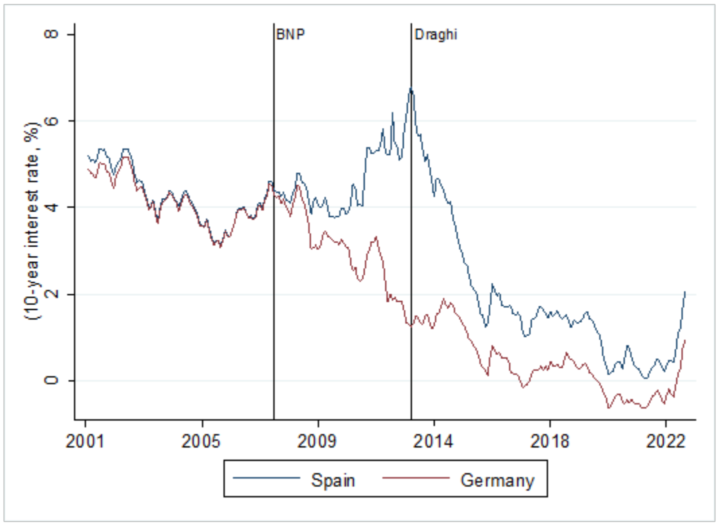
In this paper, we study how the increase in risk premia between these two events—our financial shock—affected European multinationals and their networks of affiliates. To identify

[1] A related, but distinct, literature focuses on understanding how shocks *propagate* through production networks. For example, Acemoglu et al. (2012) describe how micro shocks, in general, may lead to aggregate fluctuations through intersectoral input–output linkages. Cravino and Levchenko (2017) show that the network of foreign affiliates helps to propagate business cycle shocks to the parent domestic firm. Another strand of the literature focuses on the propagation of finance shocks (see, for example, Biermann and Huber, 2023; Demir et al., 2022). We depart from this literature by examining how the network of affiliates is affected by finance shocks rather than the propagation within a network.

[2] Our setting thus compares outcomes across MNEs. By contrast, Alviarez et al. (2017) find that multinational firms actually grew slower than domestic ones between 2008 and 2009 (the onset of the Great Recession). In a related contribution, Alfaro and Chen (2012) show that affiliates of foreign multinationals cope better with the initial shock (their study finished in 2008) than their domestic counterpart. These papers mostly focus on short-run effects and make the plausible assumption that the network of affiliates is constant. We instead examine whether and how financial shocks affect the MNE network itself and its performance in a longer time horizon.

[3] The consequences of this seemingly zero risk and the boom in Spain and other southern countries have been studied in the related literature (see, for example, Gopinath et al., 2017 or Basco et al., 2021). This paper focuses on the effect of the ensuing financial crisis on MNEs.

Figure 1: The Financial Shock in the Eurozone: Poster Child



Notes: The two vertical lines are August 2007 and July 2012. The first corresponds to the announcement of BNP Paribas of freezing subprime-related funds. The second corresponds to the "whatever it takes" announcement of Mario Draghi. Long-term interest rates obtained from ECB Statistical Data Warehouse.https://sdw.ecb.europa.eu/browse.do?node=9691124

the effect of the financial shock on European MNEs, we use the differential exposure of MNEs within a country and sector arising from their idiosyncratic exposure to the financial shock determined by their pre-shock network of affiliates (measured in 2006). We document that more exposed MNEs experience a negative effect both on relative MNE performance measures (growth of revenue and employment) and their number of affiliates. Moreover, we show that these effects build slowly over time. We also show that relatively more affected MNEs tend to reduce both the network of affiliates vertically related to the parent and their network complexity, as measured by the BHHI (Correa and Goldberg, 2022). In addition, they reduce their presence in the PIGS (Portugal, Italy, Greece, and Spain) and decrease the geographical distance with the affiliates. Finally, we provide evidence consistent with financial frictions playing a prominent role in driving these results. In particular, we show that the effect of the finance shock is exacerbated among more leveraged parents pre-shock (in 2006).

To empirically perform this exercise, we construct a long-run panel covering the network structure of MNEs. We build this panel with information on parents and affiliates taken from Merlevede and Theodorakopoulos (2023).[4] Our baseline dataset covers twenty-nine European countries and thirty-nine countries in total.[5] To the best of our knowledge, this is the most

[4]This paper extends the work of Merlevede et al. (2015).

[5]Given that our goal is to compare multinational firms located in different countries and exposed to different shocks (both domestically and through the affiliates), we choose to ignore firms with only domestic networks. Focusing on multinational firms, we mitigate the concern that these firms are different from domestic ones. Needless to say, one drawback of this choice is that we cannot compare multinational vs domestic firms. However, this type of exercise has already been performed in Alfaro and Chen (2012) and Alviarez et al. (2017), among

comprehensive panel on MNEs' activity and network of affiliates studied in the literature. We select the period 2006-2015 for our analysis (while doing pre-trend analysis starting in 2003 when possible). The initial period is selected to allow for observations before the onset of the Great Recession. At the same time, 2015 is chosen to allow for the possibility of protracted effects of the recession.[6] The dataset has two main advantages. First, it contains information on the network of affiliates of parents in different countries. This allows us to compare multinational firms in the same country and industry but with a different set of affiliates. Second, it is a long panel. Similar to the findings in other contexts of the international trade literature (e.g., Autor et al., 2014 and Dix-Carneiro and Kovak, 2017), we document that the effect of the financial shock builds slowly over time. If we only used a short-run panel, we could wrongly conclude that there were small or no effects.

Before performing our empirical analysis, we begin the paper by taking advantage of the novelty of our dataset to uncover some facts about European MNEs. First, multinational activity is highly heterogeneous across countries and concentrated in a few of them (the top-5 countries account for more than half of the parents and affiliates). Second, the distribution of the network size also exhibits substantial heterogeneity. Most networks are small (around 50% have only one or two affiliates). However, there is a significant right tail. Around 10 percent of MNEs have between 6 and 10 affiliates, while the amount of networks with more than 50 affiliates is around 2 percent. Third, roughly half of MNEs networks do not have domestic affiliates. Fourth, geographical proximity to the parent is important (roughly 90 percent of affiliates are either domestic or in European countries). Fifth, most affiliates (over 70 percent) are fully owned.

After having documented these facts, we turn to our main empirical exercise. We analyze the effect of the financial shock on European MNEs. Our dependent variables compare the outcomes from 2006 through 2015 relative to the same outcomes in 2006. As an explanatory variable, we use the pre-existing MNE-specific network to construct an MNE-specific exposure measure to the financial shock based on the location of the parent and affiliates in 2006. We assign to each MNE an exposure score constructed as a weighted average of the increase in risk premium in the countries each MNE has affiliates in 2006. For example, this allows us to compare two MNEs located in the same industry in Germany but with different affiliate networks that experienced the financial crisis with different intensities (e.g., one MNE with affiliates in Spain and Greece relative to another MNE with affiliates in Switzerland and Sweden). In our regression, we also control for initial MNE characteristics such as total assets, age, and the initial number of affiliates, in addition to country and two-digit NACE industry fixed effects.

Using this empirical specification, we first document that parents with a more financially-hit

others.

[6]It is well-known that the European recession was very uneven across countries. While Germany suffered a mild and short-term recession, GDP in Spain did not recover pre-recession boom outcomes until 2016 according to World Economic Outlook Data.

network of affiliates perform worse in both revenues and employment growth over the 2006-2015 period. The effects are substantial. Over the period 2006-2015, an MNE with a financial shock to its network equal to one standard deviation of the financial shock displays a 7.6 and 10.7 percent lower growth rate in revenues and employment, respectively. Note that this effect is identified by comparing MNEs with networks that are differentially exposed to the financial shock, and it is not driven by the direct financial shock to the country where a parent is located (since the country-fixed effects absorb it).

We then investigate how the MNE network is reshaped due to the financial shock. We first show that MNEs whose network experiences a more significant financial shock react by reducing the growth in their number of affiliates in the following years relative to less affected MNEs. The effect of a shock of magnitude equal to one standard deviation of our MNE-specific network shock is to reduce by 4.1 percent the growth rate in the number of affiliates. This reduction affects roughly equally foreign and domestic MNE affiliates. By contrast, MNEs carry all adjustments in the number of affiliates through the number of vertically related affiliates (defined as affiliates with different four-digit industry codes to the parent), while we do not find any significant adjustment for horizontally-related affiliates.

We also investigate how the effect of the financial shock builds up over time. We use the local projection method of Jordà (2005) to compute the effect of the financial shock at different time horizons. We find that for both MNE network adjustment and parents' performance, the effect of the financial shock builds up slowly over time. This finding underlies the importance of using a long panel to study the effects of the financial crisis on MNE activity. Finally, we document other margins of MNE network adjustment that can help to illuminate different theories. For example, consistent with gravity models, we show that the average distance between both parents and affiliates and between affiliates is reduced after the financial shock.[7] We also show that business complexity, as defined in Correa and Goldberg (2022), decreases in relatively more financially hit networks. By contrast, we find little support for changes in the upstreamness or input-output requirements of the network as an adjustment to the financial shock.[8]

After having documented the effect of the financial crisis operating through the MNE network, we provide evidence consistent with a financial-frictions mechanism being at play in shaping MNE adjustment. We construct an MNE-specific measure of leverage pre-shock (2006), following the work of Kalemli-Özcan et al. (2022), as the ratio of total liabilities (long-term debt, loans, trade credit, and other liabilities) over total assets. We augment our baseline specification and include the interaction of the MNE-specific leverage measure with our MNE-specific network financial shock (while adding leverage and financial shocks as controls). We find that relatively more leveraged MNEs are those more severely affected by the network shock. Both their performance measures (operating revenue and employment) and the shrinkage of the MNE

[7]This is consistent with the findings in, for example, Giroud (2013) and Gumpert et al. (2022).

[8]We note, however that this lack of evidence may be due to the little granularity of input-output coefficients and upstreamness measures (two digits).

network operate through parents that are more leveraged and that experience a more severe financial network shock. By contrast, the direct effect of the financial shock disappears once we control for its interaction with MNE leverage. This finding lends support to the interpretation of the results being driven by financial frictions.

We also observe that the MNE network adjustment pattern to the financial shock is broadly similar to the one we uncovered in our baseline exercise—but concentrated in initially more leveraged MNEs. In particular, we observe that the adjustment in the MNEs' networks is concentrated in vertically-related affiliates and that the relative reduction of affiliates operates both through domestic and foreign affiliates. A noteworthy difference is that the estimated effect on foreign affiliates is substantially larger than that for domestic affiliates. This finding suggests that leveraged MNEs adjust more on the foreign affiliates' margin. We also find again that the direct contribution of the network shock has no effect on MNE network adjustment—the interaction term absorbs all the variation. Perhaps not surprisingly, this suggests that the firm leverage mechanism plays a substantial role in adjustment to the financial network shock.[9] This dependence of the survival of the affiliate on the leverage of the parent is consistent with a mechanism in which the parent offers credit to the affiliate, i.e., internal trade credit within MNEs, as in Antràs and Yeaple (2014).

Related Literature This paper relates to different strands of the literature. First, it contributes to the large and expanding literature on the long-run economic effects of financial crises. In this sense, it is related to, for example, the works of Schularick and Taylor (2012) or Jordà et al. (2013). The latter documents that financial crises are different from normal recessions. It shows how the recovery from financial crises depends on the credit accumulated prior to the crisis. Similar to Jordà et al. (2013), we also document that financial shocks have significant and long-lasting effects. Moreover, even though we look at firms instead of countries, we also emphasize that the leverage of the firm at the onset of the financial crisis shapes its effects. The literature on financial constraints and firm performance is rich and vibrant. We refer the reader to, for example, the survey in Buera et al. (2015). A close paper is Kalemli-Özcan et al. (2022) who emphasize the role of the leverage of firms for investment during the Eurozone (EZ) financial crisis. The role of parent leverage in shaping the effects of finance network shocks (house price fluctuations) at the firm level has also been identified by Giroud and Mueller (2016) for US domestic firms. The main difference between our work and this literature is that we focus on multinational firms and how they change their network as a reaction to a financial shock.

The trade literature has emphasized the importance of multinational activity and its determinants, see the survey by Antràs and Yeaple (2014) and the references therein. Our paper

[9] This finding is also similar to Giroud and Mueller (2016), who following a similar approach to ours, find that after interacting their financial shock (house prices in their case) with leverage, all the variation is absorbed by the interaction and the effect of the shock by itself disappears.

belongs to the subset of the literature interested in the effects of economic crises. In a related contribution, Alviarez et al. (2017) compares the performance of multinational versus domestic firms during the Great Recession. They document that multinationals' sales grew slower between 2008 and 2009. There are two main differences. First, we compare multinationals located in different countries. Second, we focus on how parents change their global network.

An important contribution in this field is Alfaro and Chen (2012). They showed that foreign-owned firms coped better with the recent financial crises than domestic firms. One main difference with their work is that we focus on the MNE network (rather than affiliates' performance directly). That is, we only indirectly examine affiliates' outcomes by analyzing how the network of affiliates changes. For example, we show that financially hit networks become relatively smaller, less vertically integrated, geographically closer, and with less presence in the PIGS (Portugal, Italy, Greece, and Spain), see Table 4. Thus, it implies that if an affiliate is in a more financially hit network is more likely to be dropped from the network, especially if it is in a distant country and vertically integrated. However, we do not compare between domestic and foreign-owned affiliates, which is the exercise in Alfaro and Chen (2012). Compared to the extant related literature, an important difference is that our finance shock is at the firm level and depends on the initial composition of the network. That is, since the international network of affiliates is a parent choice, (generically) all multinational firms in the sample have different shocks. This exercise is related to Cravino and Levchenko (2017), which emphasizes that business cycle shocks to foreign countries may affect parents' performance. The main departure from this paper is that we consider a specific shock and compare multinationals within an industry and country, also allowing the MNE network to change as a reaction to the shock.

The rest of the paper is organized as follows. Section 2 introduces the database and presents some facts on multinational activity. Section 3 briefly explains the financial disruption in the Eurozone and how we build our proxies for the financial shock. Section 4 describes the empirical strategy. Section 5 reports the results. Lastly, section 6 concludes.

2 A New Database on Multinational Networks

In this section, we discuss the construction of our data set. It consists of a panel of firms spanning from 2003 through 2015. Our data contains information on the parent-affiliate relationship of each firm, in addition to information on firm characteristics and performance (e.g., employment, profits, etc.).

We use the Amadeus database by Bureau van Dijk (BvDEP), which provides comprehensive firm-level information for European firms, to construct a panel of multinational networks.[10]

[10] Amadeus can be thought of as the equivalent to the Orbis database but limited to European countries. Merlevede et al. (2015) describe the construction and representativeness of an earlier version of the dataset at length. The dataset used in this paper is an update with more recent data that have meanwhile become available.

Key for our purposes, in addition to standard firm characteristics and performance measures,[11] Amadeus contains information on whether or not each firm appearing in the database has any affiliates. For firms with affiliates, it also provides a list of its affiliates and some limited information on each of the affiliates. In particular, it includes the location of the affiliates, which allows us to construct the entire network of a multinational including affiliates that are located outside Europe. Moreover, it also includes the share held by the parent of each affiliate. To construct our measure of an MNE network, we retain affiliates where the parent holds more than 10 percent of the affiliate's share.

Affiliates that are available as separate entries in Amadeus are identified by a unique ID number. These essentially correspond to affiliates located in European countries. For these affiliates, we can retrieve full information (balance sheet, profit, and loss account, location, industry classification,...) from their own entry in the Amadeus database rather than being limited to the information provided through the parent's entry.

We use annual versions of the Amadeus database and extract parent-affiliate combinations to construct a time series of parent-affiliate links.[12] In this parent-affiliate-year dataset, we then fill out the financial and other relevant information for parents and affiliates from their own entries in the database. We focus on parents and affiliates active in the business economy (and thus exclude agriculture and non-market services from our analysis).[13] In practice, this implies that one can think of our dataset as consisting of a panel in the affiliates-year dimension with full information on the parent side attached to each affiliate-year entry.

Our parent-affiliate-year panel contains data for twenty-nine European countries between 2003 and 2015, with affiliates in one hundred and ninety countries, and it is taken from Merlevede and Theodorakopoulos (2023). The dataset captures on average 44.6% of cross-border affiliates and 62.0% and 64.3% of employees and turnover that is reported in the Foreign AffiliaTes Statistics (FATS).[14] These numbers are stable over time and draw consistently from different industries and source-destination pairs. For example, when considering source-destination-industry-year cells correlations amount to 0.72 (68,511 cells) for the number of firms, 0.67 for the number of employees (26,633 cells), and 0.39 (45,583 cells) for turnover. In our sample, there are 18,223 multinational networks in 2006, of which 12,087 are still active as networks in

[11]These include, among others, operating revenue, total assets, employees, sales, financial revenues, and expenses. See https://www.bvdinfo.com/en-gb/our-products/data/international/amadeus.

[12]Occasionally, a link is not reported in the year t issue of the database, while it is reported in the $t-1$ and $t+1$ issues. In these cases, we assume that the link existed in t as well.

[13]Both agriculture and non-market services are heavily regulated in Europe and it is unclear that the market forces we study in this paper apply to these sectors as well.

[14]The Regulation (EC) No 716/2007 on the structure and activity of foreign affiliates as the regulatory framework for the provision of foreign affiliates statistics was adopted in 2007. The main objective of Regulation (EC) No 716/2007 is to establish a common framework and statistical quality standards for the systematic production of comparable statistics on foreign affiliates. Inward FATS-statistics describe the activity of foreign affiliates resident in the compiling economy, outward FATS-statistics describe the activity of foreign affiliates abroad controlled by the compiling economy.

2015 (see Table 1 in the Online Appendix).[15]

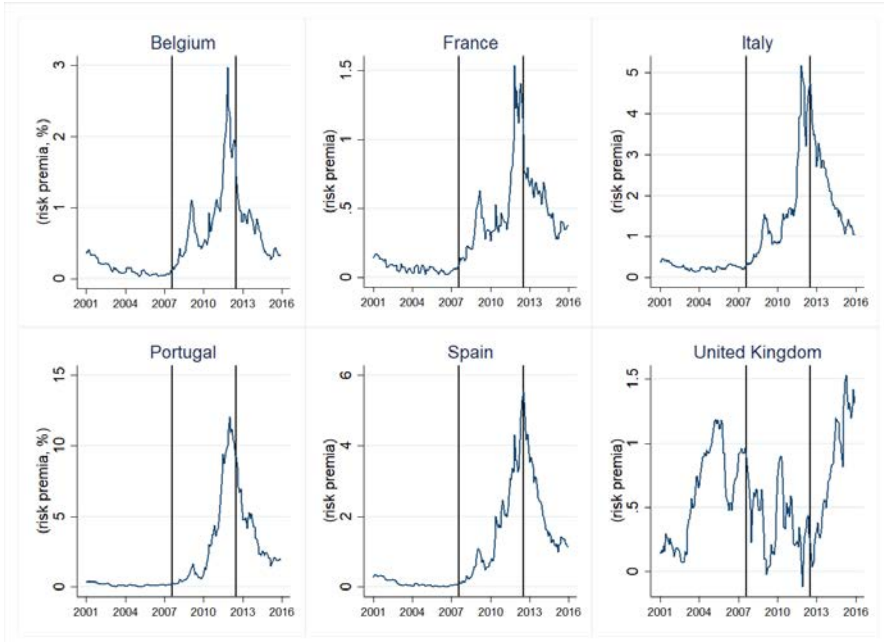
Parents and affiliates are geographically concentrated in our dataset. The majority of parents are located in a few countries (see Table 2 in Online Appendix). For example, in 2006, 62% of parents are located in the top-5 countries (Germany, Netherlands, UK, Belgium, and Italy). Similarly, affiliates are mostly located in a few mature EU economies. Indeed, roughly half of them were also located in the top-5 countries (Germany, UK, France, Netherlands, and Italy). Proximity to the parent is also a prominent feature of MNEs networks. Indeed, the vast majority of affiliates are located in Europe, while the US is the first non-European destination with 5% of affiliates (Tables 3 and 4 in Online Appendix). This geographical distribution of parents and subsidiaries is in line with the findings of Altomonte et al. (2021) for a cross-section of worldwide business groups in 2015.

Novel Facts about MNEs Networks Given the novelty of the dataset, we briefly document some facts on the characteristics of multinational networks that can be of independent interest. As shown in Table 5 in the Online Appendix, most multinational networks are small. In 2006, 43.7% of the networks had only one affiliate and 71% less than three. From 2006 to 2015, the percentage of networks with only one affiliate decreases by about 13 percentage points to the benefit of larger networks (in particular, those with more than six affiliates). Next, we turn to discuss the share of foreign affiliates in MNEs networks, which we report in Table 6 of the Online Appendix. Given that we are analyzing MNEs, MNEs with only one affiliate have, by construction, a foreign affiliate. Networks with only one affiliate represent 43.7% of the total number of networks in our sample. This disproportion of foreign-based affiliates is extensive even when we look at larger networks. Almost 70 percent of networks have, at most, one domestic affiliate. Finally, we also note that Table 6 shows that there is no clear correlation between the number of domestic and foreign affiliates.

Most multinational networks are located close to the parent. Table 7 in the Online Appendix shows that, in 2006, almost 95 percent of affiliates were either domestic or European (54% and 40.8%, respectively). Over the whole period (2006-2015), the percentage of domestic affiliates decreased (from 54% to 46%), while that of affiliates outside of Europe increased (from 5.2% to 18.7%). As for the percentage of European affiliates, we see a decreasing dynamic starting at 40.8% in 2006 and reaching 35.4% in 2015. Most multinational networks in our sample remain stable over time. Table 8 in Online Appendix shows that between 2007 and 2015, in about 64 percent of the network-year observations, no affiliation was either added or dropped. By contrast, in around 12 percent of MNEs network-years at least one affiliate is added. Similarly, more than 15 percent have at least one affiliate dropped. There is also a non-negligible 3 percent of network-years with more than five affiliates added or dropped. In our empirical analysis, we will examine whether such changes are correlated with financial shocks. Finally, Table 9 in the

[15]We identify a multinational network as having at least one cross-border affiliate in 2006.

Figure 2: Evolution of Risk Premia - Selected Countries



Notes: Long-term interest rates (10 year maturity) differential with Germany. The two vertical lines are August 2007 and July 2012. The first corresponds to the announcement of BNP Paribas of freezing subprime-related funds. The second corresponds to the "whatever it takes" announcement of Mario Draghi. Long-term interest rates are obtained from ECB Statistical Data Warehouse. They relate to interest rates for long-term government bonds denominated in Euro for euro-area Member States and in national currencies for Member States that have not adopted the Euro at the time of publication.

Online Appendix shows that most affiliates (71%) are fully owned.

3 Financial Shock: The Eurozone Financial Disruption 2007-12

We use the differential increase in countries' government long-run debt yields relative to Germany (risk premia) during the Great Recession as our measure of financial shock. In this section, we discuss the evolution of risk premia during the last two decades and explain why we can interpret the changes in risk premia between August 2007 and July 2012 as a financial shock. Then, we describe how we compute our measure of financial shock at the MNE level.

One of the defining features of the Great Recession was the differential increase in financial risk across countries within Europe and, in particular, within the Eurozone. We exploit this heterogeneous increase in financial risk across countries as an exogenous financial shock to firms to investigate how the worsening of financial conditions affects the performance of parents and affiliates. This increased financial risk is readily seen by analyzing the evolution of the "risk premia" across countries.

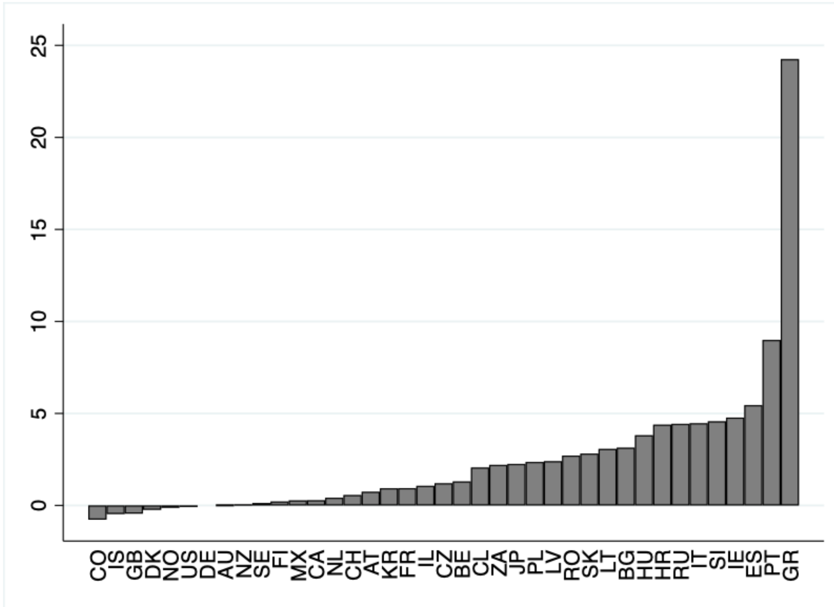
Figure 2 reports the monthly evolution of the risk premia for a selected group of six European countries, illustrating the heterogeneous financial disruption across European countries. As it is common in the literature, we define the risk premia of a country as the difference between the interest rate of the long-term government bonds issued by a given country relative to comparable bonds issued by the German government. If the risk premia of a country increases, it means that borrowers require a higher interest rate to hold the government debt of that country, which translates into worsening the financial conditions of the country. In particular, we consider the yields of 10-year government bonds to construct our measure of risk premia. The two vertical lines in the figure represent the origin and end of the financial crises: August 2007 (the announcement of BNP Paribas, which froze subprime-related funds) and July 2012 (the "whatever it takes" speech of Mario Draghi, president of the ECB at the time.). As can be seen in the figure, these two dates perfectly fit the remarkable increase in the risk premia of the periphery countries (Italy, Portugal, and Spain). Note that for core countries (Belgium and France), the qualitative pattern is the same, but the scale is much smaller. In contrast, the risk premium in the United Kingdom even declined, reflecting the fact that the perceived risk in the United Kingdom, which was not part of the Eurozone, was somewhat lower than in Germany.[16]

A reasonable concern is whether the increase in risk premia after the BNP event was a pure financial shock. Even though there is a growing consensus on this narrative (see, for example, Schoenholtz and Cecchetti, 2017), there is not yet a definitive answer. Basco et al. (2022) argues that, at least in Spain, this seems to be the case. For example, using data on mortgage credit and the municipality level, they document a break in the monthly evolution of the average loan-to-value and average mortgage value in August 2007. Note that the Spanish economy was still growing at high rates during 2007 and early 2008. The interpretation is that Spanish banks used securitization to expand their lending capacity. This market collapsed after the BNP announcement (see Jiménez et al., 2012 for empirical evidence on this mechanism). Therefore, while acknowledging this caveat, we assume that the increase in risk premia after the BNP announcement reflected a financial shock in all countries.

In practice, we have data on long-term ten-year bonds for thirty-nine countries spanning Europe and its major trade partners (e.g., the US, China, etc.). Figure 3 reports the change in the risk premium between July 2012 and August 2007 for all the countries in our sample. Table A.4 in the appendix reports the actual numbers used in the figure. As can be seen, countries like the United Kingdom or Denmark were perceived as less risky than Germany. Indeed, the change in risk premium in the United Kingdom was -0.7 percent. By contrast, periphery countries like Portugal or Spain experience a substantial increase in their risk premia (9.0 and 5.5 percent,

[16] Beyond these selected countries, there exists a consensus that these two dates marked the start and end of financial turbulence in the European Union. On the 9th of August 2007, BNP Paribas decided to freeze funds related to US subprime mortgages, thereby initiating a broad liquidity crisis. On the 26th of July 2012, Mario Draghi, the then president of the European Central Bank, gave the famous "whatever it takes" speech, which had an immediate effect on the government debt of countries at-risk.

Figure 3: The Financial Shock: Change in Risk Premia Between July 2012 and August 2007



Notes: Each bar corresponds to the difference in risk premia between July 2012 and August 2007. Risk premia is defined as the long-term interest rates differential with Germany.

respectively), reflecting higher financial risk in those countries. Our identifying assumption is that firms did not anticipate the financial crisis in 2006 and that the increase in risk premia is a good proxy for the financial shock experienced by different countries. We expect that changes in the risk premia capture well how the financial conditions of banks evolved during the crisis so that firms located in countries with larger increases in risk premium would have more difficulties accessing liquidity. It is well known that European firms depend more on loans from banks as a source of liquidity than their US counterparts (see, for example, Allen and Gale, 1995). Thus, this shock plausibly affected the capacity of firms to fund themselves or provide credit to affiliates—we will explore this channel and provide evidence consistent with it playing a substantial role. However, needless to say, the financial crisis operated through multiple channels that affected firms in several ways, e.g., through changes in demand to consumers, in addition to a tightening of the borrowing constraints.

3.1 Construction of the Main Explanatory Variables

As further explained in the next section, our empirical strategy proceeds in two steps. First, we study the reduced-form effect of the financial shock on MNEs outcomes. Second, we provide evidence consistent with the view that financial constraints play an important role in shaping the adjustment to the financial shock. We now discuss how we construct the variables we use for our empirical exercises.

Network Shock We define the *network shock* of a MNE with parent p as

$$NetworkShock_p = \sum_{c \in \mathcal{S}_p^{06}} \alpha_{p,c}^{06} \cdot \Delta Risk_c, \tag{1}$$

where $\mathcal{S}_p^{06}$ denotes the set of all countries in which the parent network p was present in the year 2006 (including both the country of the parent and all affiliates). $\Delta Risk_c$ is the change in risk premium in the country c between July 2012 and August 2007, and $\alpha_{p,c}^{06}$ is the weight of country c in the network of parent p in 2006 (i.e., the weight is taken before the shock to alleviate anticipation concerns). Note that this variable is MNE-specific since it depends on the location of the affiliates. This allows us to compare MNEs within the same industry and country that have networks with differential exposure to the financial shock. According to this definition, the network shock is larger if an MNE has most of its network in financially hit countries. These types of measures have been used in other contexts to assess how firm networks shape the adjustment of different firm outcomes to location-specific shocks, see, for example, Giroud and Mueller (2016) in the context of US firms and house prices.

For our baseline weighting scheme for the network shock, we choose to attach equal weights to all countries present in the MNE network in 2006. Even though this may introduce some noise in our measure since we are weighing equally without using any information on the importance of the country nodes of the network, this strategy has the advantage of maximizing the number of observations in our sample. The reason is that this weighting scheme requires a minimal amount of information on the MNEs network and it allows us to incorporate the entirety of an MNE network. Table 1 shows that the average and standard deviation of the network shock in our sample are 1.39 and 1.97, respectively.[17] As robustness, we also compute the same network shock using the share of the value of assets in country c[18] in 2006 as a weight for the network shock. This comes at the cost of reducing the sample size by about half because we need information on assets for all affiliates in the network to calculate the shock, especially for non-European affiliates information on assets is not available. Reassuringly, however, we find similar results when using this alternative weighting scheme.

Parent Leverage The empirical strategy that we proposed so far can only capture the overall effect of the financial shock on the MNE outcomes of interest. However, it is not informative on the mechanisms driving the results. To make progress in this direction, we propose to augment our empirical strategy by making use of the financial records of the firms in Amadeus. We create a measure of parent leverage along the lines of Kalemli-Ozcan et al. (2022) and use it to investigate whether parents with pre-shock higher leverage, which we would expect to be more affected by the financial crisis, are driving the reduced-form results we find when we regress

[17] The interquartile range is 1.90, the tenth percentile, −.15, the median, 0.76, and ninetieth, 3.49.

[18] I.e. the sum over all affiliates (and if relevant parent) located in country c.

outcomes of interest on the MNE-specific financial shock.

We calculate the pre-shock leverage as the ratio of the sum of long-term debt, loans, trade credit, and other current liabilities (total liabilities) to total assets in 2006. Table 1 reports that the average and median values are 0.50 and 0.48, respectively. The standard deviation of our leverage measure is 0.42. Note that we compute a parent-specific measure of leverage. Our empirical strategy is to interact parent-level leverage with our measure of the MNE-specific financial shock in our regressions of interest. While this strategy does not uncover the effect of leverage, it allows us to compute a correlation in the data which is identified by comparing outcomes of firms with different levels of leverage. We indeed show that networks with initially more leveraged parents tend to adjust more to financial shocks, suggesting that the financial channel is at play.

4 Empirical strategy

Our empirical strategy consists of two estimating equations. First, we study the reduced-form effect of the financial shock on MNEs outcomes. This reduced-form specification is our baseline specification. We use it to study both the effect of the financial shock on MNEs' organization and performance. We also use it to trace the effect of the financial shock over time. Second, we augment our baseline specification with an interaction of the MNE financial shock with its leverage. This specification allows us to provide evidence consistent with financial constraints playing an important role in shaping the adjustment to the financial shock. Before discussing our empirical specifications, we discuss some sample restrictions that we apply to our data.

Sample Restrictions First, in order to have meaningful variation in the MNE networks, we focus on MNEs that have at least two affiliates at the start of the period (2006) and do not have a disproportionately large network of domestic affiliates.[19] For the latter, we trim networks above the 95th percentile of the number of domestic affiliates in 2006, so that we focus on variation coming from international exposure.[20] Second, to ensure that our results are not driven by outliers, we winsorize outcomes at the 1st and 99th percentile. We also note that the number of countries covered in the estimation sample reduces due to the non-availability of risk premia for some countries (Estonia, Serbia, and Ukraine).[21]

Effect of the Financial Shock Our first empirical exercise is to examine the effect of the financial shock on MNE outcomes. Our main specification investigates the effect of the financial

[19]Table A.2 shows that our main results hold when we relax these sample restrictions in a variety of ways.

[20]This represents a cutoff of 16 domestic affiliates. Results carry through without the cutoff or with cutoffs of 10 or 20.

[21]The number of observations further varies due to the fact that financial variables are not available for all parents or affiliates.

network shock on the structure of the MNE network and parents' performance. We consider the following empirical model to assess the effect of the network shock on outcome Y_p,

$$Y_p^{06,15} = \beta_0 + \beta_1 * NetworkShock_p + \beta_2 X_p + \delta_c + \delta_i + \varepsilon_p, \tag{2}$$

where $NetworkShock_p$ is the network shock defined in Equation (1). X_p denotes parent control variables, δ_c and δ_i are parent country and industry fixed effects, and ε_p denotes an error term. $Y_p^{06,15}$ is a normalized parent or network outcome over the period 2006-2015, which we discuss in more detail below.

We are interested in two sets of outcome variables. First, we analyze how the network of affiliates associated with a parent adjusts after the financial shock. We consider the total number of affiliates and also study separately the effect on foreign and domestic affiliates, and on affiliates that are in vertical and horizontal relationships with the parent firm.[22] Then, we analyze the effect on parents' performance. In particular, we analyze employment and operating revenue for which we have the largest number of observations.

The parent-level control variables include the following variables: total assets, age of the parent, size of the network (number of affiliates), and the share in total assets of domestic affiliates. All these controls are taken in the initial year (2006). As discussed above, this $NetworkShock$ is parent-specific. This allows us to include the parent's country and industry fixed effects and, thus, better identify the shock, by comparing firms with different network exposure to the financial shock. Table 1 provides summary statistics.

Dynamics of Adjustment to the Financial Shock In addition to estimating the overall effect of the financial shock between the initial and final period in our sample, we are also interested in studying the pace at which the effects of the financial shock build up over time. To estimate the dynamics of firm responses to the financial shock, we use the local projections method developed by Jordà (2005). For a given outcome variable of interest Y_p, we estimate the following local projections:

$$Y_p^{t_0,t_0+j} = \beta_{0j} + \beta_{1j} * NetworkShock_p + \beta_{2j} X_{pt_0} + \delta_{cj} + \delta_{ij} + \varepsilon_{pj}, \tag{3}$$

with t_0 being the base year, in our case 2006, and $t_0 + j$ running from 2003 to 2015 (2006 excluded) for different outcomes Y_p. Equation (3) is estimated for each j separately. In these regressions, the coefficient β_{1j} captures the effect of the network shock after j periods from 2006. Finally, X_{pt_0} denotes firm-specific controls from the base year, and δ_{cj} and δ_{ij} denote parent country and industry fixed effects specific to end year $t_0 + j$.

[22] Affiliates are classified as horizontal or vertical based on their industrial four-digit NACE classification.

Table 1: Summary Statistics

	Obs. (1)	Mean (2)	St.Dev. (3)	p10 (4)	p50 (5)	p90 (6)
Network shock	8922	1.34	1.85	-.12	.79	3.20
Number affiliates (2006)	9655	5.39	6.51	2	3	11
Number affiliates (2015)	9655	6.29	13.31	0	3	14
(log) Real Total Assets (parent)	8962	16.73	2.47	4.00	16.85	19.51
(log) Real Revenues (parent)	6718	16.54	2.82	12.53	17.08	19.70
Number employees (parent)	7339	751.2	5857.1	1	57	986
Leverage (parent)	8352	.50	.40	.08	.48	.85
Age (parent)	9640	29.4	57.3	6	18	61

Notes: Network shock as defined in Equation (1). See text for the definition of leverage. All variables are for 2006, unless it is explicitly stated.

Inspecting the Role of Firm Leverage Lastly, we investigate one potential channel through which adjustment to the financial shock is likely to operate: financial frictions. In particular, we investigate whether part of the MNE adjustment to the financial shock can be accounted for by differences across MNEs in their pre-shock leverage levels. To this end, we use our measure of leverage discussed in the previous section. We interact firm leverage with our shock measure in our empirical specification, Equation (2), to obtain

$$\begin{aligned} Y_p^{06,15} =& \beta_0 + \beta_S * NetworkShock_p + \beta_{SL} * NetworkShock_p * FirmLeverage_p \\ &+ \beta_L * FirmLeverage_p + \beta_2 X_p + \delta_c + \delta_i + \varepsilon_p, \end{aligned} \tag{4}$$

where $FirmLeverage_p$ denotes our leverage measure of parent p. As in our baseline model, X_p denotes parent and network controls, δ_c and δ_i denote country and industry fixed effects, and ε_p, the error term. Note that the coefficient on the interaction term β_{SL} is identified by comparing firms in the same country, industry, and network shock, but different levels of leverage. Similar to (3), we also extend (4) to

Table 1 provides the summary statistics of the main variables.[23] As discussed above, there exists a remarkable amount of dispersion in the network shock across MNEs in our sample, which will allow us to identify the effects of the finance shock. Similarly, we also note substantial heterogeneity in the initial leverage of parents in the sample. Indeed, whereas the average is 0.50, the 10th percentile is almost zero, and the 90th percentile is 0.85. We will exploit this difference to investigate the potential role of financial constraints as an important mechanism driving our results. We also observe that even though the average number of affiliates increased during this period, it may be driven by opposite changes in the two tails of the distribution. We will examine whether they are related to the MNE-specific network shock.

[23] Table A.1 reports their correlation.

5 Results

This section presents the results of the paper. We begin by presenting our main results, which document the effect of the MNE-specific shock on multinational activity and its organization. Next, we explore the dynamics of adjustment over time and in terms of network characteristics. Then, we augment our baseline specification to explore the role of financial frictions as measured by firm leverage—providing evidence consistent with financial constraints playing a prominent role in the adjustment to financial shocks.

5.1 The Network Shock

In this section, we examine the effect of the network shock on the organization of MNE production and parents' operating revenues and employment. As discussed in Section 3, the network shock is a weighted average of the financial shock across all locations in which an MNE is present. Thus, the network shocks include both the shock in the country of the parent and the shocks in the countries where the MNE has affiliates. An appealing feature of this specification is that it features a parent-specific shock. This allows us to compare the outcomes of different MNE networks and parents within the same country and industry. Our baseline weighting scheme in the construction of the MNE network shock, $\alpha_{p,c}^{06}$ in Equation (1), is a uniform weighting across all countries in which the MNE is present. As a robustness check, we use the asset value of all firms in the network of parent p in 2006 to compute the weights $\alpha_{p,c}^{06}$ in our network shock measure, Equation (1). We show that our results are robust to this alternative weighting scheme.[24]

Since we are interested in both 1) the overall 2006-2015, "long-difference" effect of the shock and 2) how the effect builds up over time, we construct our outcome measures in a way that it is easy to explore both effects with comparable outcome variables. Our dependent variables are normalized changes between 2006 and year t. Given an outcome of interest Y_p, we compute $Y_p^{06,t} = Y_{p,t}/Y_{p,2006}$. This normalized variable allows us to explore how the effects build up over time by considering $Y_{p,t}$ at different horizons t, as well as the "long-difference outcome", which would correspond to $t = 2015$. Normalizing by initial outcomes facilitates the interpretation of the results as multiples of the initial levels. All our regressions include as controls the initial (2006) number of affiliates, total parent assets, parent age, and country and industry fixed effects. Since financial networks are firm-specific, we choose as a baseline to report robust standard errors.[25]

Columns (1) through (4) of Table 2 report the effect of the financial network shock on the total number of affiliates, for different sets of fixed effects. In particular, there are no fixed effects in column (1), column (2) introduces parent country fixed effects, column (3) only

[24] The main drawback of this choice of weights is that we need detailed information on all affiliates in the network, and thus, we loose a sizeable amount of observations, especially for affiliates outside of Europe.

[25] We have verified that our results remain significant when clustering by parent country.

Table 2: Number of affiliates evolution, parent outcomes, and average network shock

	Number of affiliates				Revenue	Empl't
	(1)	(2)	(3)	(4)	(5)	(6)
Network shock	-0.026***	-0.022**	-0.026***	-0.022**	-0.041**	-0.058***
	[0.006]	[0.010]	[0.006]	[0.010]	[0.020]	[0.019]
Total assets (parent)	0.107***	0.099***	0.110***	0.102***	-0.082***	-0.055***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.021]	[0.017]
Initial # affiliates	-0.066***	-0.044*	-0.079***	-0.058**	0.121***	0.120***
	[0.024]	[0.023]	[0.024]	[0.024]	[0.045]	[0.041]
Age (parent)	0.015	-0.019	0.017	-0.002	-0.068*	-0.090***
	[0.016]	[0.017]	[0.017]	[0.017]	[0.037]	[0.031]
Observations	8,220	8,220	8,217	8,217	3,684	3,912
R-squared	0.049	0.088	0.071	0.105	0.091	0.062
Country FE	N	Y	N	Y	Y	Y
Industry FE	N	N	Y	Y	Y	Y

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1. Column headings indicate parent and network outcomes. Columns 1 to 4 use the ratio of 2015 to 2006 as the dependent variable. Columns 5 and 6 use log changes between 2006 and 2015 as dependent variables (so that results can be interpreted in terms of growth rates). Outcomes are winsorized at the first and 99th percentile.

considers parent industry fixed effects, and lastly, column (4) has both sets of fixed effects. The coefficient of the network shock is negative and significant in all columns. Even though the quantitative effect is similar across specifications, our preferred specification is column (4) which includes both sets of fixed effects. Thus, it means that, within an industry and country, networks belonging to parents in more financially-hit networks grow relatively less in the years following the shock. Quantitatively, comparing two MNE experiencing two shocks that differ in magnitude one standard deviation of the network shock, our estimates in column (4) imply that the harder-hit MNE would experience a 4.1% ($=0.022 * 1.85$) lower growth in its number of affiliates relative to the other MNE.

We also examine the effect of the network shock on the performance of the parent. In particular, column (5) and column (6) of Table 2 report the effects of the network shock on parents' real operating revenues and employment. Both dependent variables are defined as changes in logarithms between 2006 and 2015. We find that parents in more financially hit networks experience a lower value of both revenues and employment growth with respect to parents in less hit networks. Quantitatively, a one standard deviation increase in the network shock reduces long-run revenues and employment growth by 7.6 percent and 10.7 percent, respectively.

Robustness Table A.2 in the appendix reports a series of robustness checks to our findings on the number of affiliates. Columns (1) to (3) show that our results are robust to the different sample restrictions we apply to obtain our baseline sample: including MNEs with large domestic networks (column 1), including MNEs with only one affiliate (column 2), and excluding MNEs reporting consolidated balance sheets[26] (column 3). All coefficients are significant and have similar sizes (around -0.020). Column (4) –using our preferred sample again– shows that our baseline result remains significant when clustering standard errors at the country level. One potential concern is that, even though we include parent country fixed effects, the results may be driven by Greece. As we discussed above, Greece was an outlier in the change in the risk premium and the lead actor in the Euro-zone crisis.[27] Column (5) shows that the estimated effect does not change when we exclude Greek parents.

Our network shock includes both domestic and foreign affiliates. A reasonable question is whether the foreign affiliates do not really matter and whether the adjustment is driven by the domestic shock. To answer this question, we compute the network shock using only foreign affiliates—that is, we exclude the shock in the parent's country when we construct the network shock, Equation (1). Column (6) shows that, even though the coefficient decreases (from -0.022 to -0.013), it is still quantitatively important and statistically different from zero. Thus, the change in risk premium in the country of the foreign affiliates also affects the structure of the network which is chosen by the domestic parent. That is, there is some propagation from foreign affiliates.[28] Lastly, our dependent variable was an average of the changes in the risk premia in the countries of the affiliates. It could be argued that the shock should be weighted with the share of assets of each affiliate in the network. One shortcoming to performing this exercise is that the sample size decreases because we do know the location of all affiliates but information on their assets is limited to a subset of affiliates. In addition, it is not clear whether this missing information is random across affiliates. In any event, column (7) reports the effect of the network on the total number of affiliates when using assets as a weight for the network shock. The coefficient of the network shock is now significantly larger (-0.038).

Examining the Change in the Type of Affiliates We have shown that the network shock has a negative effect on the relative growth of the total number of affiliates. However, it was silent about the direction in which the network changed. We perform this exercise in Table 3. Column (1) repeats, for ease of exposition, our baseline specification for the overall number of affiliates. Columns (2) and (3) break down the total number of affiliates into foreign and domestic ones. We find that the reduction in the growth of the number of affiliates happens in both domestic and foreign affiliates. We find an estimate of roughly the same magnitude for

[26] As a standard we include both networks 1) for which consolidated accounts for the parent (or only one of the affiliates) are available and 2) for which unconsolidated accounts are available. See Kalemli-Ozcan et al., 2022 for the importance of including both.

[27] Figure 8 in the appendix shows that, as expected, the network shock for networks of Greek parents is also much larger than for other parents.

[28] In Appendix B, following Biermann and Huber (2023), we show how the network shock affected affiliates' sales growth. This exercise can be interpreted as the intensive margin of adjustment, as opposed to examining the number of affiliates (our main outcome).

Table 3: Number of affiliates evolution and average network shock: different types of affiliates

	All (1)	Cross-Border (2)	Domest. (3)	Same 4-digit (4)	Diff. 4-digit (5)
Network shock	-0.022**	-0.026**	-0.025**	-0.010	-0.022**
	[0.010]	[0.013]	[0.011]	[0.016]	[0.010]
Total assets (parent)	0.102***	0.137***	0.069***	0.053***	0.084***
	[0.008]	[0.010]	[0.008]	[0.011]	[0.008]
Initial # affiliates	-0.058**	0.190***	-0.130***	0.045	-0.116***
	[0.024]	[0.032]	[0.026]	[0.037]	[0.028]
Age (parent)	-0.002	-0.022	-0.002	0.054*	0.010
	[0.017]	[0.026]	[0.019]	[0.029]	[0.019]
Observations	8,217	8,217	7,116	1,883	5,555
R-squared	0.105	0.112	0.091	0.096	0.097
Country FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1. Column headings indicate the type of affiliates considered in the dependent variable. Outcomes are winsorized at the first and 99th percentile.

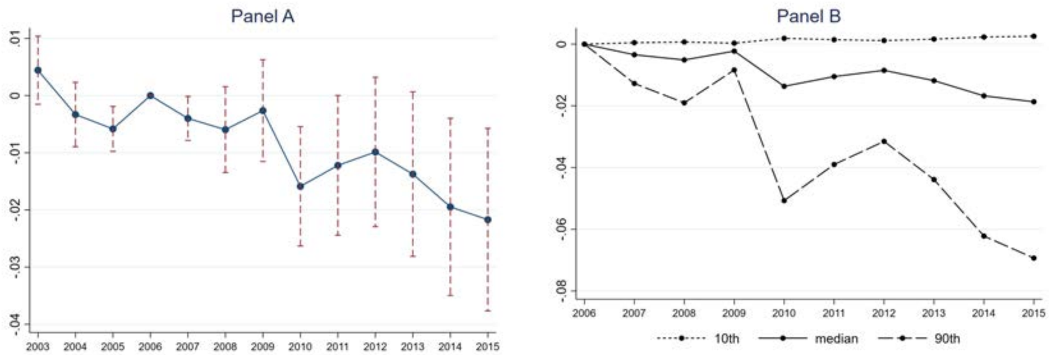
both domestic and foreign affiliates. A one standard deviation increase in the network shock implies a decline of 4.8 and 4.6 percent of the growth in the number of foreign and domestic affiliates, respectively.

Finally, in columns (4) and (5), we break down the total number of affiliates into whether they are horizontally or vertically related to the parent firm. We classify an affiliate as horizontally related to the parent if they share the same 4-digit activity code, and vertical otherwise. We find that the relative shrinkage of the network is mostly driven by affiliates in a vertical relationship with the parent. Indeed, we do not find a significant effect for horizontal affiliates (column 4). In contrast, the coefficient for vertically integrated affiliates is negative and significant, and it has the same magnitude as for the total number of affiliates (column 1). Thus, quantitatively, a one standard deviation increase in the network shock is associated with a decline of 4.1 percent of the growth in the number of vertically integrated affiliates.

Dynamics of the Adjustment to the Financial Shock After having documented the adjustment of MNE networks and performance measures from 2007 through 2015 period, we analyze how these effects build up over time. We proceed by using the local projection method described in Section 4. We use the empirical specification described in Equation (2) for our outcome variables.

Panel A in Figure 4 reports the estimated coefficient on the financial shock β_{1t} at different time horizons $t \in \{2003, 2004, 2005, \ldots, 2014, 2015\}$ for the total number of affiliates. A key finding is that the effect of the financial shock builds over time. We see that in 2003, 2004, and 2005, the pre-shock years, there is no significant effect of the financial shock (there is a mild small negative effect in 2005). However, after 2006, we see that the estimated coefficients become negative and they follow a negative trend. The downward trend continues until 2015,

Figure 4: Dynamic Effect of the Network Shock



Notes: Network shock coefficients over time and 90% confidence intervals (Panel A) and Impact evaluated at the 10th, 50th, and 90th percentile of the shock distribution (Panel B).

for which we find an estimated coefficient of -0.022 which corresponds to the total effect in the number of affiliates in 2015 relative to 2006 that we already reported in Table 2. It is interesting to notice that it is not until 2010 that the coefficient is statistically different from zero. This figure highlights the importance of considering a long panel.

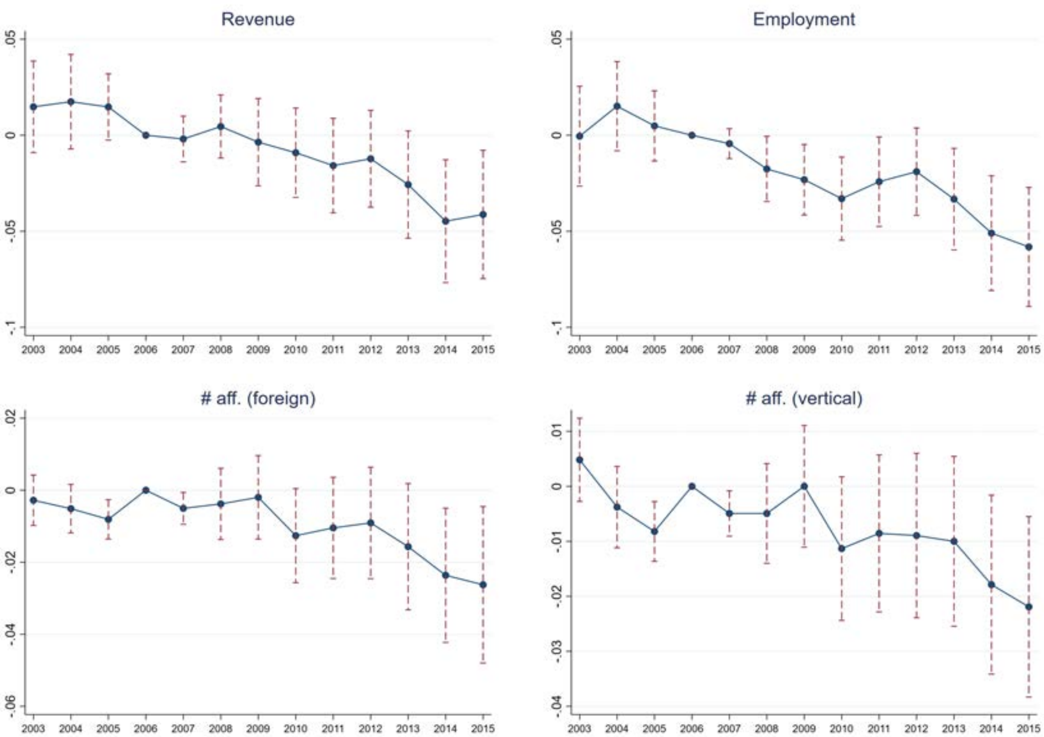
To provide suggestive evidence on the heterogeneous effects, Panel B reports the effect of the network shock for the hypothetical networks in the 10th, 50th, and 90th percentiles of the shock distribution. Perhaps interestingly, networks in the 10th percentile of the distribution (roughly no shock, see Table 1) are mostly unaffected. In contrast, networks in the 90th percentile of the distribution have a much steeper negative trend and end up in 2015 with an estimated coefficient almost 4 times larger than for the median firm ($3.9 = -0.070/-0.018$). These results imply that there is substantial variation in the adjustment of firms and that the overall effect is driven to a large extent by the most financially hit networks.

Figure 5 reports the analogous plots for revenues, employment, number of affiliates, and number of vertically integrated affiliates. We note that the pattern for the average effect is similar for all outcome variables. Also, there is no clear trend before 2006—all the coefficients are small and non-significantly different from zero. By contrast, after 2006, there is a negative trend in all outcome variables, and the effects in 2015 are negative and large as reported in the respective tables.

Taken together these results imply that adjustment to the financial shock is not instantaneous. Rather, it builds up over time, and even three years after the end of the financial crisis (2012), MNEs appear to be still adjusting their affiliates' network and their performance.

Potential Mechanisms and Theoretical Explanations Proving a theoretical model able to explain our empirical findings is beyond the scope of this paper. However, Table 4 reports the effect of the MNE-specific shocks on outcome variables related to potential channels. We start with the geographical changes of networks relatively more financially hit. Theoretically, trade

Figure 5: Effect of the Network Shock Over Time



Notes: Network shock coefficients over time with 90% confidence intervals.

costs are an important margin of adjustment when deciding the structure of the network of affiliates (Antras and Helpman, 2004). Thus, parents more exposed to the financial shock may choose to reduce costs by decreasing the physical distance between *i)* parent and affiliates, and *ii)* among affiliates. Columns (1) and (2) show that, indeed, the network shock is conducive to a significant decline in the physical distance between 2006 and 2015. Similarly, it could be thought that more exposed parents choose to minimize their presence in foreign countries. Column (3) reports the effect of the network on the change in the geographic complexity of the network.[29] Even though the coefficient is negative, it is not statically significant. However, if we focus on exposure to PIGS (Portugal, Italy, Ireland, Greece, and Spain), we do find a negative coefficient

[29] We use the definition of Correa and Goldberg (2022). They propose to measure complexity in a network as a Herfindahl-type index for the affiliates' location (denoted CHHI) or for the number of industries an MNE is present in (denoted BHHI). Specifically, the BHHI is defined as:

$$BHHI_{pt} = \frac{CountB_{pt}}{CountB_{pt} - 1}\left(1 - \sum_{b \in B}\left(\frac{count^b_{pt}}{\sum_{b \in B} count^b_{pt}}\right)^2\right) \quad (5)$$

where $CountB^b_{pt}$ is the number of industries in which network p is active in year t and $count^b_{pt}$ is the number of affiliates performing activity b in network p in year t. The measure of geographical complexity, CHHI, is obtained similarly by replacing *'sector'* with *'country'* in the equation above. In a nutshell, the geographic complexity of the network increases when it is present in more countries, while the business complexity increases as an MNE network encompasses more industries.

Table 4: Network shock and evolution of network characteristics

	Avg. Distance		CHHI	PIGS	BHHI	IO-coef		upstream
	parent	affil's			4digit	parent	affil's	affil's
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network shock	-0.032***	-0.043***	-0.277	-0.072***	-1.057**	-0.011	-0.014	-0.002
	[0.011]	[0.012]	[0.482]	[0.005]	[0.479]	[0.033]	[0.038]	[0.004]
Observations	5,245	5,245	5,333	5,333	5,333	5,314	5,314	4,092
R-squared	0.108	0.109	0.169	0.107	0.101	0.023	0.023	0.025
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors in brackets; *** $p<0.01$, ** $p<0.05$, * $p<0.1$; controls included but not reported: network size, parent size, and parent age in the initial year . Column headings indicate outcome variables that are all defined as changes between 2006 and 2015. Columns (1) and (2) focus on the log change in the average distance between parent and affiliates (column 1) and among affiliates (column 2). Column 3 considers geographic complexity as defined by Correa and Goldberg (2022). Column 4 considers 'flight from PIGS' by means of the change between 2006 and 2015 in a dummy indicating whether the parent has any affiliate in the PIGS countries (yes=1; no=0) in the given year. Column 5 focuses on business complexity (at NACE 4 digit) as defined by Correa and Goldberg (2022). Columns 6 and 7 focus on the change in the average input requirement between each affiliate and the parent (column 6) and among affiliates (column 7). Column 8 focuses on the average upstreamness of affiliates (Antràs et al., 2012). Outcomes are winsorized at the first and 99th percentile. The estimation sample is composed of surviving networks.

of the network shock (column 4). We note that, as in all tables, we include parent country fixed effects. Thus, these results are not driven by aggregate shocks in the country of the parent. Our findings are consistent with recent empirical literature emphasizing that physical distance is a relevant cost for the internal organization of firms (see, for example, Giroud, 2013; Gumpert et al., 2022).

We now turn to potential changes in the business structure of the network. It could be argued that parents in more financially hit networks may choose to focus on their core sectors and relatively decrease their presence outside them. We start with the business complexity measure BHHI proposed in Correa and Goldberg (2022) to provide supporting evidence. The BHHI index computes the Herfindahl index of the number of industries in which an MNE network is present (*cf. supra*). We define a sector as a 4-digit industry. Intuitively, this index increases as the presence of the network extends to more industries. The coefficient of the network shock is negative and statistically significant (column 5). Thus, parents with harder-hit networks seem to choose to relatively decrease their presence in non-core industries between 2006 and 2015.

A follow-up question is which are the business types of affiliates that the parent chooses to relatively cut. To indirectly address this question, we consider two broadly used measures. First, we consider the change in the average input-output requirement between parent and affiliates between 2006 and 2015.[30] If this number increases, it means that the goods produced by affiliates in 2015 are more important to complete the parent's production than in 2006. Theoretically, the direction of change is not clear. For example, Basco (2013) would predict that after a negative finance shock in the affiliate's country, the parent would choose to reduce production abroad and, in particular, to keep the relatively more important tasks in-house. Thus, it would predict a negative coefficient. Column (6) reports that the coefficient is negative but not significant. Column (7) reports the same outcome only considering input-output requirement among affiliates. We obtain a similar negative but not significant coefficient.

A second outcome to examine the change in the business types of affiliates uses the upstreamness measure derived in Antràs et al. (2012). We compute the average upstreamness of affiliates in the network both for 2006 and 2015[31], and then consider the change as outcome. A positive increase in the upstreamness measure implies that the affiliates in 2015 were, on average, closer to the core activity of the parent and further away from retail activities. As for the case of input-output, there is no clear theoretical prediction. The coefficient in column (8) is negative but it is not statistically significant. A caveat for columns (6) to (8) is that the measures of upstreamness and input-output for European industries are only available at 2-digits, in contrast to the 4-digit codes used to compute business complexity. Thus, these results should be taken with a grain of salt. One potential explanation consistent with columns (5) to (8) is that parents in relatively more hit networks chose to keep affiliates in their core industry and, if anything, they chose to produce the most important tasks in-house.

5.2 Inspecting a Mechanism: The Role of Firm Leverage

The literature on financial crises has emphasized that leverage plays a determinant role in shaping the heterogeneous response to the financial crisis across firms and countries (see, for example, Jordà et al., 2013, Giroud and Mueller (2016), and Kalemli-Ozcan et al., 2022). Building on the insights of this literature, this section investigates whether, controlling for the size of the network shock, the adjustment of parents initially more leveraged was more pronounced.[32] To do so, we augment our baseline specification and include the interaction of the network shock with the initial leverage of the firm (while also including in the regression the financial shock and leverage as controls), according to the specification that we discussed in Equation (4). Given that we are analyzing the effect of a financial shock, we would expect that the effects that we find were driven by relatively more leveraged parents.

Table 5 reports the results on the number of affiliates and parents' performance. As in Table

[30]Input-output requirements refer to 2015 and are taken from Eurostat (dataset: naio_10_coin).

[31]Specifically, we assign the 2006 sector level world average upstreamness (based on the World Input-Output Database-WIOD) by Mancini et al. (2023) to affiliates and calculate network averages for the years 2006 and 2015.

[32]We do not attempt to identify the specific channel through which the network shock may have different effects depending on the initial leverage of the firm. We leave this question for future research.

Table 5: Leverage as a mechanism: Number of affiliates and parent outcomes.

	Number of affiliates				Revenue	Empl't
	(1)	(2)	(3)	(4)	(5)	(6)
Network shock	-0.001	0.011	0.003	0.012	0.048	-0.008
	[0.013]	[0.016]	[0.013]	[0.016]	[0.035]	[0.029]
Shock × leverage	-0.057***	-0.056***	-0.059***	-0.056***	-0.157***	-0.091*
	[0.018]	[0.017]	[0.018]	[0.017]	[0.058]	[0.047]
Leverage (parent)	-0.019	-0.029	-0.014	-0.018	-0.268*	-0.109
	[0.033]	[0.032]	[0.032]	[0.032]	[0.142]	[0.106]
Total assets (parent)	0.155***	0.134***	0.155***	0.137***	-0.080***	-0.057***
	[0.009]	[0.009]	[0.010]	[0.010]	[0.022]	[0.018]
Initial # affiliates	-0.148***	-0.106***	-0.158***	-0.122***	0.105**	0.122***
	[0.025]	[0.025]	[0.025]	[0.025]	[0.045]	[0.042]
Age (parent)	0.006	-0.025	0.012	-0.005	-0.079**	-0.088***
	[0.017]	[0.017]	[0.018]	[0.018]	[0.037]	[0.032]
Observations	7,640	7,640	7,637	7,637	3,601	3,796
R-squared	0.069	0.102	0.089	0.119	0.104	0.066
Country FE	N	Y	N	Y	Y	Y
Industry FE	N	N	Y	Y	Y	Y

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1. Column headings indicate parent and network outcomes. Columns 1 to 4 use the ratio of 2015 to 2006 as a dependent variable. Columns 5 and 6 use log changes between 2006 and 2015 as dependent variables. Outcomes are winsorized at the first and 99th percentile.

2, columns (1) through (4) examine the effect on the number of affiliates for different sets of fixed effects, and columns (5) and (6) report the effect on revenues and employment, respectively. As expected, we find that relatively more leveraged MNEs are those more severely affected by the network shock. Both their performance measures (operating revenue and employment) and the relative shrinkage of the MNE network operate through MNEs whose parents are more leveraged and that experience a more severe financial network shock.[33]

We also observe that the pattern of adjustment of the MNE network to the financial shock is broadly similar to the one we uncovered for the financial shock in Table 3. In particular, we observe in Table 6 that the adjustment is concentrated in vertically-related affiliates (columns 4 and 5) and that it operates both through domestic and foreign affiliates (columns 1 and 2). The only noteworthy difference is that the coefficient on foreign affiliates in column (2) becomes substantially larger relative to domestic affiliates reported in column (3), suggesting that leveraged MNEs tend to adjust more on the foreign affiliates' margin. Comparing two MNEs at the average level of the financial shock but one standard deviation apart in their leverage, the more leveraged MNE would reduce its initial level of foreign affiliates by a 3.9 ($= -7.2 \cdot 1.34 \cdot 0.4$) percent by 2015, while only a 2.5 percent for domestic affiliates.

[33]Table A.3 in the appendix reports that our regression results for the interaction are robust to the same robustness checks discussed for the network shock above.

Table 6: Number of affiliates, average network shock, and leverage: different types of affiliates.

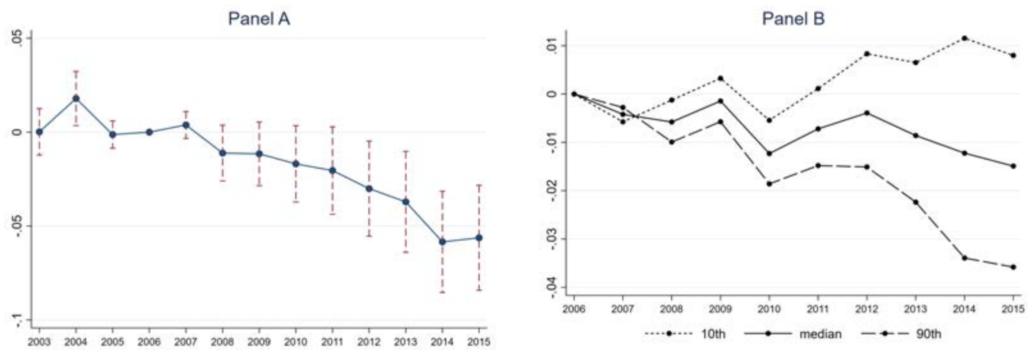
	All (1)	Cross-Border (2)	Domest. (3)	Same 4-digit (4)	Diff. 4digit (5)
Network shock	0.012	0.018	0.003	0.007	0.003
	[0.016]	[0.023]	[0.018]	[0.027]	[0.017]
Shock × Leverage	-0.056***	-0.072***	-0.047***	-0.019	-0.043**
	[0.017]	[0.026]	[0.018]	[0.033]	[0.021]
Leverage (parent)	-0.018	0.029	-0.085**	-0.022	-0.023
	[0.032]	[0.044]	[0.035]	[0.057]	[0.039]
Total assets (parent)	0.137***	0.178***	0.094***	0.070***	0.103***
	[0.010]	[0.013]	[0.011]	[0.015]	[0.010]
Initial # affiliates	-0.122***	0.129***	-0.186***	0.021	-0.145***
	[0.025]	[0.034]	[0.028]	[0.040]	[0.029]
Age (parent)	-0.005	-0.027	-0.005	0.053*	0.012
	[0.018]	[0.027]	[0.020]	[0.030]	[0.020]
Observations	7,637	7,637	6,664	1,749	5,120
R-squared	0.119	0.121	0.102	0.101	0.104
Country FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1. Column headings indicate the type of affiliates considered in the dependent variable. Outcomes are winsorized at the first and 99th percentile.

In contrast to the interaction results, Tables 5 and 6 show that the direct contribution of the network shock or parents' leverage has little to no effect on either MNE performance and network adjustment. This is remarkable since the correlation between the average network shock and parent leverage is virtually zero, 0.07 (see Table A.1). This very low correlation suggests that the MNE networks of parents with high or low leverage are *not* systematically exposed to network shocks of different magnitudes (barring unobservables). Perhaps not surprisingly, this finding is consistent with the firm leverage mechanism that we focus on playing a very substantial role in the adjustment to financial network shocks. This result is also similar to Giroud and Mueller (2016), who following a similar approach, show that after interacting their financial shock (housing prices in their case) with leverage, all the variation is absorbed by the interaction of the two and the effect of the shock by itself disappears.

Dynamics of Adjustment across Different Leverage Levels Analogously to our previous exercise, we investigate how the adjustment to the financial network shock builds over time using the local projections method described in Section 4, Equation (2). As in the previous section, we report both the evolution of the average effect and three initial (2006) levels of leverage, corresponding to the 10th, 50th, and 90th levels. Holding these levels fixed, we report the sum of the estimated coefficient of the financial shock, β_S, and the interaction term between parent leverage and the financial shock, β_{SL}, at different time horizons $t \in \{2006, 2007, \dots, 2014, 2015\}$, multiplied by each of these three leverage levels. The goal of this exercise is to help visualize

Figure 6: Dynamic Effects of the Network Shock and Leverage



Notes: Leverage and network shock interaction coefficients over time with 90% confidence intervals (Panel A) and network shock coefficient plus network shock-leverage interaction coefficient evaluated at the 10th, 50th, and 90th percentile of the leverage distribution (Panel B).

the dynamic heterogeneous response of MNEs with different levels of leverage at the onset of the financial crisis.

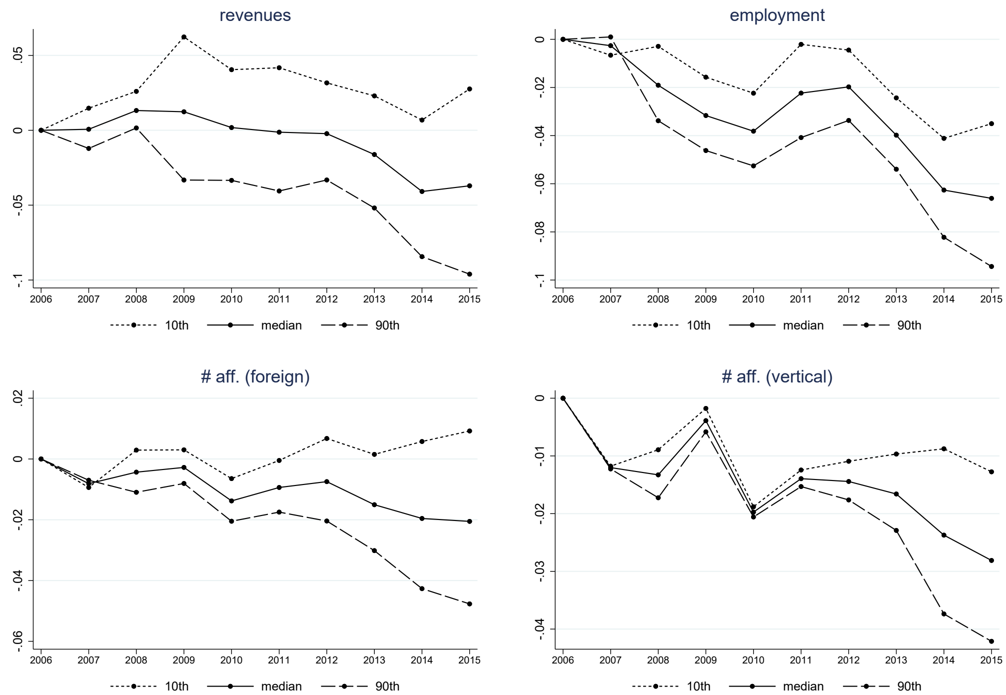
Figures 6 and 7 report the analogous counterpart to the figures for the network shock. Panel A of Figure 6 reports the evolution of the estimate on the interaction term, while panel B reports the estimated coefficients for the three different levels of leverage. Figure 7 reports the results for revenues, employment, foreign affiliates, and vertically integrated affiliates. We see that, across the board, the adjustment to the financial shock builds slowly over time. More importantly, we observe the large heterogeneity in responses depending on the initial leverage of the parent. Consider the number of foreign affiliates, denoted by "# aff. (foreign)" in the figure. For a parent at the 10th percentile of the leverage distribution in 2006, the effect of the financial shock is hovering around zero over the entire period, with the exact point estimate fluctuating between small positive and negative numbers.[34] By contrast, a MNE at the 90th percentile of the 2006 leverage distribution, experiences a sustained cumulative decline over the entire period. These patterns are similar for all other outcomes. Taken together, these figures suggest again that parent initial leverage plays a substantial role in the adjustment to the financial shock.

6 Concluding Remarks

Financial crises are recurrent throughout history and usually hit several countries at the same time. Even though there exists an extensive literature on their aggregate effects (see, for example, Schularick and Taylor, 2012), their effects on MNEs and the organization of the global supply chain have remained largely unexplored. Indeed, the literature examining the effect of

[34]Recall that we normalize country-level shocks relative to Germany. Some countries have a smaller risk premium than Germany and thus experience a "negative" shock.

Figure 7: Heterogeneous Effects of the Network Shock Across Three Initial Leverage Levels



Notes: Network shock coefficient plus network shock-leverage interaction coefficient evaluated at the 10th, 50th, and 90th percentile of the leverage distribution.

economic crises on multinational activity has mostly focused on sales (see, for example, Alfaro and Chen, 2012 or Alviarez et al., 2017). One important reason for this omission is data availability. In this paper, we used a novel panel dataset of parents and affiliates spanning twenty-nine European countries and thirty-nine in total from 2003 through 2015 to examine the effect of a financial crisis on multinational activity and its network structure.

We create an MNE-specific shock using the pre-shock MNE network of affiliates and document that parents in more financially hit networks experience a decline in the growth of revenues and employment size. In addition, they display a lower growth rate of the number of affiliates, mostly driven by vertical relationships. We also show that most of this variation is accounted for initially more leveraged MNEs, especially for the decline in foreign affiliates. The picture that emerges from this evidence is that financial crises have long-run effects on MNEs and affect the performance of both affiliates and parents. More importantly, we have shown that MNEs' networks adjust after a financial shock. This result is important not only from a policy perspective, but it is also relevant to understand the propagation of shocks. In an important contribution, Cravino and Levchenko (2017) quantifies how business-cycle shocks to a given network of affiliates affect parents' outcomes. Building on our evidence, it would be interesting to investigate how their results may change when the MNE network itself also changes with a financial shock. We leave a quantitative analysis of this question for future research.

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A Additional Tables

Table A.1: Correlations between network shock and MNE characteristics in the base-year (2006)

	(1)	(2)	(3)	(4)
	network shock	# aff. 06	TA	age
initial network size (# aff. 06)	0.042			
log real total assets (parent)	0.147	0.437		
age (parent)	0.042	0.094	0.137	
leverage (parent)	0.066	-0.028	-0.108	-0.010

Number of observations is 7,686 networks for which all variables are available.

Table A.2: Number of affiliates evolution and average network shock: Robustness

	Sample Restrictions Sensitivity			Clustered s.e.	No Greece	foreign shock	TA shock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Network shock	-0.019**	-0.018**	-0.022**	-0.022***	-0.022**	-0.013**	-0.038**
	[0.010]	[0.009]	[0.010]	[0.007]	[0.010]	[0.005]	[0.016]
Total assets (parent)	0.096***	0.109***	0.077***	0.102***	0.102***	0.102***	0.075***
	[0.008]	[0.006]	[0.008]	[0.017]	[0.008]	[0.008]	[0.023]
Initial # affiliates	-0.021	-0.064***	-0.062**	-0.058	-0.060**	-0.058**	-0.035
	[0.021]	[0.016]	[0.026]	[0.054]	[0.024]	[0.024]	[0.063]
Age (parent)	0.004	-0.006	0.017	-0.002	-0.001	-0.002	0.004
	[0.017]	[0.014]	[0.019]	[0.025]	[0.017]	[0.017]	[0.044]
Observations	8,670	14,825	6,586	8,217	8,156	8,217	4,345
R-squared	0.108	0.093	0.093	0.105	0.104	0.105	0.061
Country FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y
Sample:							
# aff.	2	1	2	2	2	2	2
large dom. NW	incl	excl	excl	excl	excl	excl	excl
consolidated	incl	incl	excl	incl	incl	incl	incl

Notes: Robust standard errors in brackets (except column 4); *** p<0.01, ** p<0.05, * p<0.1. Outcomes are winsorized at the first and 99th percentile. Columns 1 to 3 consider alternative samples: including MNEs with large domestic networks (1), including MNEs with only one affiliate (2), and excluding MNEs reporting consolidated balance sheets (3). Column 4 uses standard errors clustered at the country level rather than robust standard errors. Column 5 excludes networks with parents in Greece. Column 6 excludes the shock in the parent country from the calculation of the network shock. Column 7 uses a shock calculated as a weighted average over affiliates using total assets in 2006 as a weighting variable (note that this decreases the sample size by half due to missing information on total assets for one or more affiliates in the network).

Table A.3: Leverage as a mechanism: Robustness

	Sample Restrictions			clustered	no Greece	foreign shock	TA shock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Network shock	0.012	-0.004	0.009	0.012	0.014	0.012	-0.005
	[0.015]	[0.012]	[0.016]	[0.012]	[0.017]	[0.016]	[0.027]
Shock × Leverage	-0.052***	-0.037***	-0.054***	-0.056**	-0.061***	-0.056***	-0.064**
	[0.016]	[0.012]	[0.018]	[0.021]	[0.019]	[0.017]	[0.031]
Leverage (parent)	-0.021	-0.018	-0.008	-0.018	-0.014	-0.018	0.039
	[0.032]	[0.023]	[0.034]	[0.035]	[0.033]	[0.032]	[0.068]
Total assets (parent)	0.136***	0.149***	0.110***	0.137***	0.137***	0.137***	0.102***
	[0.010]	[0.007]	[0.010]	[0.015]	[0.010]	[0.010]	[0.037]
Initial # affiliates	-0.095***	-0.140***	-0.123***	-0.122***	-0.125***	-0.122***	-0.092
	[0.023]	[0.018]	[0.028]	[0.027]	[0.026]	[0.025]	[0.077]
Age (parent)	-0.003	-0.007	0.017	-0.005	-0.005	-0.005	0.009
	[0.017]	[0.015]	[0.020]	[0.024]	[0.018]	[0.018]	[0.048]
Observations	8,072	13,244	6,069	7,637	7,576	7,637	3,981
R-squared	0.124	0.105	0.105	0.119	0.118	0.119	0.064
Country FE	Y	Y	Y	Y	N	Y	Y
Industry FE	Y	Y	Y	Y	N	Y	Y
Sample:							
# aff.	2	1	2	2	2	2	2
large dom. NW	incl	excl	excl	excl	excl	excl	excl
consolidated	incl	incl	excl	incl	incl	incl	incl

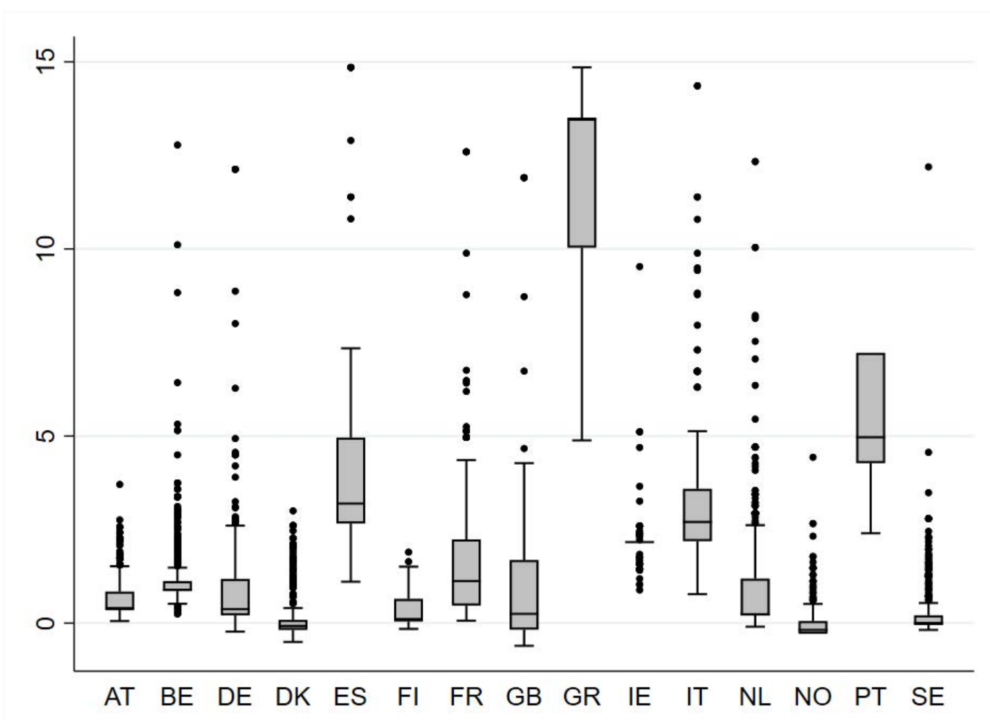
Notes: Robust standard errors in brackets (except column 4); *** p<0.01, ** p<0.05, * p<0.1. Outcomes are winsorized at the first and 99th percentile. Columns 1 to 3 consider alternative samples: including MNEs with large domestic networks (1), including MNEs with only one affiliate (2), and excluding MNEs reporting consolidated balance sheets (3). Column 4 uses standard errors clustered at the country level rather than robust standard errors. Column 5 excludes networks with parents in Greece. Column 6 excludes the shock in the parent country from the calculation of the network shock. Column 7 uses a shock calculated as a weighted average over affiliates using total assets in 2006 as a weighting variable (note that this decreases the sample size by half due to missing information on total assets for one or more affiliates in the network).

Table A.4: Country-level shocks

country	shock	country	shock	country	shock
Austria	0.744	France	0.941	Mexico	0.274
Australia	0.016	UK	-0.443	Netherlands	0.418
Belgium	1.304	Greece	24.254	Norway	-0.126
Bulgaria	3.140	Croatia	4.390	New Zealand	0.054
Canada	0.282	Hungary	3.814	Poland	2.364
Switzerland	0.565	Ireland	4.774	Portugal	8.994
Chile	2.062	Israel	1.064	Romania	2.710
Colombia	-0.771	Iceland	-0.466	Russia	4.434
Czech Republic	1.204	Italy	4.466	Sweden	0.134
Germany	0	Japan	2.257	Slovenia	4.571
Denmark	-0.237	South Korea	0.934	Slovakia	2.820
Spain	5.451	Lithuania	3.073	US	-0.086
Finland	0.214	Latvia	2.404	South Africa	2.204

Source: Authors' calculation based on OECD

Figure 8: Distribution of Network Shock Across Countries



Notes: Boxplot of MNE-specific network shock for countries with at least 50 parents of MNE networks.

B Within-network shock propagation

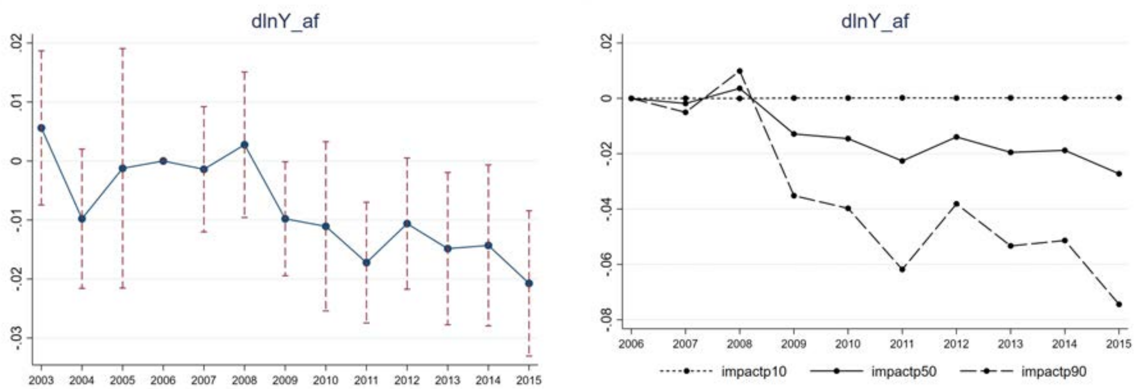
Following the seminal contribution of Acemoglu et al. (2012) on the propagation of shocks through networks, recent contributions have analyzed the propagation of shocks through, for example, ownership networks Biermann and Huber (2023) and transactions beyond the boundaries of the firm Demir et al. (2022). These studies differ from ours in their focus on shock propagation within the "given" network, whereas we focus on how the network itself may change due to the shock. To complement this related literature, in this appendix, we estimate how the network shock affects the growth of sales of affiliates. This exercise can be interpreted as the intensive margin of adjustment. In contrast to our main results on the change in the overall number of affiliates (extensive). Specifically, following Biermann and Huber (2023), we estimate the next specification (B.1):

$$\Delta lnOR_{apjct} = \beta_a + \sum_{\tau=2003}^{2015} \beta_\tau \times NetworkShock_p \times \mathbb{1}(t=\tau) + \beta_2 X_{at-1} + \delta_{ct} + \delta_{jt} + \delta_p + \varepsilon_{at}, \quad \text{(B.1)}$$

where the dependent variable is sales growth measured as the change in real operating revenues of affiliate a in industry j in country c belonging to network p at time t. Operating revenues are deflated using country-specific industry deflators at 2-digit level. X_{at-1} is a vector of one-period lagged controls at affiliate level (age and size). The specification further controls for the following set of fixed effects: affiliate level, network level, affiliate country-year, and affiliate industry-year. The coefficients of interest are the β_τs that estimate the dynamic effects of the network shock on sales growth (relative to the base year 2006). The network shock is defined as in the main text.

The left hand-side of Figure 9 plots the estimated β_τ coefficients. Reassuringly there is no pre-shock effect. The effect of the network shock on sales growth starts having a significant effect from 2009 onward and remains significant until the end of the period. The right hand-side panel shows the impact of the network shock evaluated at the 10th, 50th, and 90th percentile of the in-sample network shock distribution. Sales growth is found to be around four to six percent lower at the 90th than at the 10th percentile in real terms. This suggestive evidence indicates that the shock is at least partially transmitted through within-network sales relationships given that affiliate country and industry business cycle effects are absorbed by our set of fixed effects.

Figure 9: Intensive Margin: Effect of Network Shock on Affiliate Sales Growth



Notes: Network shock coefficients over time and 90% confidence intervals (left-hand side) and Impact evaluated at the 10th, 50th, and 90th percentile of the shock distribution (right-hand side).

Online Appendix for Financial Crises and the Global Supply Network: Evidence from Multinational Enterprises

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A Additional Tables - Facts on the dataset

Table 1: Number of networks (network/parent-year observations)

	No.	%
2006	18,223	12.1
2007	17,480	11.6
2008	17,010	11.3
2009	16,057	10.7
2010	15,159	10.1
2011	14,442	9.6
2012	13,758	9.2
2013	13,390	8.9
2014	12,551	8.4
2015	12,087	8
Total	150,157	100.0

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Table 2: Parent country location frequency (unique parents) in 2006

	No.	%
Parent home country		
DE	2,685	14.7
NL	2,475	13.6
GB	2,206	12.1
BE	2,083	11.4
IT	1,839	10.1
FR	1,426	7.8
DK	1,108	6.1
SE	1,051	5.8
ES	1,027	5.6
AT	622	3.4
IE	447	2.5
NO	350	1.9
FI	292	1.6
GR	111	0.6
PT	111	0.6
HU	77	0.4
EE	60	0.3
PL	56	0.3
CZ	51	0.3
SI	30	0.2
HR	22	0.1
UA	22	0.1
RO	18	0.1
LV	15	0.1
RU	12	0.1
LT	10	0.1
BG	7	0.0
SK	7	0.0
RS	3	0.0
Total	18,223	100.0

Table 3: Affiliate country location frequency (unique affiliates over period 2006-15, i.e. each affiliate counted once irrespective of the number of years and when it exists)

	No.	%
DE	36,006	14.1
GB	29,474	11.5
FR	25,117	9.8
NL	19,810	7.8
IT	17,611	6.9
ES	14,584	5.7
US	14,456	5.7
SE	11,217	4.4
BE	9,703	3.8
AT	5,380	2.1
NO	5,363	2.1
DK	5,351	2.1
IE	4,339	1.7
PL	4,317	1.7
FI	3,738	1.5
RO	2,904	1.1
CH	2,853	1.1
PT	2,661	1.0
CZ	2,418	0.9
BR	2,022	0.8
RU	2,013	0.8
CA	1,946	0.8
CN	1,908	0.7
AU	1,738	0.7
HU	1,543	0.6
LU	1,453	0.6
ZA	1,435	0.6
HK	1,380	0.5
MX	1,379	0.5
IN	1,327	0.5
GR	1,305	0.5
EE	1,013	0.4
SK	860	0.3
UA	828	0.3
AR	786	0.3
JP	738	0.3
CL	709	0.3
TR	676	0.3
SG	669	0.3
MY	636	0.2
HR	580	0.2
LV	513	0.2
... *continued in next table*		

Table 4: Affiliate country location frequency (unique affiliates) ... *continued*

	No.	%
... *continued*		
BG	497	0.2
TH	486	0.2
LT	476	0.2
KR	472	0.2
SI	468	0.2
RS	410	0.2
CY	401	0.2
CO	394	0.2
AE	391	0.2
MA	385	0.2
NZ	366	0.1
PE	308	0.1
TN	224	0.1
ID	222	0.1
PH	214	0.1
TW	214	0.1
PA	206	0.1
BM	195	0.1
EG	194	0.1
IL	183	0.1
MU	176	0.1
MT	154	0.1
SA	135	0.1
BA	128	0.1
CR	127	0.0
VE	125	0.0
DZ	116	0.0
NG	112	0.0
UY	100	0.0
KZ	99	0.0
ZW	96	0.0
EC	92	0.0
GT	87	0.0
PK	86	0.0
KE	81	0.0
DO	77	0.0
VN	73	0.0
AL	71	0.0
Total	255,494	100.0

Affiliate locations with less than 70 affiliates counted in total but not represented in table

Table 5: Number of affiliates per parent (parent-year observations in 2006 and 2015)

	2006		**2015**	
	No.	%	No.	%
1	7,971	43.7	3,728	30.8
2	3,166	17.4	1,934	16.0
3	1,800	9.9	1,303	10.8
4	1,123	6.2	865	7.2
5	790	4.3	624	5.2
6 to 10	1,730	9.5	1,667	13.8
11 to 20	852	4.7	937	7.8
21 to 50	520	2.9	585	4.8
51 and more	271	1.5	444	3.7
Total	18,223	100.0	12,087	100.0

Table 6: Cross-tabulation of domestic and cross-border affiliates per network-year for the year 2006 (parent-year observations)

	Crossborder affiliates					
	1	**2**	**3**	**4**	**5-...**	Total
Domestic						
0	43.7	4.9	1.1	0.4	0.7	50.9
1	12.5	2.2	0.9	0.4	0.6	16.6
2	6.5	1.3	0.6	0.3	0.6	9.4
3	3.6	1.0	0.4	0.2	0.4	5.5
4	2.1	0.6	0.3	0.2	0.4	3.5
5-...	5.8	2.4	1.1	0.7	4.1	14.1
Total	74.2	12.4	4.4	2.2	6.9	100.0

Table 7: Frequency of all parent-affiliate-year observations over years by *'grand'* affiliate location

	Affiliate location (observations)...							
	Domestic		**Europe**		**Extra-Europe**		**Total**	
	n	row%	n	row%	n	row%	n	col%
2006	55,621	54.0	41,983	40.8	5,330	5.2	102,934	6.6
2007	59,359	54.1	44,007	40.1	6,265	5.7	109,631	7.0
2008	63,968	54.1	46,847	39.6	7,501	6.3	118,316	7.5
2009	64,832	53.7	47,331	39.2	8,544	7.1	120,707	7.7
2010	63,596	53.6	45,872	38.7	9,165	7.7	118,633	7.6
2011	64,102	52.7	46,052	37.8	11,517	9.5	121,671	7.8
2012	62,532	51.4	45,089	37.1	13,949	11.5	121,570	7.7
2013	64,063	50.4	46,708	36.7	16,387	12.9	127,158	8.1
2014	63,339	49.4	46,056	35.9	18,734	14.6	128,129	8.2
2015	63,258	45.9	48,890	35.4	25,774	18.7	137,922	8.8

Table 8: Cross-tabulation of affiliates added and dropped per network-year (cells indicate share in total panel observations, network-year observations 2007-2015)

	# affiliates dropped						
	0	**1**	**2**	**3**	**4**	**5-...**	**Total**
# added							
			Panel A - All networks				
0	64.6	10.2	1.8	0.5	0.2	0.4	77.7
1	7.5	2.8	0.9	0.3	0.1	0.3	12.0
2	2.0	1.0	0.5	0.2	0.1	0.2	4.0
3	0.7	0.5	0.3	0.2	0.1	0.2	1.9
4	0.3	0.2	0.1	0.1	0.1	0.2	1.0
5-...	0.4	0.4	0.3	0.3	0.2	1.8	3.5
Total	75.5	15.0	3.9	1.6	0.9	3.0	100.0

Table 9: Distribution of ownership shares (observations)

	No.	%
fully-owned (more than 95%)	1,118,942	71.3
strictly more than 50% but not fully owned	191,904	12.2
between 10% and 50%	251,973	16.1
less than 10%	6,185	0.4
Total	1,569,004	100.0