Multinational Production and Labor Share*

Daisuke Adachi† Yukiko U. Saito‡

December 7, 2020

[Click here for the latest version]

Abstract

We investigate the impact of multinational enterprises (MNEs) on the labor share in the source country. We propose an equilibrium model that features a production function with factor inputs in foreign countries. Each firm receives a shock that shifts the productivity of foreign factor inputs. We conduct comparative statics regarding the foreign factor productivity shock and show that the difference in factor demand elasticities with respect to foreign factor prices affects aggregate labor share. To identify these elasticities, we develop a method-of-moments estimator that leverages a foreign factor productivity shock. We then apply the estimator to a unique natural experiment: the 2011 Thailand Floods. The floods had a strong impact on manufacturing clusters in areas north of Bangkok city and affected Japanese MNEs by forcing them to halt operations of plants located in the cluster. We employ a uniquely combined Japanese firm- and plant-level dataset that tracks wages, employment, fixed assets in Japan, and employment in foreign subsidiary plants. The estimated factor demand elasticities indicate that foreign factor augmentation increased capital demand in Japan more than labor demand, suggesting that the foreign factor augmentation contributes to reducing the labor share in Japan.

Keywords: Multinational enterprise, Labor share, Bias in technological change, Elasticity of factor substitution, Natural experiment, The 2011 Thailand Flood.

JEL codes: F23, E25, J23, F21, F66

*We appreciate helpful comments by Pol Antras, Costas Arkolakis, Dominick Bartelme, Kirill Borusyak, Bill Brainard, Lorenzo Caliendo, Cheng Chen, Rafael Dix-Carneiro, Michal Fabinger, Pablo Fajgelbaum, Ana Cecilia Fieler, Teresa Fort, Sharat Ganapati, Kailin Gao, Jay Junsik Hyun, Sam Kortum, Giovanni Maggi, Kentaro Nakajima, Guillermo Noguera, Nitya Pandalai-Nayar, Micheal Peters, Peter Schott, Daisy Sun, Yuta Takahashi, Lucas Zavala, Ray Zhang, and seminar participants at Colorado Boulder, Columbia, IU Bloomington, NYU, RIETI, SNU, and Yale. This study was conducted as part of the "Dynamics of Inter-organizational Network and Firm Lifecycle" project undertaken at the Research Institute of Economy, Trade and Industry (RIETI), using survey micro data based on "the Census of Manufacture", "the Basic Survey on Japanese Business Structure and Activities" and "the Basic Survey on Overseas Business Activities" which are conducted by the Ministry of Economy, Trade and Industry (METI). We acknowledge data provision from Costas Arkolakis. We also thank Takashi Iino for outstanding research assistance and Philip C. MacLellan for editorial assistance. All remaining errors are ours.

†Yale University. daisuke.adachi@yale.edu

‡Waseda University and RIETI, SF. saito-yukiko@waseda.jp

1 Introduction

A growing body of evidence suggests that in recent decades, the labor share of national income has decreased in several developed countries (Karabarbounis and Neiman, 2013), raising concerns both for policymakers and economists. For policymakers, the decrease might be interpreted as an increase in income inequality between capital holders and laborers. For economists, it challenges one of the stylized facts of growth models (Kaldor, 1961).

The broad question of the current paper is what drove the decrease in the labor share. Several potential explanations have been proposed in the literature, including the role of bias in technological change (Oberfield and Raval, 2014), for if changes in productivity augment capital more than labor, then the total payment to labor will decrease relative to capital. Although this is a theoretically coherent and straightforward explanation, there are several potential mechanisms behind such factor-specific augmentation. For example, the production processes are fragmenting across the world (Johnson and Noguera, 2012, 2017). If international direct investment and employment of foreign labor by multinational enterprises (MNEs) complements capital in the source country, there can be a relative increase in the demand for capital relative to labor.[1] In this paper, we formalize this idea and ask if and to what extent it may explain the labor share trend in the source country of foreign direct investment (FDI).

This surge in MNE international factor employment has been brought about by a wide range of changes in the economic environment, including technological change, policy and institutional reform, and growth of developing economies. For example, better global communication technologies, removal of political barriers regarding international direct investment and employment of foreign labor, and increasing demand by external economies all may have increased the availability and productivity of foreign factors. We take these events as exogenous augmentations of foreign factors for MNEs and study the effects on the labor share of the source country.

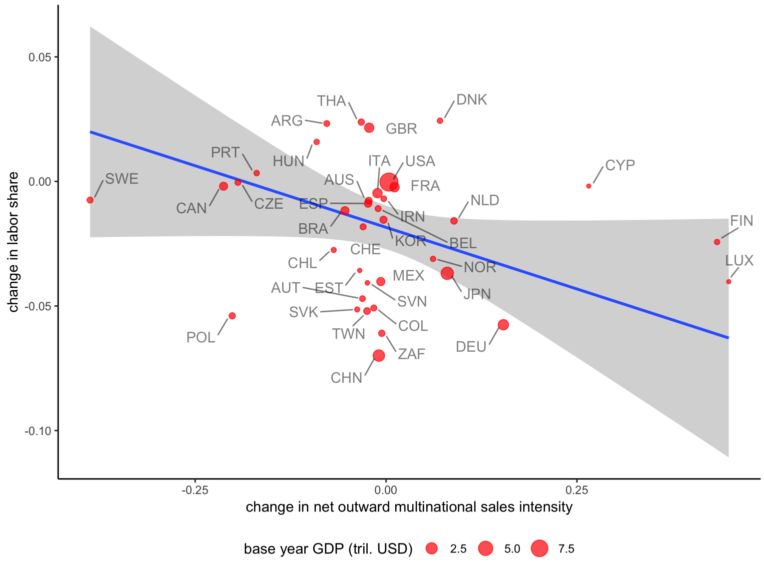
As first-pass evidence, Figure 1 shows a significant negative ralationship between the change in net MNE sales and labor share among countries[2]. Although we do not suggest that the correlation is causal, this negative relationship is consistent with the idea that the outward activities of MNEs complement capital demand more than labor in the source country.

To formally answer the question if and how much foreign factor augmentation decreased the labor share in the source country, we proceed in three steps. First, we develop a general equilibrium model that features heterogeneous and non-parametric production functions that include the employment and exogenous augmentations of the foreign factors. In the model, the factor market-clearing wages are the key endogenous variables determining labor share, and we show that to the first order, the elasticity structure of factor demand is critical to the the direction and size of the change in labor share. This first order approximation is robust across several existing models of multinational production and many factors, including models of offshoring (Feenstra and Hanson,

[1] Other examples include other forms of globalization, such as global value chains and intermediate goods trade and technological growth represented by, for example, industrial robot penetration and computerization.

[2] Details of the construction of the data are discussed in Section B.1.

Figure 1: Net Outward Multinational Sales and Labor Share



Note: Authors' calculation using data from Karabarbounis Neiman (2014) and UNCTAD. The horizontal axis is the change in the average sums of bilateral net outward multinational sales between 1991-1995 and 1996-2000. The vertical axis is the change in labor share from 1991 to 2000. Singapore was dropped because it has an outlier value for outward multinational sales.

1997) and multinational production with export platforms (e.g., Arkolakis et al., 2017). We then show how the key elasticities may be identified given the foreign augmentation shocks, describing the moment conditions and explaining how to back out the structural errors that depend on the elasticity matrix which contains our parameters of interest.

Since our baseline model spans broad production technologies, we first discuss the example of homogeneous nested CES production in order to provide the intuition behind the theoretical results and some guidance for the empirical application. Out of the specified model, our key theoretical results are twofold. First, the difference in the elasticities of substitution between nests is key to the impact of foreign factor augmentation on home labor share. Namely, if home labor is more substitutable with the foreign factor than home capital, then foreign factor augmentation implies a reduction in the home labor share. Intuitively, if foreign factor augmentation occurs, both home labor and capital are substituted away for a given level of output. But if the substitution is larger for labor, so is the *relative* decline in home labor demand, causing the labor share to decrease. One of the challenges is to identify the novel parameter of our model, the foreign factor-home factor elasticity of substitution. To proceed, we assume the existence of an exogenous change in foreign factor productivity. Our second key theoretical result is that the shock-induced derivative of home-foreign employment with respect to the shock is informative of the key parameter.

Armed with these theoretical results, we estimate the model empirically by applying it to the *2011 Thailand Floods*. These floods, which extended throughout the latter half of 2011, causing 65 of 76 provinces to be declared disaster zones, affecting more than 13 million people, and creating an estimated 1,425 trillion baht (USD 46.5 billion) in economic losses (World Bank), were a severe negative foreign factor productivity shock to Japanese MNEs operating in the flooded regions. To study this unique event, we employ and combine firm- and establishment-level microdata sourced from the *Basic Survey on Japanese Business Structure and Activities* (BSJBSA), *the Basic Survey on Overseas Business Activities* (BSOBA), and the *Orbis* database from Bureau van Dijk (Orbis BvD). First, we calibrate the capital-labor substitutability by the first order condition and a shift-share-type instrumental variable (Raval, 2019). Consistent with the previous literature, we find that capital-labor are gross complements. Second, by regressing the log-home employment on the log-foreign employment (with the instrumental variable relating the intensity of the flood damage) and a firm-level fixed effect, we obtain a two-stage least squares estimate which indicates that home labor and foreign labor are gross substitutes, in keeping with our theory. This result is based on our homogeneous nested CES specification.

Given the home labor-foreign labor substitutability implied by our estimate, we find that foreign factor augmentation (from the perspective of Japan) did contribute to a decrease in labor share in Japan. We thus have shown that foreign factor augmentation decreases home labor share. To quantify this, we exploit the nested CES specification to back out the aggregate evolution of foreign factor-augmenting productivities. Applying our implied elasticities of substitution, we find that foreign factor augmentation alone explains 59 percent of the decrease in Japan's labor share between 1995 and 2007.

We also derive an elasticity estimate from a more general production function based on the method of moments. As in the nested CES case, the result shows that foreign factor augmentation increases the *relative* demand for capital, which implies that the relative labor wage decreases, as does the labor share.

The paper is structured as follows. After discussing the related literature below, Section 2 provides some of the motivating facts about labor share and MNEs. Section 3 then provides the conceptual framework modeling labor share and foreign factor augmentation, presenting both a general foreign factor demand model and a nested CES specification. Section 4 discusses the empirical setting, data, specification and reduced-form estimates, while Section 5 shows the derived structural parameters and estimation under both the general and nested CES models. Section 6 concludes the paper.

1.1 Related Literature

This paper relates to two strands of literature: research concerning the recent decreasing labor share (or increasing capital share) of production, and studies on MNEs and their impact on the source country's labor market.

1.1.1 Changing Factor Shares

Seminal research on changing factor shares that empirically finds a decreasing labor share includes Elsby et al. (2013) in the U.S and Karabarbounis and Neiman (2013), whose comparable cross-country data show a declining labor share in many developed countries in particular, which Piketty and Zucman (2014) have suggested leads to expanding within-country income inequalities. However, there are several conceptual qualifications and labor share measurement issues that raise concerns about these empirical findings. For instance, Rognlie (2016, 2018); Bridgman (2018) stress that the treatment of capital depreciation and the self-employee income allotment to each factor entails strong assumptions. Making a different argument, Koh et al. (2018) claim that the decline in the labor share in the U.S is attributable mainly to the capitalization of intellectual property, while Cette et al. (2019) discuss a similar effect regarding the accounting of real estate income. In our view, even after taking these qualifications into account, Japan's labor share between 1995 and 2007 still decreased, as discussed further in Section 2.2.2.

There are several possibilities suggested in the literature as to why the labor share is decreasing, including bias in technological change. For instance, Oberfield and Raval (2014) emphasize the role of "technology, broadly defined, including automation and offshoring, rather than mechanisms that work solely through factor prices", and Elsby et al. (2013) conclude that the offshoring of labor-intensive activities within the supply chain is "the leading potential explanation of the decline in the U.S. labor share over the past 25 years." On the technology side, among others, Acemoglu and Restrepo (2017) find that exposure to industrial robots within U.S. commuting zones reduced both employment and wages. To these, we add globalization as a partial explanation, particularly in our context of Japan from 1995-2007. We offer evidence based on a particular mechanism that features the role of MNEs, providing a novel identification strategy and empirical evidence from the 2011 Thailand Floods.

Other potential explanations for declining labor share include lower capital prices. For example, Karabarbounis and Neiman (2013); Hubmer (2018) explore if and how much a decrease in capital goods prices causes demand for labor to be substituted by demand for capital. Also, since capital income is intrinsically related to the financial sector, some authors discuss the possibility that labor share may have fallen due to financial-market features such as increasing risk premiums (Caballero et al., 2017) or equity values (Greenwald et al., 2019). In addition to these explanations based on changing factor prices or risk premiums, an increase in market power (and thus profit) by dominant corporations has also been proposed as a reason for decreasing labor share, as market power can emerge both in the goods market (Autor et al., 2017a,b; Barkai, 2017; De Loecker and Eeckhout, 2017) and in the labor market (Gouin-Bonenfant et al., 2018; Berger et al., 2019). [3] Although market power is not our main focus, we explore its potential role to help validate our mechanism. Applying the De Loecker and Eeckhout method to our Japanese data, we find that the markup did not increase as much in Japan as in the U.S. The detailed discussion is given in Section 2.2.4.

Our contribution to this literature is adding multinational enterprises (MNEs) to the discussion of potential reasons for the observed decrease in labor share. Among this growing literature, we regard our work to be closest to Oberfield and Raval (2014) who, as mentioned above, emphasize the role of biased technological change in the production function as opposed to the factor-price story of Karabarbounis and Neiman (2013). For this purpose, they employ plant-level microdata in the U.S. and estimate the capital-labor substitution elasticity by estimating the first order condition for

[3] Berger et al. (2019), however, argue that labor market concentration contributed in the opposite direction, if at all, as the U.S. local labor market concentration has been decreasing since the 1970s.

factor demand with a Bartik-type instrument. They find that since the 1970s, the aggregate capital-labor elasticity has been constant at around 0.7, which indicates that capital and labor are indeed gross complements, while a capital cost decline like that emphasized by Karabarbounis and Neiman (2013) would imply an increasing labor share. Our analysis draws upon and extends Oberfield and Raval (2014), first applying their method of estimating capital-labor elasticity to firm- and plant-level data in Japan to confirm that the elasticity is below one. We depart from their analysis to the extent that we explicitly incorporate the foreign factor employment of home firms in our model in order to consider the effect of foreign factor augmentation on the home labor share. Section 3.1 explains how our production function nests that of Oberfield and Raval (2014).

1.1.2 Labor Market Impact of MNEs

This paper also relates to a second line of research that examines the impact of foreign production on the source country's labor market (Desai et al., 2009; Muendler and Becker, 2010; Harrison and McMillan, 2011; Ebenstein et al., 2014; Boehm et al., 2017; Kovak et al., 2017). Notably, as does the current paper, this literature explicitly uses exogenous variation that changes the profitability from engaging in foreign production. For example, Desai et al. (2009) take the source country's economic indicators and construct a shift-share-style instrumental variable, whereas Kovak et al. (2017) use a change in bilateral tax treaties between the U.S. and other countries to construct the IVs. Bernard et al. (2018) study the effect on firms' occupational organization using a shift-share-type instrument from a detailed set of firm-specific variables regarding changes in import share, while Setzler and Tintelnot (2019) use the geographic clustering of MNEs as the source of exogenous variation and find that when foreign MNEs enter the U.S., there are two effects on local wages: a direct foreign MNE premium on worker wages and an indirect wage-bidding-up effect on incumbent domestic firms. Our contribution to this literature is both empirical and theoretical. Empirically, our approach adds another piece of evidence based on a negative productivity shock resulting from an unexpected natural disaster that affects firms' foreign production and domestic employment decisions.[4]

More importantly, unlike these studies, we are able to provide a clear structural interpretation of the shock and its impact on employment by specifying the foreign production model in Section 3. As will be clear, this is indeed the key to identifying the model parameters.[5] Specifically, both Desai et al. (2009) and Kovak et al. (2017) find positive causal effects of foreign employment on home employment, which is consistent with our finding that the decrease in employment in the foreign country due to flooding is accompanied by a *decrease* in home employment. Our model further

[4] Kato and Okubo (2017) study the same event to learn about the loss of vertical linkages in the destination country, while Boehm et al. (2018) study another dimension of the impact of a shock on multinational firms. While they consider the effect of the 2011 Tohoku Earthquake in Japan on the Japanese HQ and its subsequent impact on foreign (U.S.) affiliates, this paper is interested instead in the impact of a foreign shock on foreign affiliates in Thailand and its impact on domestic headquarters in Japan.

[5] For example, while Desai et al. (2009) use a Bartik shock with GDP growth rates as the 'shift' component, if we do not know whether the GDP growth is due to increased consumer demand or firm productivity in the short-run, then it is not clear how to interpret their coefficients. On the other hand, Kovak et al. (2017) employ the enforcement of a bilateral tax treaty, which is arguably a supply-side shock. However, their approach does not permit backing out substitution parameters, as they use a different sourcing model and therefore do not estimate the 2SLS specification but only an event-study regression.

implies that this positive association caused by an exogenous shock to foreign productivity can be interpreted as home labor and foreign labor being gross substitutes.

Other studies rely on observed rather than experimental or exogenous variation in factor costs, with earlier studies in this vein including Brainard and Riker (1997); Slaughter (2000); Head and Ries (2002), which estimate the short-run cost function by regressing domestic skill demand on foreign wages, implicitly assuming that foreign capital cannot be adjusted. Several papers relax this assumption and estimate the long-run cost function by regressing source-country labor demand on destination-country wage and rental rate (Harrison and McMillan, 2011). Regardless of whether the function estimated is short-run or long-run, these cost function approaches usually take local wages as a regressor, with the identification assumption being that after controlling for a detailed set of control variables, variation in local wages is exogenous. Ebenstein et al. (2014) study the effect of trade and offshoring using worker-level data, and their results corroborate those of Harrison and McMillan (2011). [6]

Although the literature on the relationship between MNEs and factor intensities is not extensive, different factor intensities across firms may have quantitative implications for labor shares through the reallocation of factors across firms. Like Sun (2020), who studies the differential capital intensities between MNEs and other firms, we also study heterogeneous factor intensities by firm-level MNE data and provide some evidence as to the role of the heterogeneity. As opposed to Sun's (2020) focus on host countries, our focus is on the labor share of the source country of FDI. Furthermore, Sun (2020) does not focus on estimating the elasticity between home and foreign factors, but calibrates his model of export platforms to global affiliate data using the cross-section variation. In contrast, we use a natural experiment to formally identify the elasticity between factors in the MNE-source and destination countries.

Lastly, our paper is related to the literature which argues that automation may displace labor demand and thus reduce labor share. Our goal is to establish that instead of technological changes in automation, MNE activities play a substantial role in decreasing labor share. However, it is difficult to separate the effect of globalization from that of technological change, both conceptually and empirically (Fort et al., 2018). To partially address the concern, in Section 2.2.4, we provide evidence that the growth in automation technology in Japan during the 1990s and 2000s was not rapid relative to other countries.

[6] Additionally, Boehm et al. (2017) study the impact of outsourcing by multinational firms on domestic labor demand. While their mechanism specifically focuses on outsourcing, whereby multinational firms import intermediate goods otherwise produced domestically and so a firm reduces its labor demand when it becomes multinational, our study focuses mainly on offshoring. In our model, a firm reduces its labor when it becomes multinational as it stops producing particular tasks domestically for export. Another strand of literature distinguishes the intensive and extensive margins of the impact of foreign production. Muendler and Becker (2010) establish two-stage estimators of the wage gradient of domestic input shares, whereby the first stage predicts the destination country and the second stage estimates the wage gradient, correcting the selection by the control function approach. Although they consider choice of location focusing exclusively on multinational firms, we also take into account purely domestic firms and thus add another layer of complexity to the extensive margin analysis of foreign production. Boehm et al. (2017) also study the effect of initiating outsourcing in foreign countries on domestic employment and establishments. Our use of an unexpected natural disaster as an identification strategy thus complements their observational findings since the natural disaster leads to halt of operation instead of initiating it.

2 Motivating Facts

In this section, we provide further evidence that suggests that a surge in MNE growth was behind the decrease in labor share in recent decades. For this purpose, we focus on our context of Japan from 1995-2007, as overviewed in Section 1. In Section 2.1 we describe the major data source for our analysis and then, using this data, we show relevant facts in Section 2.2.

2.1 Data

This study utilizes four main datasets, the first being the *Basic Survey on Japanese Business Structure and Activities* (BSJBSA), an annual survey of large firms in Japan administered by the Ministry of Economy, Trade, and Industry (METI).[7] BSJBSA has a detailed set of variables providing Japanese firm-level information such as the firm's address, division-level employment distribution, holding relationships, balance sheet components, itemized sales by goods, costs by type, export and import by region, outsourcing, research and development, technology and patents, among others. The data spans the years from 1995-2017.

In order to match foreign production information to the BSJBSA, we employ a second dataset, the *Basic Survey of Overseas Business Activities* (BSOBA), another annual survey administered since 1995 by METI in which *all* (i.e. both private and public) Japanese MNEs are asked about their domestic and foreign business information as of March each year.[8] The BSOBA is comprised of a Headquarter File and a Subsidiary File, and this study employs mostly the Subsidiary File which asks for information about all child and grandchild foreign subsidiaries of each MNE.[9] The questions consist of the destination country, local employment and sales, which are allocated to the following destination categories: Japan (home country), Asia, Europe, and America. To check the quality of its employment and labor compensation data, we compare the variables to those obtained from PWT, as discussed in Section B.3.1.

Although the BSOBA contains the country in which each subsidiary is located, it does not provide a detailed address. As we saw in Section 4.1, while the Thai floods caused extensive damage, it was mainly concentrated in Ayutthaya and Pathum Thani provinces, which we define as the flood-affected regions, following JETRO (2012). The exact location in Thailand of the Japanese MNE subsidiaries is thus necessary to properly assign treatment status. To do this, we use the address variable from the Bureau van Dijk *Orbis* database.

Finally, as the above datasets do not share firm IDs, we matched the firm names, locations, and phone numbers using a firm-level dataset collected by private credit agency *Tokyo Shoko Research*

[7] On March 31st each year, all firms with more than 50 employees and assets of JPY 30 million (USD 0.3 million) are asked to complete the questionnaire.

[8] BSOBA defines MNEs and foreign activities as the following: A firm is defined as an MNE if it has a foreign subsidiary, which can be either a "child subsidiary" or "grandchild subsidiary". A child subsidiary firm is a foreign corporation whose Japanese ownership ratio is 10% or more, while a grandchild subsidiary is a foreign corporation whose ownership ratio is 50% or more by the foreign subsidiaries whose Japanese ownership ratio is 50% or more. Therefore, the definition of foreign production is not limited to greenfield investment but also includes purchases of foreign companies such as M&A.

[9] We drop subsidiaries located in tax-haven countries, following the Gravelle (2015) definition. We thank Cheng Chen for kindly sharing the code for the sample selection.

(TSR). The match rate from BSOBA is 93.0%. Because the scope of BSOBA is exclusively Japanese MNEs, we interpret each firm in TSR as an MNE if and only if the firm also appears in BSOBA for that year. The details of the matching process can be found in Section B.3.2. Since TSR access is limited only back to 2007, the BSJBSA-BSOBA match can occur only for years 2007-2016.

2.2 Stylized Facts from Japan, 1995-2007

Armed with these data, we overview some relevant aggregate trends of our case of Japan from 1995-2007, which will guide us in developing the model of labor share and multinational activities in the following sections. In Section 2.2.1, we show the negative time-series correlation between labor share and multinational activities, and Section 2.2.2 shows that this decrease in labor share is robust to other measures discussed in the literature. To provide another perspective on the role of MNEs, we then compare trends in labor share among MNEs and non-MNEs, and the composition of MNEs in Section 2.2.3. Finally, to provide partial evidence about other mechanisms discussed above, we show in Section 2.2.4 that (i) the increase in the stock of industrial robot is likely to have happened *before* the period of our analysis, and (ii) market power in Japan was low and relatively constant during 1995-2007.

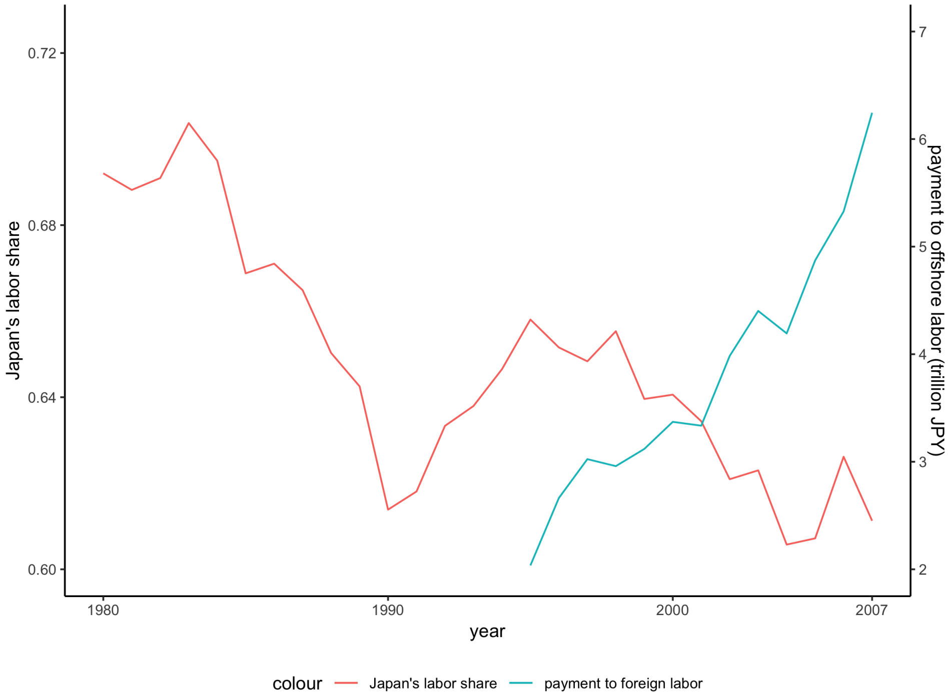
2.2.1 Negative Time-series Correlation between Labor Share and Multinational Activities

Figure 2 shows trends in Japan's labor share and aggregate payment to foreign employees. The red line shows the overall decreasing labor share in Japan since 1980.[10] As outlined above, the current paper aims to explain such a decrease by foreign factor augmentation from the perspective of Japan, which potentially increases both factor prices and employment, as detailed in the section describing our model. Therefore, one of the augmentation measures is the aggregated payment from Japanese multinational enterprises (MNEs) to foreign workers. The blue line shows this trend since 1995, which is the first year of our dataset. As can be seen, the trend increased rapidly, at least partly indicating the augmentation of the foreign factor. Given this finding, the current paper asks if, how, and under which conditions is there a logical link between foreign factor augmentation and labor share, and quantitatively what portion of the observed labor share decline can be attributed to this foreign factor augmentation.

While Figure 2 is concerned about labor compensation, Figure 3 shows the trends of both labor and capital earnings by Japanese MNEs from the BSOBA data. Note that capital income has been increasing since 1995, but the trend is more volatile than payment to labor. This increase can partly explain the more rapid increase in GNI than GDP in Japan because the income from the foreign capital is accounted for under the positive net primary income from abroad. It will be a crucial step to explicitly allow foreign capital in our model.

[10] Readers might notice a countercyclical component in the trend, which is observed in many countries. Schneider (2011) surveys the literature on the labor share and business cycles.

Figure 2: Labor Share and Payment to Foreign Employment, Japan

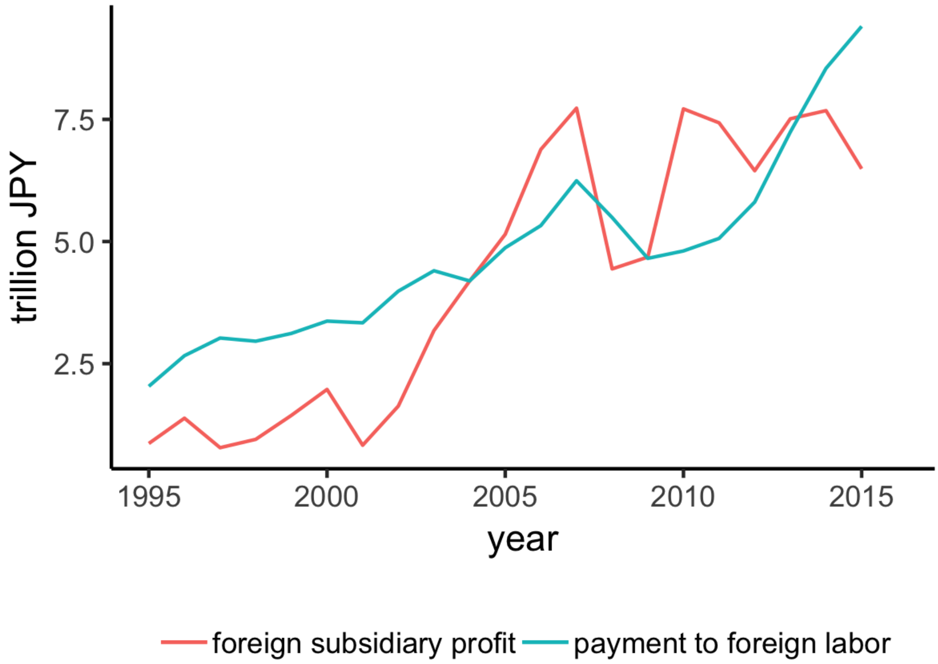


Source: Authors' calculation based on Japan Industrial Productivity (JIP) Database 2015 from Research Institute of Economy, Trade and Industry (RIETI) and the Basic Survey on Overseas Business Activities (BSOBA) 1996-2008. The labor share is calculated by the share of the nominal labor cost in the value added of JIP market economies in nominal terms. The payment to offshore labor is the sum of worker compensation to foreign subsidiaries of all Japanese multinational corporations in BSOBA.

2.2.2 Robust Labor Share Decrease

As explained in Section 1.1, neither the conceptual or operational measurement of labor share is trivial. In this section, we overview several measures of the labor share in Japan between 1995 and 2007 to see that irrespective of the measurement process, we have robust evidence that the labor share has been decreasing. First, the green line in Figure 4 shows our preferred measure, the total labor cost divided by GDP. However, since GDP or value added includes capital depreciation, it overstates net capital income (Bridgman, 2018). To overcome this, we take the SNA data from the Japan Cabinet Office Long-run Economic Statistics and calculate the trend in the share of nominal employee compensation over nominal national income, which excludes capital depreciation (as well as indirect tax, while including subsidies). This trend is shown by the blue line. Another issue is the treatment of the mixed income of self-employees. Since self-employees are typically owners of both the production capital and labor, the allocation of the generated income to labor and capital can be distorted (e.g., Rognlie, 2018). To remove any biases due to the misallocation of such mixed income, we take the trend of domestic corporate factor income and their compensation payment to the labor, which is shown by the red line. We can see in Figure 4 that all of these trends are decreasing.

Figure 3: Earnings by Foreign Labor and Capital



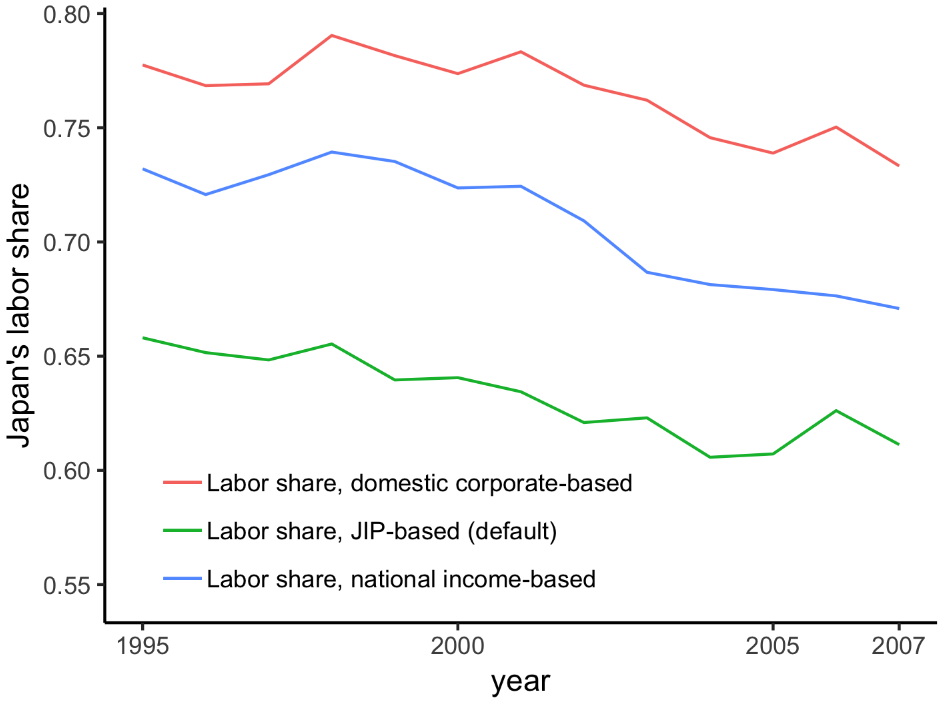
Source: Authors' calculation based on the Basic Survey on Overseas Business Activities (BSOBA) 1996-2017. Foreign subsidiary profit is the sum of current net profit of all subsidiaries of Japanese multinational corporations in BSOBA, and payment to offshore labor is the sum of worker compensation to foreign subsidiaries of all Japanese multinational corporations in BSOBA.

2.2.3 Comparison of MNEs and Non-MNEs

To further analyze the role of MNEs in the decrease in labor share, we conduct a simple decomposition analysis across MNEs and non-MNEs by aggregating total sales, labor compensation and net income separately for MNEs and non-MNEs. We then calculate the labor share for the two groups. Figure 5 shows the trends for labor share and MNE composition. The blue line depicts the trends in the share of the sum of MNE HQ sales relative to the sum of sales of all firms. In 1995, the share was roughly 12 percent, which rose to close to 15 percent in 2007. Therefore, the composition of sales became skewed toward MNEs over the period. The red lines show the labor share trends among MNEs (solid line) and non-MNEs (dashed line), and we can see that the labor share of MNEs decreases more rapidly. Additionally, throughout the period, MNEs had a lower labor share than non-MNEs. Since the labor share composition by MNEs increased (as shown by the blue line), both of the these facts have contributed to the decrease in aggregate labor share.

One of the interpretations of these facts is that within MNEs, the payment to labor relative to capital decreased over the period, *and* more firms become MNEs. In the model section, we develop a framework in which *both* of these may be explained by foreign factor augmentation.

Figure 4: Several Labor Share Measures, Japan, 1995-2007



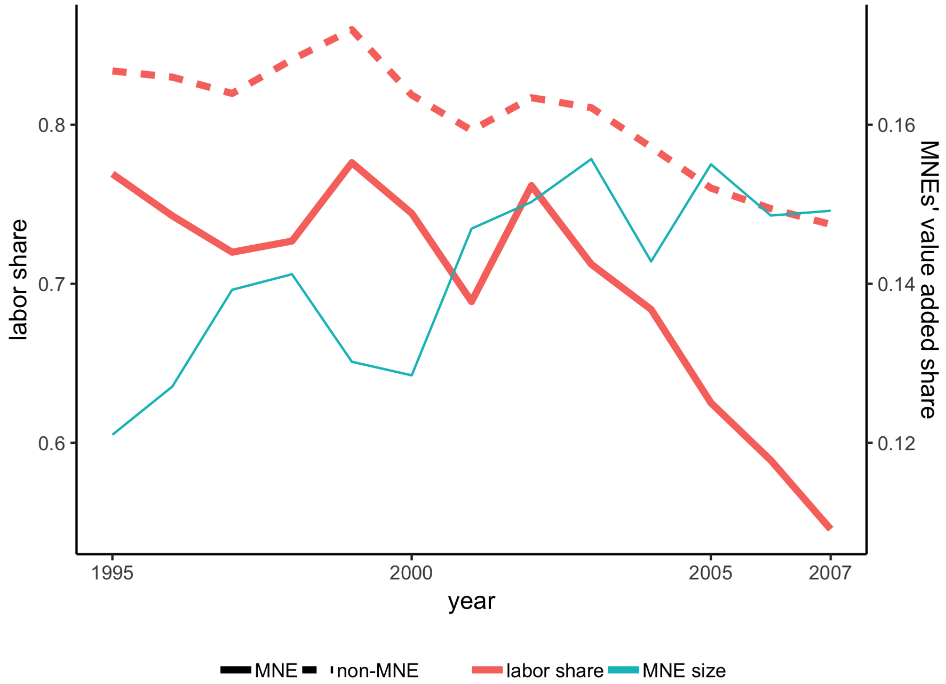
Source: Authors' calculation based on the 2015 Japan Industrial Productivity (JIP) Database from Research Institute of Economy, Trade and Industry (RIETI), Cabinet Office Long-Run Economic Statistics (COLES, https://www5.cao.go.jp/j-j/wp/wp-je12/h10_data01.html, accessed on May 13, 2019), and Japan SNA, Generation of Income Account, 2009. JIP-based labor share is calculated by the share of nominal labor cost in the nominal value added of JIP market economies. National income-based labor share is the fraction of nominal employee compensation over nominal national income from COLES. Domestic corporate-based labor share is the net labor share of domestic corporate factor income, calculated from the SNA by the fraction of the item "Wages and salaries" over the sum of "Wages and salaries" and "Operating surplus, net."

2.2.4 Other Potential Mechanisms

Automation in Japan As discussed in Section 1.1, bias in technological change can arise from at least two sources: automation and offshoring. Since the current paper focuses on offshoring; in particular, factor offshoring as opposed to goods offshoring (Hummels et al., 2014), the evolution of automation technology in Japan is not our main focus. However, by examining the aggregate data used in automation literature (e.g., Acemoglu and Restrepo, 2017), we see suggestive evidence that automation acceleration was not observed in Japan as rapidly as in other highly automating countries from the 1990s to 2010s.

To examine this, we employ data from the *International Federation of Robotics* (IFR) to obtain the operational stock of industrial robots in each country by year. Figure 6 shows the trends for the five most robot-adopting countries (China, Japan, United States, South Korea, Germany). All countries other than Japan rapidly introduced industrial robots from 1993 to 2016. In particular, China's absorption has been extraordinarily fast since the mid 2000s, when it entered the international trade markets after being granted membership in the WTO following the removal of a number of political and institutional barriers. In contrast, Japan's automation capital stock was declining during this period.

Figure 5: Labor Shares of MNEs and Non-MNEs



Source: Authors' calculation based on the Basic Survey on Overseas Business Activities (BSOBA) 2007-2016, the Basic Survey on Japanese Business Structure and Activities (BSJBSA) 1996-2017, and the JIP 2015. Multinational is defined as firms that appeared in BSOBA at least once during 2007-2016. For each firm, labor share is calculated as the fraction of total payroll over the sum of total payroll and current profit from BSJBSA. We then aggregate to multinational groups and non-multinationals. Share of MNE size is calculated as the fraction of aggregated sales of all multinational firms over the total nominal output from JIP 2015.

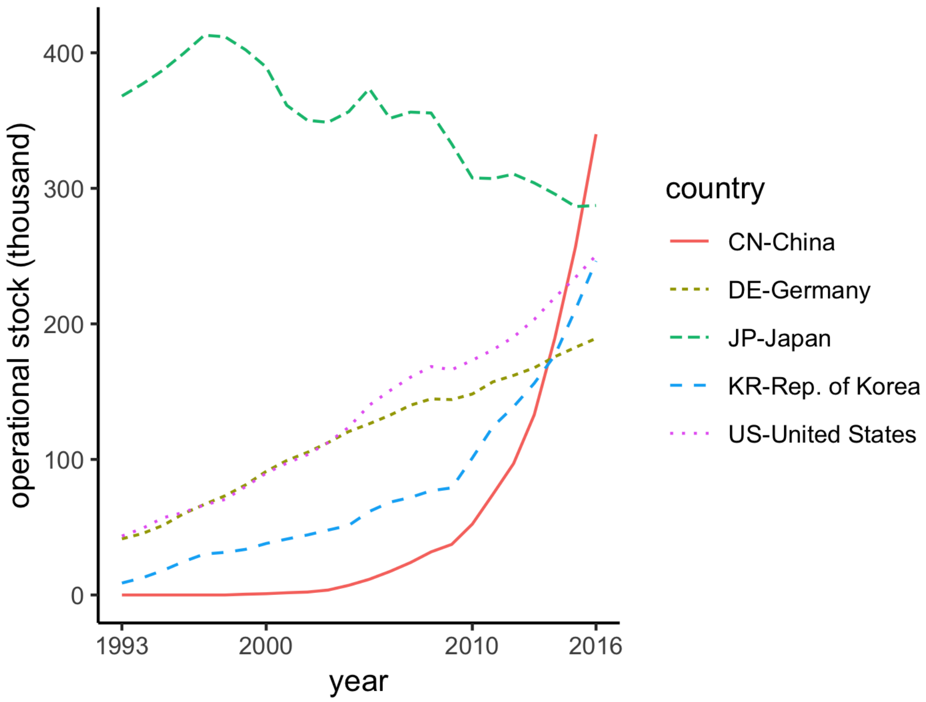
In a related argument, Fort et al. (2018) emphasizes the impact of globalization on country-level labor markets, but qualifies this statement because "providing a definitive accounting of the amount of employment change attributable to either factor is extraordinarily difficult." Given this difficulty, focusing on Japan might offer insight because the analysis is not contaminated by concurrent extensive technological growth.

A Surge in Market Powers Another potential explanation for the labor share decline is provided by De Loecker and Eeckhout (2017), who argue that it is explained by a surge in market power. They develop a parsimonious but versatile method to back out the markups from the firm- or plant-level data and conclude that the markup in the U.S. has been increasing remarkably since around 1980. Applying this method to our Japanese firm-level data (BSJBSA), we find a much smaller increase in markups relative to the U.S., a finding that is in line with De Loecker and Eeckhout (2018).

3 Conceptual Framework

In this section, we set up our conceptual framework for the estimation and quantification that follows. First, in Section 3.1, we discuss a general framework that features foreign production which has the same first order implications for labor share as several offshoring (Feenstra and Hanson,

Figure 6: Industrial Robot Stock, Top 5 Countries in 2016



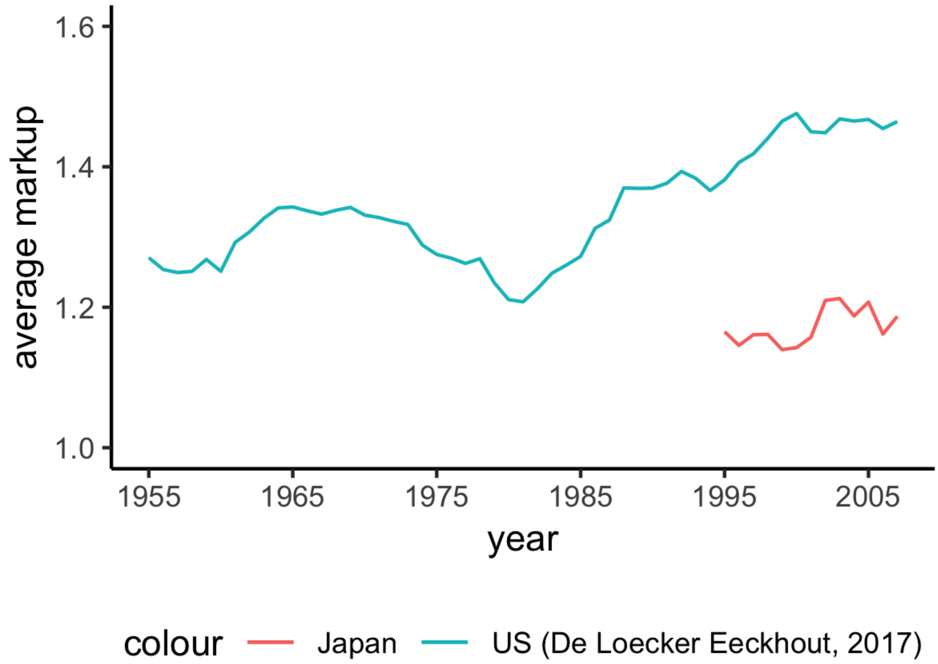
Source: International Federation of Robotics

1997) and MNE models (among others, Ramondo and Rodríguez-Clare 2013; Arkolakis et al. 2017). This framework contains foreign factor augmentation representing a reduction in the cost of multinational production, and factor market clearing conditions to discuss labor share. A detailed discussion of the relationship between these models is in Section A of the Appendix. Section 3.2 discusses the implications of foreign factor augmentation on labor share to the first order. Out of this section, readers will know which statistics from the model are necessary to qualitatively and quantitatively understand the impact on labor share. In Section 3.3, we discuss the methodology for identifying these statistics given a foreign factor augmentation shock, and then in the estimation section, we apply this methodology to the 2011 Thailand Floods. In Section 3.4, we discuss a specific version of our general model; namely, a homogeneous nested CES production function. This setup allows us to discuss the solution to the labor share in a closed form, the necessary statistic in the form of constant parameters, and the identification through a simple linear regression. By doing so, we aim to offer a simpler intuition of the mechanisms of our model and guide our estimation and quantification, as we discuss later.

3.1 Setup

The environment is static, with two countries H and F. There are no trade costs but factors cannot move between countries. Firms originate from both countries and produce firm-specific output $i \in I$. Each good i is contestable and so firms are perfectly competitive in the output market. Country H is small-open in the sense that the set I_H of firms from country H constitutes zero measure among all firms I and the total demand is determined by F demand. Next, we describe the consumption setup,

Figure 7: Markup Estimates for Japan; De Loecker and Eeckhout (2017) Method



Note: Authors' calculation based on De Loecker and Eeckhout (2017) using data from the Basic Survey on Japanese Business Structure and Activities (BSJBSA) 1995-2016. Variable input cost is the sum of labor compensation and intermediate purchases. Output elasticity is estimated by Olley and Pakes' (1996) method for each JSIC 3-digit industry. The average is calculated using the weight of each firm's sales.

production setup, and equilibrium in turn. The representative consumer has a CES preference across all goods $i \in I$. Hence the demand function is

$$q_i = \left(\frac{p_i}{P}\right)^{-\varepsilon} Q, \tag{1}$$

where $P = \int_{i \in I} (p_i)^{1-\varepsilon} di$ is the ideal price index. Since H is small-open, P and Q are determined exogenously to country H. Firm i in H may hire intermediate inputs m_i. Note that foreign inputs are so general that they may entail foreign-produced intermediate inputs (e.g., Feenstra and Hanson, 1997) or foreign factors of production (e.g., Helpman et al., 2004; Ramondo and Rodríguez-Clare, 2013; Arkolakis et al., 2017). A firm i from H produces a firm-specific output with domestic factors k_i and l_i, and foreign inputs m_i according to the constant returns to scale production function:

$$F\left(\widetilde{k_i}, \widetilde{l_i}, \widetilde{m_i}\right),$$

where $\widetilde{k_i} \equiv a_i^K k_i$, $\widetilde{l_i} \equiv a_i^L l_i$, and $\widetilde{m_i} \equiv a_i^M m_i$ are the augmented factors. We assume F is increasing, strictly concave, and twice continuously differentiable (so that Young's theorem applies in Section A.7). Note that there are factor augmentations $\left(a_i^K, a_i^L, a_i^M\right)$. Below, our theoretical interest is the effect of changes in foreign factor augmentation a_i^M. In particular, in our comparative statics, we are concerned about positive log-augmentation $d \ln a_i^M > 0$, whereas in our identification argument and empirical application, we consider a negative log-augmentation. One may interpret the foreign factor augmentation as policy or institutional changes that reduce the cost of firms' multinational activities, or technological or economic growth in country F that increases the productivity of the factors.[11]

Factors from country H are hired competitively in each factor market. As we will see, capital and labor markets in country H clear at prices r and w respectively, but F's factor prices are given to small-open country H. Firms solve the augmented factor demands by the standard cost-minimizing problem given the quantity q_i in terms of augmentation-controlled prices $\widetilde{r}_i \equiv r/a_i^K$, $\widetilde{w}_i \equiv w/a_i^L$, and $\widetilde{p_i^M} \equiv p_i^M/a_i^M$, with $\widetilde{p_i^f} \equiv \left(\widetilde{r}_i, \widetilde{w}_i, \widetilde{p_i^M}\right)'$ the vector of the augmentation-controlled factor prices. Given CES world demand (1), we have the quantity q_i that depends on firm i's price p_i. Given perfect competition, p_i further depends on augmentation-controlled factor prices $\widetilde{p_i^f}$. Substituting this relationship between q_i and $\widetilde{p_i^f}$ in the cost-minimizing factor demand, we have the *reduced* factor demand functions that only depend on augmentation-controlled factor prices:

$$\widetilde{k}_i = \widetilde{k}_i\left(\widetilde{p_i^f}\right), \widetilde{l}_i = \widetilde{l}_i\left(\widetilde{p_i^f}\right), \widetilde{m}_i = \widetilde{m}_i\left(\widetilde{p_i^f}\right). \tag{2}$$

The factor prices are determined by market clearing. The small-open H assumption implies that the hiring of foreign input m_i by $i \in I_H$ does not affect the prices p_i^M, so that we write $p_i^M = \overline{p_i^M}$ and $\widetilde{p_i^M} = \overline{p_i^M}/a_i^M$. In H, capital and labor are supplied inelastically at level K and L. The H factor markets are cleared at the factor market conditions

$$K = \int_{i\in I_H} \frac{\widetilde{k}_i\left(\widetilde{p_i^f}\right)}{a_i^K} di,\ L = \int_{i\in I_H} \frac{\widetilde{l}_i\left(\widetilde{p_i^f}\right)}{a_i^L} di. \tag{3}$$

Hence, the small-open equilibrium is $\left(\{k_i, l_i, m_i\}_{i\in I_H}, r, w\right)$ that satisfies (i) the factor demands given by (2) and (ii) the factor prices solving (3).

Under the environment with continuous demand and supply functions like ours, it is routine to show the existence of an equilibrium. Furthermore, as consumers are homogeneous (since H is small-open), the uniqueness of the equilibrium can be proven (see Section A.1 of the Appendix). Given this unique equilibrium, the following subsections discuss the first-order properties of labor share and identification, and then provide an example in the form of a nested CES specification.

3.2 Labor Shares

With a unique equilibrium, we can analyze the implication of a foreign productivity shock to labor share as follows. Labor share is defined as

$$LS \equiv \frac{wL}{wL + rK}. \tag{4}$$

[11] Sun (2020) conducts a counterfactual analysis of bilateral multinational production cost, but notes that the calibration strategy does not identify bilateral productivity. Thus, this counterfactual analysis corresponds to our study in that either a decline in multinational production cost or productivity growth in the foreign country may induce a change in equilibrium, including the labor share.

Note that the endogenous variables in expression (4) are w and r, so the solution to the model should transform the endogenous expression into an exogenous one. Taking the log-first order approximation of labor share definition (4) gives us

$$dLS = LS_0 \left(1 - LS_0\right) \left(d \ln w - d \ln r\right). \tag{5}$$

Thus, the labor share increases if and only if the Home wage grew more than the Home rental rate. To study this, we revisit the factor market clearing condition (3) and take the log-first order approximation to obtain:

$$0 = \int_{i \in I_H} s_i^K \left[\sigma_{\widetilde{k}\widetilde{r},i} d \ln r + \sigma_{\widetilde{k}\widetilde{w},i} d \ln w - \sigma_{\widetilde{k}\widetilde{p^M},i} d \ln a_i^M\right] di,$$

$$0 = \int_{i \in I_H} s_i^L \left[\sigma_{\widetilde{l}\widetilde{r},i} d \ln r + \sigma_{\widetilde{l}\widetilde{w},i} d \ln w - \sigma_{\widetilde{l}\widetilde{p^M},i} d \ln a_i^M\right] di,$$

or

$$\overline{\Sigma_H} \times \begin{pmatrix} d \ln r \\ d \ln w \end{pmatrix} = \begin{pmatrix} \int_{i \in I_H} s_i^K \sigma_{\widetilde{k}\widetilde{p^M},i} d \ln a_i^M di \\ \int_{i \in I_H} s_i^L \sigma_{\widetilde{l}\widetilde{p^M},i} d \ln a_i^M di \end{pmatrix}, \tag{6}$$

where $s_i^K \equiv rk_i/rK$ (resp. $s_i^L \equiv wl_i/wL$) is the capital (resp. labor) employment share of firm i among all H-origin firms I_H.

$$\overline{\Sigma_H} \equiv \begin{pmatrix} \int_{i \in I_H} s_i^K \sigma_{\widetilde{k}\widetilde{r},i} di & \int_{i \in I_H} s_i^K \sigma_{\widetilde{k}\widetilde{w},i} di \\ \int_{i \in I_H} s_i^L \sigma_{\widetilde{l}\widetilde{r},i} di & \int_{i \in I_H} s_i^L \sigma_{\widetilde{l}\widetilde{w},i} di \end{pmatrix} \tag{7}$$

is the weighted Home factor elasticity matrix. If $\overline{\Sigma_H}$ is negative definite, then

$$d \ln w - d \ln r = \begin{pmatrix} -1 & 1 \end{pmatrix} \left(\overline{\Sigma_H}\right)^{-1} \begin{pmatrix} \int_{i \in I_H} s_i^K \sigma_{\widetilde{k}\widetilde{p^M},i} d \ln a_i^M di \\ \int_{i \in I_H} s_i^L \sigma_{\widetilde{l}\widetilde{p^M},i} d \ln a_i^M di \end{pmatrix}. \tag{8}$$

It is worth noting the relationship between our general equilibrium setup and the offshoring and multinational production models in the literature. Specifically, our general equilibrium model nests modified versions of models of offshoring (Feenstra and Hanson, 1997) and multinational production (e.g., Arkolakis et al., 2017) in terms of the first order approximation of factor prices (6). This equivalence is formally shown in Section A.2 of the Appendix. Consequently, for our purposes, we may turn away from these detailed models of international trade and multinational production to focus exclusively on the sufficient statistics of the elasticity matrix given by equation (7). We discuss how to identify these elasticities in the following section.

3.3 Identification

In this section, we discuss our identification strategy by formally introducing a foreign factor-augmenting negative productivity shock to a measure-zero subset of firms.[12] In Section 4.1, we apply the model

[12]This simplifying assumption is helpful because otherwise the equilibrium effect on factor prices (r, w^H, w^L) would emerge and complicate the analysis. This assumption is realistic because the set of Japanese firms hit by the flooding is small relative to the population. Having said that, mulitnational firms are larger and comprise a significant portion of factor employment both theoretically (Helpman et al., 2004; Arkolakis et al., 2017 among others) and empirically (Ramondo

to empirically estimate the effect on labor share of the devastating 2011 Thailand Floods. To begin, first assume that there exists an instrumental variable Z_i that correlates with the Foreign productivity shock $d\ln a_i^M$ but not with Home productivity shocks $d\ln a_i^K$ and $d\ln a_i^L$. Then we may construct the moment conditions:

$$E\left[Z_i\begin{pmatrix} d\ln a_i^K \\ d\ln a_i^L \end{pmatrix}\right]=0. \tag{9}$$

To obtain the structural productivity shocks $d\ln a_i^K$ and $d\ln a_i^L$, consider the following model inversion. By factor demand functions (2), we have

$$\begin{aligned}
d\ln(rk_i) = d\ln\left(\widetilde{r}_i\widetilde{k}_i\right) &= \left(1+\sigma_{\widetilde{k}\widetilde{r},i}\right)d\ln\widetilde{r}_i+\sigma_{\widetilde{k}\widetilde{w},i}d\ln\widetilde{w}_i+\sigma_{\widetilde{k}\widetilde{p^M},i}d\ln\widetilde{p_i^M},\\
d\ln(wl_i) = d\ln\left(\widetilde{w}_i\widetilde{l}_i\right) &= \sigma_{\widetilde{l}\widetilde{r},i}d\ln\widetilde{r}_i+\left(1+\sigma_{\widetilde{l}\widetilde{w},i}\right)d\ln\widetilde{w}_i+\sigma_{\widetilde{l}\widetilde{p^M},i}d\ln\widetilde{p_i^M},\\
d\ln\left(p^M m_i\right) = d\ln\left(\widetilde{p_i^M}\widetilde{m}_i\right) &= \sigma_{\widetilde{m}\widetilde{r},i}d\ln\widetilde{r}_i+\sigma_{\widetilde{m}\widetilde{w},i}d\ln\widetilde{w}_i+\left(1+\sigma_{\widetilde{m}\widetilde{p^M},i}\right)d\ln\widetilde{p_i^M},
\end{aligned}$$

or, in matrix form,

$$\begin{pmatrix} d\ln(rk_i) \\ d\ln(wl_i) \\ d\ln\left(p^M m_i\right) \end{pmatrix} = (I+\Sigma_i)\begin{pmatrix} d\ln(\widetilde{r}_i) \\ d\ln(\widetilde{w}_i) \\ d\ln\left(\widetilde{p_i^M}\right) \end{pmatrix} = (I+\Sigma_i)\begin{pmatrix} d\ln r - d\ln\left(a_i^K\right) \\ d\ln w - d\ln\left(a_i^L\right) \\ d\ln p^M - d\ln\left(a_i^M\right) \end{pmatrix},$$

where

$$\Sigma_i \equiv \begin{pmatrix} \sigma_{\widetilde{k}\widetilde{r},i} & \sigma_{\widetilde{k}\widetilde{w},i} & \sigma_{\widetilde{k}\widetilde{p^M},i} \\ \sigma_{\widetilde{l}\widetilde{r},i} & \sigma_{\widetilde{l}\widetilde{w},i} & \sigma_{\widetilde{l}\widetilde{p^M},i} \\ \sigma_{\widetilde{m}\widetilde{r},i} & \sigma_{\widetilde{m}\widetilde{w},i} & \sigma_{\widetilde{m}\widetilde{p^M},i} \end{pmatrix}. \tag{10}$$

Thus we have

$$\begin{pmatrix} d\ln\left(a_i^K\right) \\ d\ln\left(a_i^L\right) \\ d\ln\left(a_i^M\right) \end{pmatrix} = \begin{pmatrix} d\ln r \\ d\ln w \\ d\ln p^M \end{pmatrix} - (I+\Sigma_i)^{-1}\begin{pmatrix} d\ln(rk_i) \\ d\ln(wl_i) \\ d\ln\left(p^M m_i\right) \end{pmatrix}. \tag{11}$$

Therefore, conditional on parameter restrictions, we may identify two elasticity parameters from elasticity matrix (10) given moment condition (9). The empirical details are discussed in Section 4.

At this point, we discuss the nature of our identification strategy. A typical method for identifying labor demand-side elasticity such as our Σ_i is to use labor-supply side elasticity such as a short-run surge in migration. In fact, the idea that a labor supply shock can identify the supply elasticity is through the change in wages exogenous to producers (Ottaviano and Peri, 2012). The benefit of our approach is that we do not need to have such exogenous changes observed, since our approach does not rely on factor price changes but instead on the change in *effective* factor prices, which are specific to firms. This implies that our identification method is free of any assumptions

et al., 2015), so a quantitatively relevant extension is to allow the shock to extend to a positive-measured set of firms for identification.

about labor market delineation or competition structure within the labor market.

3.4 Example: Nested CES

In this section, we discuss a special case of our non-parametric and heterogeneous framework presented in Section 3.1. This clarifies the intuition of our general setup and simplifies the identification strategy. We rely on this example to calibrate some aspects of the general model in later sections.

Setup In this example, we maintain the same setup for countries and consumer preferences but assume that there is a homogeneous set of firms. We continue denoting I as the set of firms in any country and I_H as that from country H. To achieve a different elasticity of substitution between the foreign factor and home factors, we assume a parsimonious nested CES production function. Namely, each firm produces output q with nested CES production function:

$$F\left(k,l,m\right)=\left(\left(a^{K}k\right)^{\frac{\sigma-1}{\sigma}}+x^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where $\sigma>0$ is an upper substitution of elasticity and

$$x=\left(\left(a^{L}l\right)^{\frac{\lambda-1}{\lambda}}+\left(a^{M}m\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}, \tag{12}$$

where $\lambda>0$ is a lower elasticity substitution. Note that the special case of $\lambda=\sigma$ implies the single-nest CES production function. Finally, suppose factor supplies (K,L,M) are fixed. Factor market clearing $k=K,l=L$, and $m=M$ gives the factor prices w^{c} and r, and the labor share is given by equation (4).

Several discussions follow. First, to relate our production function choice with the one in Oberfield and Raval (2014), note that firms need not hire foreign factor m in reality. If this is the case, we can define the production function with $m=0$, which would yield CES $q=\left(\left(a^{K}k\right)^{\frac{\sigma-1}{\sigma}}+\left(a^{L}l\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$. On the other hand, Oberfield and Raval (2014) consider the CES production function with heterogeneous augmentation a^{K} and a^{L} at the firm level. Note also that firms need not hire the foreign factor, which guides us to the restriction that labor and the foreign factor are gross substitutes, or $\lambda>1$.

As for further potential parameter restrictions, to the extent that typical firms hold some form of capital to produce output, we have an educated guess that capital and aggregate labor are gross complements, or $\sigma<1$. Because the parameter restrictions so far turn out to be useful for some of the theoretical arguments, we formalize these as the following assumption:

Assumption 1. $\lambda>1>\sigma>0$.

In what follows, we show that under Assumption 1, foreign labor (log-)augmentation $d\ln a_{i}^{M}>0$ implies that the reduction in labor share $dLS<0$. As explained in Section 1.1, Oberfield and Raval (2014) indeed estimate that σ is well-below unity using U.S. plant-level microdata. In our empirical and quantitative exercise, we apply this method, modified to our nested CES assumption and with

Japanese firm- and plant-level data, and confirm that $\sigma < 1$ is also the case in Japan. Moreover, our identification method applied to the natural experiment- based IV estimate reveals that, in fact, $\lambda > 1$. Therefore, we find that Assumption 1 holds empirically. Notwithstanding this, a number of results in the following section do not depend on a particular parameter restriction 1.

Labor Share Our proof in Section A.3 of the Appendix shows that under our setting, the labor share expression may be solved analytically as

$$LS = \frac{\left(a^L L\right)^{1-\lambda^{-1}} X^{\lambda^{-1}-\sigma^{-1}}}{\left(a^L L\right)^{1-\lambda^{-1}} X^{\lambda^{-1}-\sigma^{-1}} + \left(a^K K\right)^{1-\sigma^{-1}}}, \tag{13}$$

where

$$X \equiv \left(\left(a^L L\right)^{\frac{\lambda-1}{\lambda}} + \left(a^M M\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}$$

is the aggregate value of the factor supplies to country H measured by function (12). Note that X is increasing in a^M. Hence, if $\lambda^{-1} - \sigma^{-1} < 0$ or $\lambda > \sigma$, LS is decreasing in a^M. Intuitively, if within the lower nest the factors are more substitutable, then the increase in the productivity of the offshore worker relatively strongly substitutes away domestic labor. More specifically, note that cost-minimizing factor demand (A.44) implies $d \ln L = WS_0^M d \ln A^M$ to the first order, where $WS^M \equiv p^M m / \left(wl + p^M m\right)$ is the aggregate share of payments to foreign labor within the total payments to home and foreign labor. Throughout the paper, subscript 0 denotes the variable at the base year. Hence WS_0^M is the base-year value of the aggregate share of payments to foreign labor.

It is worthwhile to highlight the role of the simplifying assumptions, homogeneous nested CES and fixed foreign factor supplies, in deriving the closed form equation (13). Note that wage rate w and capital rental rate r are endogenous objects that may be solved according to factor market clearing conditions. With homogeneous and nested CES structures, we may solve these relative factor prices analytically. Furthermore, the assumption that the foreign factor market clears with the foreign factor supply fixed at M plays a crucial role in deriving the closed form in exogenous terms. Namely, without it, the lower aggregate term L contains the foreign factor supply M, which is endogenous and needs to be solved as other exogenous elements in the model.

With these assumptions, other exogenous variables being fixed, the first order approximation with respect to $d \ln a^M$ implies

$$\begin{aligned} dLS &= LS_0 \left(1 - LS_0\right) \left(\lambda^{-1} - \sigma^{-1}\right) d \ln L \\ &= LS_0 \left(1 - LS_0\right) \left(\lambda^{-1} - \sigma^{-1}\right) WS_0^M d \ln a^M. \end{aligned} \tag{14}$$

Therefore, it is again crucial to know the relative values of λ and σ to learn the sign of the effects of foreign labor augmentation on labor share. Thus, our informed guess in Section 3.1 establishes the following formal result.

Lemma 1. *Under assumption 1, foreign factor augmentation $d \ln a^M$ implies $dLS < 0$.*

One implication is that, in a special case, the single-nest CES production function $\lambda = \sigma$ would not permit a discussion of the effect of foreign factor augmentation on home labor share. In other words, this is one of the manifestations of the restrictive implication of *independence from irrelevant alternatives* (IIA) that the CES function features. Namely, since the foreign factor is an irrelevant alternative to home capital and labor, the augmentation does not affect the *relative* factor demands of home capital and labor. Thus, we need the nested structure in the production function in our simplest setting.

Quantitatively, identifying the value of $\lambda^{-1} - \sigma^{-1}$ is critical to understanding the labor share implication. In what follows, we obtain an even stronger result for identification – we identify the absolute value of λ and σ – by employing a shift-share instrument to identify σ (Oberfield and Raval, 2014; Raval, 2019). In contrast, the foreign negative productivity shock is used for identification of λ as described below.

Since the homogeneous nested CES case is a special case of the general setup in Section 3.1, we may also relate the theoretical implications in terms of the general substitution elasticity matrix (10). This is discussed in Section A.5 of the Appendix.

Identification We then show the identification result given the foreign factor augmentation shocks as in Section 3.3. In Section A.4, we prove the following equations:

$$d \ln l = \left[(\lambda - \sigma)\, WS_0^M + (\sigma - \varepsilon)\, CS_0^M \right] d \ln a^M, \tag{15}$$

$$d \ln m = \left[-\lambda + (\lambda - \sigma)\, WS_0^M + (\sigma - \varepsilon)\, CS_0^M \right] d \ln a^M. \tag{16}$$

These equations mean that the elasticities of the foreign factor-augmenting productivity shock are summarized by three parameters $\lambda, \sigma, \varepsilon$ and constants WS_0^M and CS_0^M. The intuition is as follows. A negative foreign factor-augmenting productivity shock has both *direct* and *indirect* effects on factor employment. The direct effect speaks to the *biasedness* of the factor-augmenting shock, such as when the shock is biased to foreign factor demand, or $\lambda > 1$, whereby the lower nest features gross substitutes, as formalized in Assumption 1.[13] It then has the force to decrease foreign factor demand given the negative shock by the elasticity of $\lambda - 1$. On the other hand, the indirect effect is as follows. To the first order, a one percent decrease in the foreign factor-augmenting productivity shock increases the lower nest aggregate cost by WS_0^M percent and the marginal cost by CS_0^M percent. These increases have the effect on the total demand through the elasticities governed by the nested CES structure, $\lambda - \sigma$ and $\sigma - \varepsilon$, respectively. Due to the CES production function, this effect applies to labor demand l and foreign factor demand m alike. Therefore, the direct effect matters for foreign labor employment, whereas the indirect one matters for the demand for all factors.

However, it is not trivial to observe the size of the foreign factor-augmenting productivity shock $d \ln a^M$ empirically. Therefore, we consider the elasticity of foreign labor with respect to domestic

[13] A detailed discussion of factor augmentation and bias is given in Acemoglu (1998).

labor given the arbitrary size of the shock $d\ln a^M$.[14] Namely, if elasticity σ_{lm,a^M} is

$$\sigma_{lm,a^M} \equiv \frac{\frac{d\ln l}{d\ln a^M}}{\frac{d\ln m}{d\ln a^M}}. \tag{17}$$

, then by equations (15) and (16), we have

$$\sigma_{lm,a^M} = \frac{(\lambda-\sigma)\,WS_0^M + (\sigma-\varepsilon)\,CS_0^M}{-\lambda + (\lambda-\sigma)\,WS_0^M + (\sigma-\varepsilon)\,CS_0^M}. \tag{18}$$

In equation (18), readers might wonder why an increase in λ would result in a decrease in shock-induced elasticity σ_{lm,a^M}. To clarify, we discuss an extreme case when $\lambda < 1$, which means that the foreign factor augmentation is biased to *country-H* labor. In such a case, the negative foreign factor-augmenting productivity shock would *increase* hiring of the foreign factor. This is because the home and foreign factors would be gross complements, which in turn means that the foreign factor compression would result in the need to replenish the physical foreign factor rather than substituting for it. Therefore, relative to the case $\lambda > 1$, the denominator of equation (18) would be small, which would result in a *large* value of σ_{lm,a^M}, so long as $-\lambda + (\lambda-\sigma)\,WS_0^M + (\sigma-\varepsilon)\,CS_0^M > 0$.

To summarize the discussion, by equation (18), we can identify λ given the knowledge of σ_{lm,a^M}, constants $\left(WS_0^M, CS_0^M\right)$, and other parameters (σ, ε). We discuss how to obtain these constants and parameters in detail in the following sections as well as how to identify and estimate σ_{lm,a^M}. Finally, in the following sections, we use the identification arguments based on both equations (9) and (18).

4 Empirical Application–the *2011 Thailand Flood*

Given our theoretical result of identification in Section 3, we next discuss how we may obtain Σ_i in equation (10). Finding a plausibly exogenous shock to the multinational activities of MNEs is not trivial. For example, there are challenges that emerge from the small number of MNEs relative to the total number of firms. In particular, Boehm et al. (2017) mentions "the notorious difficulty to construct convincing instruments with sufficient power at the firm level."[15] In this paper, our approach is to focus on a unique natural experiment, the *2011 Thailand Floods*. We first describe the event and the interpretation for our purpose in Section 4.1, and then discuss how the firm- and plant-level data described in Section 2.1 capture the event.

For our main empirical results, we rely on the homogeneous nested CES specification and identify parameters of interest based on the moment condition (18). Section 4.2 details the process. Section 5.3 discusses the alternative general approach based on the moment condition (9).

[14] Although here we consider the foreign factor-augmenting productivity shock that does not change any domestic productivities, in estimation, we conjecture it is possible to relax this assumption and consider more formal moment conditions. In this line of argument, Adao et al. (2018) offer a rigorous derivation.

[15] Such difficulty is reaffirmed in Section B.7.1 by analyzing substitution parameter λ by means of shift-share instruments in the manner of Desai et al. (2009) and Hummels et al. (2014).

4.1 Background

Between July 2011 and January 2012, massive flooding occurred along the Mekong and Chao Phraya river basins in Thailand, which caused numerous factories in the area to halt operation. The magnitude of this shock to the production economy was extraordinary, causing an estimated $46.5 billion in economic damage, which was then the fourth costliest disaster in history (World Bank, 2011).[16] To the extent that the firms could not anticipate the flooding beforehand, we take this event as an exogenous shock. Section B.3.5 describes the results of a balancing test to confirm that there are not large systematic differences between the Japanese MNEs that had subsidiaries located in the flooded regions and those that did not.

Next, we argue that the flood can be interpreted as a *negative foreign productivity shock* for Japanese MNEs. First, as to whether or not it can be seen as a productivity shock, it is worthwhile to confirm that the shock was local. Thailand is subdivided into several provinces, and among them, Ayutthaya and Pathum Thani provinces along the flood-prone Chao Phraya river suffered severely from the flood. In these areas, the flood inundation reached its peak in October 2011. Adachi et al. (2016) find in their survey of local firms that in Ayutthaya and Pathum Thani provinces, the maximum days of inundation were 84 and 77, respectively, with maximal depth of flooding of 6 and 4 meters. In contrast, no firms from regions outside of Ayutthaya or Pathum Thani provinces claimed any days or height of inundation due to the 2011 floods.

In the severely damaged localities of Ayutthaya province and Pathum Thani province, there were seven industrial clusters where roughly 800 factories were located (Tamada et al., 2013).[17] A large proportion of firms in these industry clusters are engaged in the automobile and electronics industries (Haraguchi and Lall, 2015). Therefore, the flood shook local regions within Thailand that are intensively involved in industrial production, particularly automobile and electronics.

To further provide suggestive evidence that the flood was shock on the production side of the economy, we observe that, after the Floods, Thailand experienced a decrease in exports but not in imports. The observed pattern can be seen as evidence that the production side was hit by a shock rather than the demand side, as Benguria and Taylor (2019) argue in their interpretation of the shock origin of the global financial crisis of 2008. Section B.2 of the Appendix discusses this in detail.

What makes this event unique for our study is that although it hit localized regions of Thailand, it can be considered to be a *sizable foreign productivity shock* from the perspective of Japanese MNEs. To see this, we describe the close relationship between the two countries as investment destination and source country. Among the roughly 800 factories in the heavily flood-inundated industrial clusters, roughly 450 are Japanese subsidiaries.[18] Section B.3.3 describes the industrial patterns of factories

[16] To the extent that the economic damage includes the values of property damaged, natural disasters in developed countries are likely to be costlier. In fact, the three disasters whose economic damage surpassed the 2011 Thailand Floods at that time were the *2011 Tohoku Earthquake and tsunami* (Japan), the *1995 Great Hanshin Earthquake* (Japan), and the *2005 Hurricane Katrina* (U.S.). Given the extent of the economic damage, the physical shock to a developing country like Thailand should be regarded as even larger.

[17] Reinsurance broker Aon Benfield reported on the flood area and the locations of the inundated industrial clusters. Exhibit 16 of the report (available at http://thoughtleadership.aonbenfield.com/Documents/20120314_impact_forecasting_thailand_flood_event_recap.pdf) shows the relevant map.

[18] Exhibit 15 of the Aon Benfield report mentioned above shows a photo of the inundated Honda Ayutthaya Plant, which

that are subsidiaries of Japanese MNEs from our dataset, and the flood indeed created a large negative shock for Japanese producers. In Section B.3.4, we also show from our dataset that Thailand is a major destination country of Japanese MNEs.

Recall that our dataset in Section 2.1 covers the information well needed to study the impact of the flooding shock on factor employment. BSJBSA contains comprehensive data on firms, with domestic factor employment including employment, labor compensation, fixed assets and net income. BSOBA includes data on the universe of factories worldwide of Japanese MNEs. The plant-level variables contain the plant name, the parent firm name, employment, labor compensation, and net income. Orbis provides the exact addresses of these overseas plants, and TSR data facilitates the matching of these datasets since it contains the universe of Japanese firms. Together, these datasets allow us to analyze the flood shock that hit a subset of firms in our analysis sample by micro-econometric methods.

4.1.1 The Thai Floods and Aggregate Trends

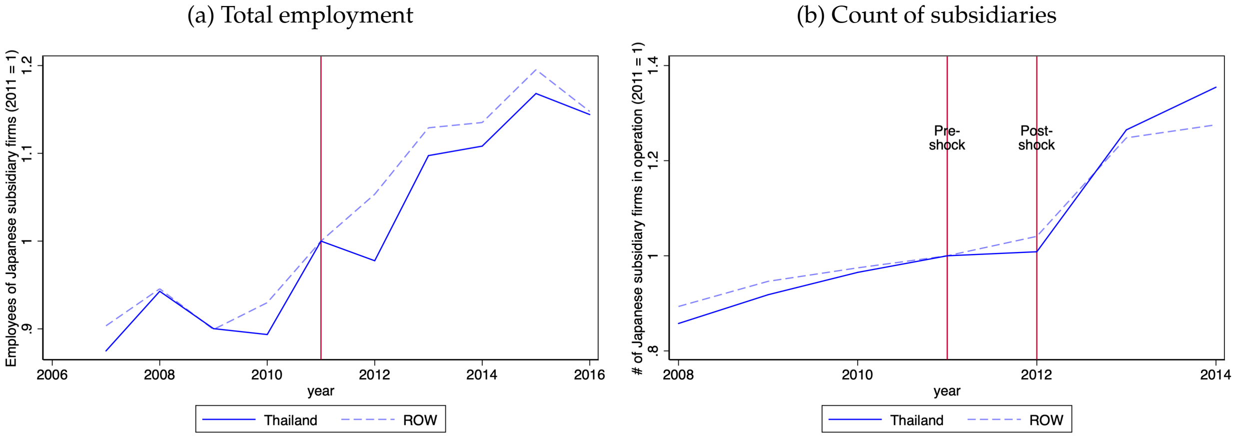
In this section, we provide the first-pass evidence of the effect of the floods on Japanese MNEs from our combined dataset described in Section 2.1. Figure 8 shows the relative trends for total employment (Panel 8a) and number of subsidiaries (Panel 8b) in the flooded regions versus the rest of the world, excluding Japan. In both panels, the solid line shows the trend for the flooded region and the dashed line shows that for the other regions excluding Japan (labeled ROW). Both trends are normalized at one in 2011. One can see that, for both statistics, the ROW trend is increasing over the sample period. This reflects the fact that more firms are entering the pool of MNEs, investing in Thailand, opening subsidiaries and hiring local workers, while MNEs already with Thai subsidiaries are expanding and hiring more local workers. When we turn to the flooded regions, however, the pattern is noticeably different. While the trend until 2011 is similarly rapid or even slightly faster than the ROW, indicating that those flooded regions had taken measures to attract foreign capital before the floods, the 2011 floods abruptly stopped this trend, creating a peak that year or with a year lag, after which both variables declined in magnitude.

What is further noteworthy is the *persistence* of the decrease. Even though the flood itself had subsided by early 2012, the decline in both total employment and number of subsidiaries continued at least up to 2016. A potential explanation can be found in news articles and academic discussions. Because the one-time event was large enough for firms to update their risk perception regarding future flooding, companies "move[d] to avoid potential supply chain disruptions" (Nikkei Asian Review, 2014). Similar arguments can be found in academic discussions of the negative effects of policy uncertainty on international trade and investment (Pierce and Schott, 2016; Handley and Limão, 2017; Steinberg et al., 2017). See Section B.3.6 for other trends in investment and intermediate purchases beyond those discussed here.

Given the findings in Figure 8, we regard the elasticity findings below as the medium- to long-run elasticities as opposed to short-run. We return to this issue when we set out our empirical

is located in Rojana Industrial Park, one of the seven severely flooded industrial clusters.

Figure 8: Relative Trends of Aggregate Variables in Flooded Regions



Note: Authors' calculation from BSOBA 2007-2016. "Flooded" shows the evolution of total employment in factories located in the flooded area of *Ayutthaya* and *Pathum Thani* provinces. "ROW" shows that from outside the flooded area. Both trends are normalized to 1 in 2011.

specification.

4.2 Estimation

For our main empirical results, we apply the identification strategy based on a linear regression (18). Specifically, we first calibrate the standard parameter values σ, ε and constants CS_0^F and WS_0^F as discussed in Section 4.2.1. Given these values and the reduced-form parameter of σ_{lm,a^M}, we may back out λ from equation (18). Section 4.2.2 discusses how we identify and estimate σ_{lm,a^M}.

4.2.1 Step 1: Calibration under Homogeneous Nested CES

We first discuss how we back out σ and ε from the data and then how to obtain λ from equation (18). As for the capital-aggregate labor elasticity σ, we employ the method developed in recent studies (Oberfield and Raval, 2014; Raval, 2019). Specifically, the cost-minimizing factor demands (A.41) and (A.42) imply $\ln\left(rk/p^X x\right) = (\sigma - 1)\ln\left(p^X/r\right) + \text{const}$. Furthermore, recall that for non MNEs, $p^X = w$ and $p^X x = wl$. Therefore, for non MNEs,

$$\ln\frac{rk}{p^X x} = (\sigma - 1)\ln\frac{p^X}{r} + \text{const}. \tag{19}$$

Based on this estimation equation, if we can obtain the coefficient on the log-relative factor price term, we can back out the substitution parameter σ. To operationalize the first-order condition relationship (19) to the data, we use the location m-level variation of each plant i, or $m\left(i\right)$. Because local regions constitute labor markets due to commuting immobility, wages vary across m's. Moreover, these variations are empirically persistent, so the coefficient obtained by this variation reveals the medium- to long-run elasticity of substitution. Note that the location-level variation in wage can be sourced from many shocks. Oberfield and Raval (2014); Raval (2019) let the location-level wage vary by a shift-share instrument. Therefore, the regression specification is

Table 1: Estimates of $\sigma - 1$

	IV, CO	IV, BSWS, all	IV, BSWS, manuf.
$\log(w_{m(i)})$	-1.15^{***}	-1.24^{***}	-0.88^{***}
	(0.18)	(0.18)	(0.13)
Num. obs.	51477	51477	51477

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: CO indicates that the wage data is from the Cabinet Office."BSWS, all" indicates that the wage variable is taken from all industries from the Basic Survey on Wage Structures (BSWS), while "BSWS, manuf." indicates that the wage variable is taken from only manufacturing industries from the BSWS. All regressions include industry FE and multiunit status indicators. Standard errors are clustered at the municipality level.

$$\ln\left(\frac{rk}{wl}\right)_i = b_0 + b_1 \ln\left(w_{m(i)}\right) + X_i b_2 + e_i, \tag{20}$$

with a shift-share instrument $z_m = \sum_{j\in\mathcal{J}^{NM}} \omega_{mj,-10} g_j$, where X_i is a plant-level control variable, j is an industry, $\mathcal{J}^{NM}$ is the set of non-manufacturing industries, $\omega_{mj,-10}$ is the employment share of industry j in location m in the ten-year prior to the analysis period, and g_j is the leave-m-out growth rate of national employment in industry j over the ten years that preceded the analysis year.

We apply this method to Japan's Census of Manufacture plant-level data, selecting only firms that do not have international factories, as the estimation equation (19) applies to non-MNEs. We define the unit of location m as the municipality.[19] There are several sources of municipality-level wage data, including the Japan Cabinet Office (CO) which provides municipality-level average wages. In addition, the *Basic Survey on Wage Structures* (BSWS) administered by Japan's Ministry of Health, Labour and Welfare offers national survey-based estimates of average municipal wages for each industry. Therefore, we have three alternatives for the w_m variable, and details of the estimation procedure are discussed in Section B.4.1.

The estimation results for our main specification are shown in Table 1. Depending on the choice of regressors, our estimates imply a *lower* substitution parameter $\sigma \leq 0.2$ than Oberfield and Raval (2014) (see Section B.4.1 of the Appendix for detailed comparison of this estimate to the values in the literature). The low substitution parameter would imply a larger effect of $d\ln A^F$ on dLS according to equation (14). We take the conservative result by choosing the upper bound $\sigma = 0.2$ in the following quantitative exercise.

As for the demand elasticity ε, we again employ Japan's 2011 Census of Manufacture. Following Oberfield and Raval (2014), we back out ε by $\varepsilon = m/(m-1)$, where $m \equiv sales/cost$ is the measured markup.[20] The measured markup distribution is shown in Figure B.13. The implied average markup implies $\varepsilon \in [3.98, 4.88]$, depending on the treatment of extreme values. This lies well within the range

[19]The total number of municipalities was roughly 1700 as of 2005. This is a fairly small definition of the local labor market, resembling counties in the U.S., of which there are roughly 3000. Another potential choice for local labor markets in Japan are commuting zones recently used by Adachi et al. (2019), following the seminal method introduced and popularized by Tolbert and Sizer (1996). In 2005, there were 331 commuting zones in Japan.

[20]Note that we use the 2011 survey because equations (15) and (16) should be evaluated at the time of the shock, which is 2011 in our case.

of the demand elasticity estimate using firm-level markups. For a conservative impact on the labor share, we choose the low-end $\varepsilon = 4$, which is within the range of demand elasticities of different industries in the U.S. reported in Oberfield and Raval (2014).

To obtain the value for the foreign labor cost share of total cost $CS^M \equiv p^M m / \left(rk + wl + p^M m\right)$, we use the 2011 BSOBA survey data. Since our purpose is to back out λ from our estimate of ε_{lm,a^M}, we focus on firms located in the flooded region and then calculate, for each headquarter firm i,

$$CS^M_{i,2011} = \frac{\sum_{l \in flooded} \text{total payroll}^l_{f,2011}}{\sum_{l \in world} \text{total cost}^l_{f,2011}},$$

where $flooded$ is the set of locations that were hit by the Floods. The definitions of total payroll and total cost are provided in Section C.1. We then obtain the 2011 firm-level average value of $CS^M = 2.4\%$ (see Figure B.14 for the complete CS^M distribution). Accordingly, we obtain the 2011 average value of $WS^M = 4.0\%$ by replacing the denominator of CS^M_i with the sum of payrolls at all locations l in the world. Section B.4.2 provides estimation results for ε and CS^M.

4.2.2 Step 2: Estimating λ by Natural Experiment

For obtaining λ by Equation (18), our goal is to estimate the left-hand side parameter σ_{lm,a^M}. In our empirical application, we specify $H = JPN$ and $F = ROW$. We measure foreign factor employment m_{it} by total foreign labor employment since in our data, the quantity of factor employment is only available for labor. We thus specify the factor substitution between country H and F in the model as the substitution of labor across countries. As discussed further below, our result is robust to other choices for measuring m_{it}. Hence, we use the notation l^{JPN} as employment in Japan and l^{ROW} as employment in the rest of the world, measuring factor employment in the rest of the world.

We run the following regression

$$\ln\left(l^{JPN}_{it}\right) = a_i + a_t + b \ln\left(l^{ROW}_{it}\right) + e_{it}, \tag{21}$$

where $\ln\left(l^{JPN}_{it}\right)$ is log of firm i in year t, $\ln\left(l^{ROW}_{it}\right)$ is the log factor employment in the rest of the world, a_i and a_t are firm- and year-fixed effects, and e_{it} is the error term.

It is critical to control these rich fixed effects. In fact, controlling firm fixed effects restricts ourselves to leverage within-firm variations, since high-productivity firms are likely to hire workers in the ROW (or conduct FDI and become an MNE, as in Helpman et al., 2004). On the other hand, controlling for year fixed effects enhances the validity of our analysis given the economic environment in which an increasing number of firms become MNEs and hire more local workers in foreign countries, as we saw in Figure 8.

In the data, the variation in the explanatory variable $\ln\left(l^{ROW}_{it}\right)$ can emerge from many sources, one of which is the firm-specific exchange rate that occurs through demand shocks or total factor productivity. Since we look for a foreign factor-augmenting productivity shock in equation (17), we construct an instrumental variable (IV) based on the 2011 Thailand Floods. For this purpose, note that the flooding was local, it occurred during one limited period of time relative to the coverage of our dataset and, most importantly, it was unexpected. We construct an IV that interacts in the Thailand location before the flood and the year after the flood. Because the shock was unexpected, the IV is exogenous to firms' foreign production decisions, after controlling for the firm and year fixed effects. To leverage the variation in $\ln\left(l_{it}^{ROW}\right)$ caused by this foreign productivity shock, an IV of a shock intensity measure is used:

$$Z_{it} \equiv \frac{l_{i,2011}^{flooded}}{l_{i,2011}^{JPN} + l_{i,2011}^{ROW}} \times \mathbf{1}\left\{t \geq 2012\right\}, \tag{22}$$

where $l_{i,2011}^{flooded}$ is firm-i's total employment in the flooded regions in year 2011, right before the flooding. This measure captures how much each MNE i relies on employment in the flooded region. Namely, if a firm hires a relatively large number of workers in the flooded region immediately before the flood, the firm is likely to be hit by the flood severely, thus receiving a large negative (firm-i) foreign factor-augmenting productivity shock.

Given this instrument, the two-stage least square (2SLS) estimator is based on the following equations:

$$\ln\left(l_{it}^{ROW}\right) = \widetilde{a}_i + \widetilde{a}_t + \widetilde{b}Z_{it} + \widetilde{e}_{it}, and \tag{23}$$

$$\ln\left(l_{it}^{JPN}\right) = a_i + a_t + bZ_{it} + e_{it}. \tag{24}$$

Therefore, we expect the first stage regression will yield a negative correlation between $\ln\left(l_{it}^{ROW}\right)$ and Z_{it} conditional on the fixed effects. Given the validity of the first stage, we interpret

$$\widehat{b_{IV}} = \widehat{\sigma_{lm,a^M}}.$$

As shown in Section 4.1.1, the floods had medium- to long-run effects rather than short-run effects on employment, so coefficient $\widehat{b}_{IV}$ or, in turn, λ as meduim- to long-run elasticity rather than short-run. Specifically, we relate the decline in employment found in aggregate in Panel 8a as an exogenous-sourced decline in ROW log-employment $\ln\left(l_{it}^{ROW}\right)$, and relate that to the change in log-employment in Home $\ln\left(l_{it}^{JPN}\right)$. This point is crucial when we move on to the quantitative exercise, because our concern is a relatively long-run change in labor share. In the discussion below, we conduct a robustness check of the long-difference specification and extension to the event-study regressions.

Table 2 shows the estimation result from the 2SLS specification (23) and (24), with the robust standard errors reported in parentheses. All columns show that the coefficients are statistically significant at the two-sided one-percent level.

Column 1 shows the result of the OLS specification without any fixed effects; that is, under the restriction $a_i = a_t = 0$ for all i and t, column 2 the fixed effect specification, and column 3 the instrumental variable specification in equation (22). Comparing Columns 1 and 2, we see that while both coefficients are positive, the coefficient magnitude becomes small after controlling for fixed

Table 2: Estimating σ_{lm,a^M}

VARIABLES	(1) $\ln l_{it}^{JPN}$	(2) $\ln l_{it}^{JPN}$	(3) $\ln l_{it}^{JPN}$	(4) $\ln l_{it}^{ROW}$	(5) $\ln l_{it}^{JPN}$
$\ln l_{it}^{ROW}$	0.446***	0.0604***	0.192***		
	(0.00686)	(0.0106)	(0.0502)		
Z_{it}				-0.728***	-0.140***
				(0.108)	(0.0367)
Observations	5,563	5,563	5,563	5,563	5,563
Model	OLS	FE	2SLS	2SLS-1st	2SLS-reduced
Firm FE	-	YES	YES	YES	YES
Year FE	-	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

effects as to heterogeneity in the productivity of firms.

Column 3 shows that a one-percent decrease in employment in the rest of the world due to the 2011 Thailand Floods caused Japanse MNEs to *decrease* home employment by 0.192 percent. Although this coefficient is a composite of model parameters as shown in equation (18) without any meaningful interpretation by itself, it is produced by the 2SLS first stage and reduced-form regressions shown in columns 4 and 5. Column 4 shows that a firm that did not rely on employment in the flooded region in 2011 would have reduced its employment in the rest of the world by 72.8 percent had it relied completely on the employment there.[21] Given that a few firms resumed operations relatively quickly after the flooding subsided, a reduction less than 100 percent is reasonable. As mentioned in Section 3.3, this number is proportional to the composite direct and indirect effect of the flood shock, related to equation (16). More interestingly, column 5 reveals that the same hypothetical increase in the reliance in Thailand employment would cause the firm to *reduce* employment in Japan by 14.0 percent. Again, this cross effect of a foreign factor-augmenting productivity shock on home employment is indicative of the indirect effect described in equation (15). Thus, the fraction of these two coefficients, 0.192 in column 3, indicates the direct effect of the flood, or the implied elasticity of substitution between home and foreign labor inputs. Since the sign of the regression coefficient in column 5 is the key to the sign of the 2SLS estimate and thus the value of λ, we conduct a robustness check in Section B.6.2.

Before turning to the backing out of our parameter of interest λ, it is worthwhile to note that the column 3 estimates of foreign employment are higher than in column 2. This is due to the difference in the source of identifying variation and is indicative of the benefit of our natural experiment approach. Namely, in the 2SLS specification, the source of variation is the offshore productivity shock, so the coefficient reflects only the structural interpretation (i.e. the function of structural parameters). However, the fixed effect specification does not identify any structural parameters. For example, if

[21] The standard deviation of our IV is 0.157, so a one standard deviation increase in our IV translates to an 11.4% decrease in employment in foreign countries.

the underlying variation is an increase in wages in the offshore country relative to Japan caused by, for example, TFP growth in the offshore country, then the substitution from offshore labor to Japanese labor (so-called inshoring) would have a negative correlation between offshore labor and Japanese labor. This potentially explains why the coefficient for the fixed effect specification would be smaller in magnitude than that for 2SLS.

Based on the calibrations of σ and ε from Section 4.2.1, equation (17) implies that $\lambda = 1.4$. Since ε_{lm,a^M} has a valid standard error from the 2SLS estimation, we can obtain the standard error of λ as 0.13 by the Delta method, indicating that we reject the gross-complementary home and foreign labor $\lambda \leq 1$ at the 0.1 percent significance level, as discussed in detail in Section B.5. Therefore, our calibrations $\sigma = 0.2$ and $\lambda = 1.4$ imply that Assumption 1 is satisfied empirically. Applying Lemma 1, we conclude that a positive foreign factor augmentation causes a qualitative decrease in labor share. To proceed to the quantitative implication, in what follows we back out the foreign factor augmentation from the aggregate data.

Discussion Here, we present evidence to show that our results are robust to other specifications, sample selections, and variable choices. First, our IV is meant to capture the variation in foreign employment caused by the 2011 Thailand Floods. Section B.6.1 of the Appendix shows that the 2SLS estimate produced by other definitions of the IV also produces qualitatively similar results. Second, note that our chosen IV does not explicitly separate firms that have subsidiaries in Thailand from others. Thus our estimation strategy does not depend on the comparison of control and treatment groups. The main empirical results discussed in this section are from the sample of firms located in Thailand to best control for any unobserved differences across the many worldwide factories of an MNE. In Section B.6.2, we check the validity of this sample selection by considering the reduced form estimation (24) for different samples of firms. Third, readers may notice that in 2011, the year of our natural experiment, the *Tohoku Earthquake and tsunami* also caused severe devastation that affected many Japanese firms. Section B.6.3 presents a robustness check showing that our result is robust to the sample which excludes firms severely affected by the earthquake, which indicates that our finding is not driven by the earthquake in Japan but by the flooding in Thailand. Fourth, we conducted robustness checks regarding the choice of our foreign factor employment variable m_{it} and the instrumental variable Z_{it} (see Section B.6.4). Specifically, instead of those based on foreign employment of labor, we checked to ensure that our results were qualitatively unchanged if we used value added measures in the foreign subsidiaries. Finally, since our goal is to identify the long-run elasticities, we expect that our fixed effect specification (23) and (24) could also be analyzed with the long-difference specification relating the difference between before- and after-flood observations and the qualitative results would remain similar. We confirm that this hypothesis is correct in Section B.6.5.

In addition to the robustness checks described above, we also conduct extension exercises. First, a shift-share instrument is widely used in the literature (Bartik, 1991; Card, 2001). As described in Section B.7.1, we find that the shift-share instrument does not identify the reduced-form parameter of interest well, which we regard as supporting evidence that our natural experiment-based identification strategy fits our purpose. Second, although we have shown in Table 2 a unique estimate that helps identify our parameter of interest, λ, since firms' response to the flooding lasted at least five years, which allows us to conduct an event-study type regression to see how the effects evolve dynamically. The analysis reveals that the flood impacted foreign employment in all years after the flood, which confirms our interpretation that the flood effect was not short-run, but medium-to long-run. We also examined the flood impact on employment in Japan. Section B.7.2 specifies the regression in detail and discusses the result that the Japanese employment-reducing effect of the flooding continued at least five years after the flood. We also study the substitution between Thailand and third countries in Section B.7.3, and find that the flood did not necessarily induce firms to substitute their operations to third countries. Finally, some regression results that separate the sample into different industries are reported in Section B.7.4.

5 Discussions

5.1 Quantitative Implication of Foreign Factor Augmentations

In Section 4, we discussed how we backed out the *elasticity* of labor share with respect to the foreign factor augmentation. To derive the implication quantitatively, we need to know how much foreign factor-augmenting productivity grew over the period of interest. For this purpose, we invert the factor demand functions (A.43) and (A.44) in the aggregate. We proxy the quantity of employment of foreign factors M by the foreign employment L^{ROW} and accordingly the foreign factor prices by labor wage w^{ROW}. We apply $H = JPN$ and $F = ROW$ to obtain[22]

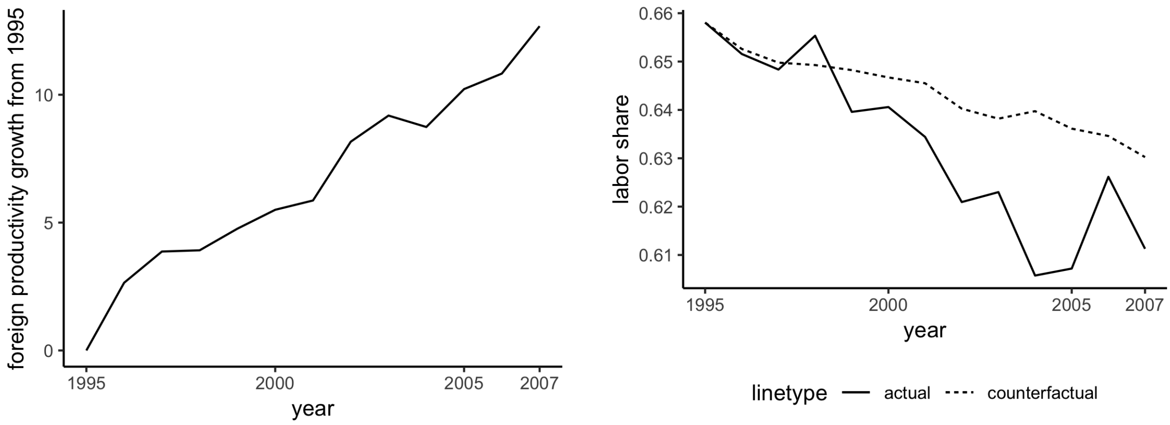
$$\frac{a^M}{a^L} = \left(\frac{L^{ROW}}{L^{JPN}}\right)^{\frac{1}{\lambda-1}} \left(\frac{w^{ROW}}{w^{JPN}}\right)^{\frac{\lambda}{\lambda-1}}. \tag{25}$$

Therefore, given the measures of aggregate employment and average wage in the home and foreign countries, and the backed-out elasticity between home and foreign labor, we can obtain the implied relative productivity in the rest of the world. The intuition behind the relationship is as follows. Suppose, as we calibrated, $\lambda > 1$, or factor augmentation is biased to that factor. Then given the wage structure in the rest of the world and Japan, relatively large employment in the rest of the world implies relatively augmentingly productive labor in the rest of the world. On the other hand, given the employment structure, a relatively high wage in the rest of the world also reflects relatively augmentingly productive labor in the rest of the world.[23] We measure $\left(L^{ROW}, w^{ROW}\right)$ by BSOBA. In particular, we calculate L^{ROW} by aggregating all foreign employment in all countries except for Japan and w^{ROW} by dividing the aggregate total labor compensation by L^{ROW}. For $\left(L^{JPN}, w^{JPN}\right)$, we apply the JIP database, a Japanese project for assembling KLEMS database.

[22]It is an important extension to consider a multi-country version of our model and its empirical implementations. Section B.3.1 overviews the country-level aggregate trends.

[23]Note our qualification $\lambda > 1$. In fact, if $\lambda < 1$, then the discussion in the text reverses, which means that an observed increase in foreign employment and wages would imply *decreasing* relative foreign factor augmentation. To the extent that such a decrease is implausible, this observation is more supporting evidence for $\lambda > 1$. Section C.1.2 shows the implication to A^{ROW} when it is nonetheless assumed that $\lambda < 1$.

Figure 9: Quantitative Implications



(a) Evolution of Foreign Factor Augmentation $d \ln A^F$ (b) Actual and Counterfactual Labor Share Evolution

To obtain the absolute productivity a^M as opposed to the relative productivity a^M/a^L, we calibrate Japan's labor-augmenting productivity growth by JIP database's Quality of Labor measure. The JIP measure reflects changes in the composition of workers–gender, age, education, employment status– which is standard representation of factor augmentation. We argue that this affects the efficiency units of labor, thereby Japan's labor-augmenting productivity. Given this trend, we can separate the trends of factor augmentation in Japan and the rest of the world. As a result, in Figure 10a, the left panel shows the trend of the evolution of $d \ln a_t^M \approx \ln a_t^M - \ln a_{1995}^M$, with our base year 1995, while Figure C.1 shows the growth in Japan's labor augmentation.

We emphasize the relative importance of $d \ln a_t^M$ and $d \ln a_t^L$. By comparing the y-axes, we confirm that the growth $d \ln a^L$ is relatively minor in the relative factor augmentation evolution $d \ln \left(a^M/a^L\right) = d \ln a^M - d \ln a^L$ in equation (25). This could be interpreted as due to at least two factors. First, the relative augmentation was fast in the rest of the world relative to in Japan. This is plausible given that our BSOBA-based measure of L^{ROW} and w^{ROW}, the ingredients in equation (25), comes from employment data in many rapidly expanding economies including Thailand. Second, globalization may contribute to the relative importance of $d \ln a^M$, comprising declining transportation and communication costs as well as the removal of political barriers to investment. These imply higher employment in the rest of the world by Japanese MNEs given the factor costs, according to our estimated elasticity of substitution $\lambda = 1.4$.

With these calibrations, we may learn the evolution of the effect of foreign factor augmentation on labor share. We calculate WS_0^M as the fraction of total payment to foreign labor taken from BSOBA over the sum of that and the total payment to workers in Japan in the base year, which gives $WS_0^M = 0.8\%$. In Figure 10b, we show the counterfactual labor share had there been only the foreign augmentation from equation (14). Again, we set the base year to 1995, the first year of the BSOBA data. The solid line shows the actual evolution, whereas the dashed line shows the counterfactual one, and we see that foreign factor augmentation played a substantial role in explaining the observed labor share decline from 1995-2007. Quantitatively, it explains 59 percent of the decline during the period.

Discussion One might naturally ask whether this large effect is an artifact of our choice of sample period. We chose a baseline final year of 2007 for our analysis both because the Great Recession would complicate the interpretation and also because the international System of National Accounts (SNA) changed drastically after 2008. However, Section C.2 shows the corresponding results for a more recent trend in labor share up to 2015,[24] and we find that 58 percent of the decrease in labor share from 1995 to 2015 may be attributed to our mechanism of increased foreign productivity. Our mechanism is also successful in explaining the countercyclical component of labor share trend in the data.

We also conduct the same quantitative analysis from peak to peak to further control for potential effects of business cycle. We take peak years, 1997, 2000, and 2008, from the Cabinet Office of Japan. When we conduct the quantitative analysis from 1997 to 2008 and 2000 to 2008, our mechanism could explain the decrease in the labor share by 77 percent and 112 percent. The reason we obtain large values for the recent waves of the business cycle is that the actual decrease in the labor share was small, especially between 2000 and 2008, so the fraction that our mechanism explains becomes large.

Finally, we investigate how our quantitative results may differ given the error in the estimate of our key parameter, λ. To do this, we use the standard error estimate $\widehat{se(\lambda)} = 0.13$ that we derive in Section B.5 of the Appendix. In particular, we conduct the same quantitative analysis with values of λ one standard error smaller and larger. The results indicate that the quantitative magnitude relative to the observed decrease in the labor share varies between 48 percent to 83 percent depending on the value of λ. Although there is an uncertainty in the exact size of the impact, we conclude that there was clearly a significantly negative effect on the labor share in Japan due to foreign factor augmentation.

5.2 Role of Firm Heterogeneity

Our estimation and quantitative implications have relied on the homogeneous production function derived in Section 3.4. An implication of this restriction is the coincidence of micro- and macro-elasticities (Oberfield and Raval, 2014). However, since we observe rich heterogeneity at the firm level, foreign factor augmentation could potentially *reallocate* factor resources from one firm to another. Since factor prices clear the factor markets, such heterogeneity and reallocation may matter for the relative wage, which through equation (5) affects the labor share. To examine this effect clearly, we consider a modified version of the model in Section 3.4; a general equilibrium with the same nested CES production function but with firm-level *heterogeneous* augmentations. To facilitate the comparison, we also consider a case with the same foreign factor augmentation across firms, $d \ln a_i^M = d \ln a^M$ for any i. This is consistent with the interpretation that the foreign factor augments because policy and institutional changes or technological progress in country F affects all firms in

[24] As a reservation, the quantitative result is sensitive to our parameter values, in particular the estimate of σ. Section C.1.3 shows different results under several parameter values of λ and σ.

country H alike.

In Section A.6, we prove that the change in the relative wage in this case may be solved as

$$d\ln w - d\ln r \propto \left[-(\lambda-\sigma)\,WS_l^M + (\sigma-\varepsilon)\left(CS_k^M - CS_l^M\right)\right] d\ln a^M, \tag{26}$$

where

$$WS_l^M \equiv \int \frac{wl_i}{wL}\frac{p^M m_i}{wl_i}di, CS_k^M \equiv \int \frac{rk_i}{rK}\frac{p^M m_i}{p_i q_i}di, CS_l^M \equiv \int \frac{wl_i}{wL}\frac{p^M m_i}{piq_i}di.$$

To interpret the terms in equation (26), note that the first term reflects the differences in the elasticities in the upper σ and lower nest λ. If $\lambda > \sigma$, then the increase in foreign productivity substitutes labor in country H relatively more than capital in country H, which results in a downward pressure to the wage relative to capital return and, in turn, the labor share. This effect depends on the average wage payment share to the foreign factor WS_l^M. These arguments do not involve the firm heterogeneity and appear in the homogeneous model as well. We call this term the *substitution effect.*

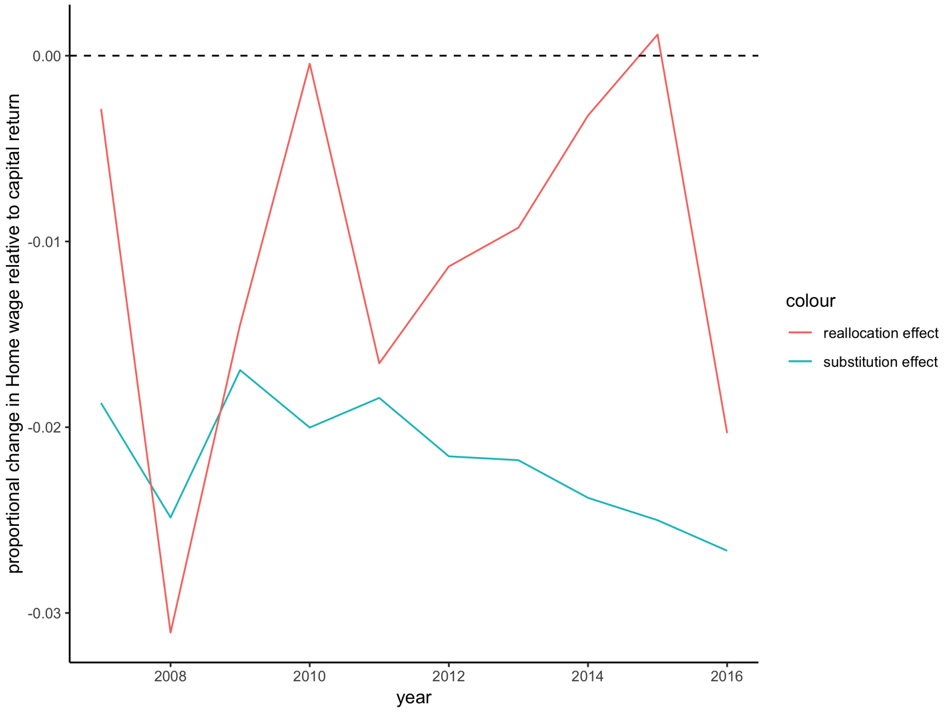
On the other hand, the second term involves the weighted averages of the cost share to the foreign factor CS_k^M and CS_l^M. More specifically, the difference between the differentially weighted averages $CS_k^M - CS_l^M$ matters. To understand this term, suppose that (i) demand elasticity ε is so elastic that $\varepsilon > \sigma$, and (ii) the foreign factor share distribution is *more skewed* to capital intensive firms than it is to Home labor intensive firms, or $CS_k^M - CS_l^M > 0$.[25] Then, the increase in the foreign factor productivity results in a reduction in the marginal cost of production, which causes high demand if ε is large. Across firms, this is moreso for firms that use relatively more foreign factors. If such firms are more capital intensive than Home labor intensive, the aggregate demand for capital increases more than that for Home labor. This causes the capital return to increase more than the Home wage, which results in a reduction in the labor share. We call this effect the *reallocation effect.* Note that the argument above crucially depends on the heterogeneity in firms' factor intensities. Indeed, if firms are homogeneous, the weight of the weighted average of cost shares does not matter, so that $CS_k^M - CS_l^M = CS^M - CS^M = 0$. Therefore, when there is no heterogeneity in firm factor intensity, there is no reallocation effect and the effect on the Home relative wage only emerges as the substitution effect.

To measure the size of the substitution and reallocation effects, we employ our matched dataset. BSJBSA data contains the variable of cost of labor compensation in the domestic firms and net operating surplus. We take these measures as wl_i and rk_i, respectively. From BSOBA, we can obtain the total compensation of MNEs in each foreign plant, which we aggregate to form a measure of $p^M m_i$. We match these datasets and calculate CS_k^M, CS_l^M, and WS_l^M that are relevant in equation (26). The matched data is available for 2007-2016. With values $\lambda = 1.4, \sigma = 0.2, \varepsilon = 4$, we plot the size of the substitution and reallocation effects according to data from each year (Figure 10).

Figure 10 provides two takeaways. First, both the substitution and reallocation effects are negative for most years. Indeed, except for the reallocation effect in 2015, all effects head to the negative side. This implies that when foreign factor productivity increases, the relative Home wage decreases,

[25]Note that assumption (ii) is consistent with the finding by Sun (2020) that "multinational firms are on average larger firms and larger firms on average use more capital-intensive technologies."

Figure 10: Relative Size of the Effects



which pushes down the Home labor share. Moreover, introducing heterogeneity into the model *strengthens* the negative effect of a given increase in the foreign productivity due to the reallocation effect. Note that the substitution effect is negative because $\lambda > \sigma$. The reallocation effect is mostly negative both because (i) $\varepsilon > \sigma$ and (ii) in most of the years $CS_k^M > CS_l^M$ in the data. Second, in many years, the reallocation effect is smaller than the substitution effect in absolute value. Therefore, although the reallocation amplifies the negative substitution effect, it does not contribute to the overall effect in a dominant way.[26] Combining these two observations, we conclude that firm heterogeneity and the reallocation effect does not alter our conclusion that foreign factor augmentation worked as a force that decreased the labor share in Japan from 1995-2007.

5.3 Method of Moments Estimation

In this section, we apply the estimation method based on the general moment conditions (9). For this purpose, we take a two-step approach. First, we separate the set of parameters estimated by equation (9) and other nuisance parameters.[27]. We then fix the nuisance parameters by the method based on the nested CES specification discussed so far. Second, given these parameters, we identify and estimate the parameters of our interest.

In particular, given the elasticity matrix discussed in Section A.5, for all i, we set $\sigma_{\widetilde{k}\widetilde{r},i} = -\sigma + (\sigma - \varepsilon) CS_i^K$, $\sigma_{\widetilde{k}\widetilde{w},i} = (\sigma - \varepsilon) CS_i^L$, $\sigma_{\widetilde{l}\widetilde{r},i} = (\sigma - \varepsilon) CS_i^K$, $\sigma_{\widetilde{l}\widetilde{w},i} = -\lambda + (\lambda - \sigma) WS_i^L + (\sigma - \varepsilon) CS_i^L$, $\sigma_{\widetilde{m}\widetilde{p^M},i} = -\lambda + (\lambda - \sigma) WS_i^M + (\sigma - \varepsilon) CS_i^M$, where σ and λ are constants reflecting the substitution parame-

[26]One may see relatively high volatility of the reallocation effect. This is due in part to the fact that we measure the capital payment by accounting net operating surplus which is volatile.

[27]Section C.3 discusses the estimation of standard errors of the estimator defined by equation (9)

ters under nested CES, CS_i^f are firm i's factor-f cost share for $f = K, L, M$, and WS_i^f are firm i's factor-f payment share between L and M for $f = L, M$. We take CS_i^f and WS_i^f from our firm-level Japanese MNE data, and calibrate $\lambda = 1.4$, $\sigma = 0.2$, and $\varepsilon = 4$.

We then estimate the remaining parameters, elasticities of country-H capital and labor demand with respect to foreign factor prices. We employ the method of moments (9) and the flood-based instrumental variable. In particular, first, to have restrictions on $\sigma_{\widetilde{m}\widetilde{r},i}$ and $\sigma_{\widetilde{m}\widetilde{w},i}$, note that by the symmetry of the Hessian matrix of the cost function, demand structure (1), and Shephard's lemma, we have

$$CS_i^M \sigma_{\widetilde{m}\widetilde{r},i} = CS_i^K \sigma_{\widetilde{k}\widetilde{p^M},i}, \tag{27}$$

$$CS_i^M \sigma_{\widetilde{m}\widetilde{l},i} = CS_i^L \sigma_{\widetilde{l}\widetilde{p^M},i}. \tag{28}$$

Proof of these equations is given in Section A.7. Finally, to implement the estimation, we assume the following constant parameter assumption.

Assumption 2. *$\sigma_{\widetilde{k}\widetilde{p^M},i} = \sigma_{\widetilde{k}\widetilde{p^M}}$ and $\sigma_{\widetilde{l}\widetilde{p^M},i} = \sigma_{\widetilde{l}\widetilde{p^M}}$ for all $i \in I_H$.*

Given this setup, we implement the method of moments estimation based on equation (9) as follows.

1. Set $n = 0$. Guess $\left(\sigma_{\widetilde{k}\widetilde{p^M}}, \sigma_{\widetilde{l}\widetilde{p^M}}\right) = \left(\sigma^{(n)}_{\widetilde{k}\widetilde{p^M}}, \sigma^{(n)}_{\widetilde{l}\widetilde{p^M}}\right)$ and generate implied firm-level elasticity matrix $\Sigma^{(n)}$ based on equation (10) and our set of partial identification assumptions and the factor augmentation
$$\begin{pmatrix} d\ln\left(a_{it}^{K,(n)}\right) \\ d\ln\left(a_{it}^{L,(n)}\right) \\ d\ln\left(a_{it}^{M,(n)}\right) \end{pmatrix}$$
based on equation (11).

2. Remove the year fixed effects from the factor augmentation and instrumental variables Z_{it}.

3. Evaluate the sample-analog of the moment condition (9).

4. If a closed-form solution is not obtained, update n, go back to process 1 and iterate until convergence.

Out of the above algorithm, we obtain

$$\widehat{\sigma_{\widetilde{k}\widetilde{p^M}}} = -0.20 \text{ (std. err. 0.13)}, \tag{29}$$

$$\widehat{\sigma_{\widetilde{l}\widetilde{p^M}}} = -0.09 \text{ (std. err. 0.04)}. \tag{30}$$

Recall that our finding that the capital demand is more elastic, $\widehat{\sigma_{\widetilde{k}\widetilde{p^M}}} < \widehat{\sigma_{\widetilde{l}\widetilde{p^M}}}$, suggests that a negative cost shock (or positive factor augmentation) increases the demand for Home capital *relatively more than* Home labor. Given that capital demand is more negatively elastic to the capital rental rate and labor demand is to wage, the capital rental rate must increase while the wage for labor must decrease to restore the factor market clearing conditions (3).

Note that the last part of this logic is reminiscent of the celebrated Stolper-Samuelson theorem: Consider a two-factor economy. If the factor demand increases *differentially* for one factor, then the relative wage of that factor increases (more than the increase in the factor demands) while the wage of the other decreases. In the Stolper-Samuelson setup, the factor demand increase is caused by an exogenous change in the terms of trade. On the other hand, in our setup, what drives the changes in factor demands in H is the combination of foreign factor augmentation and (total) elasticity with respect to it of factors in H. If (same-sized) foreign factor augmentation elastically increases the relative demand for one factor (in our empirical case, capital relative to labor), that means that the demand for the factor increases differentially, or the factor is complementary to the foreign factor that was augmented.

6 Conclusion

What impact does increased employment of foreign factors of production by an MNE have on labor share in the home country? To address this question, we proceeded in three steps. First, we developed an equilibrium model of production featuring augmented employment of foreign factors with varying elasticities of substitution. From this theory, we then pinpointed the key elasticities relevant to labor share: the relative size of labor, and capital substitution with foreign factors, and showed how a foreign factor-augmenting productivity shock to a small set of firms may help to identify these elasticities. Armed with these theoretical results, we then applied the theory to the 2011 Thailand Floods, which was experienced as a large negative foreign factor productivity shock for a subset of Japanese MNEs. Using firm- and plant-level data from Japan, we estimated the reduced-form parameter with the instrumental variable related to the flood shock, finding that home and foreign labor are gross substitutes. This estimate, combined with the estimates of capital-labor elasticity based on our Japanese plant-level data, indicates that foreign factor augmentation contributed to the decline in the labor share in Japan from 1995-2007. Our further quantitative counterfactual analyses show that 59 percent of the observed labor share decline in the period can be attributed to foreign factor augmentation.

There are at least three different directions for extending the model. First, we may incorporate rich heterogeneity at the firm level as discussed in Section A.6 and at the destination country level as we empirically suggest in Section B.3.1. Second, our production model could potentially generalize an influential model of factor offshoring such as Feenstra and Hanson (1997), which would tighten the connection with the literature. For this purpose, we suggest a generalized production function in Section A.2. Finally, while our model extends to a more complete general equilibrium with factor supplies and a large open economy, all of the results of this paper in terms of identification, empirical application, and quantification depend on the specific model choice, so this is another theoretical development left for future study.

We conclude with a further implication for policy. There is a growing concern about the implications of changing demographic trends, particularly rapid aging and shrinking workforces in several developed countries. We may introduce basic economic conditions including demographic changes into our model to analyze "the race between MNEs and aging." In Japan in particular, the issue of demographic change is tightly connected to a policy debate regarding whether or not to host foreign workers under the rubric of a *Technical Intern Training Program*.

References

Acemoglu, Daron, "Why do new technologies complement skills? Directed technical change and wage inequality," *The Quarterly Journal of Economics*, 1998, *113* (4), 1055–1089.

_ **and Pascual Restrepo**, "Robots and jobs: Evidence from US labor markets," 2017.

Adachi, Daisuke, Daiji Kawaguchi, and Yukiko U. Saito, "Robot, Employment, and Population: Evidence from Articulated Robot in Japan's Local Labor Markets," Technical Report, ESRI Working Paper 2019.

_ **, Hiroyuki Nakata, Yasuyuki Sawada, and Kunio Sekiguchi**, "Adverse Selection and Moral Hazard in the Corporate Insurance Market: Evidence from the 2011 Thailand floods," Technical Report, Research Institute of Economy, Trade and Industry (RIETI) 2016.

Adao, Rodrigo, Costas Arkolakis, and Federico Esposito, "Spatial Linkages, Global Shocks, and Local Labor Markets: Theory and Evidence," 2018.

Arkolakis, Costas, Natalia Ramondo, Andrés Rodrıguez-Clare, and Stephen Yeaple, "Innovation and Production in the Global Economy," 2017.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen, "Concentrating on the Fall of the Labor Share," *American Economic Review*, 2017, *107* (5), 180–85.

_ **,** _ **,** _ **,** _ **, and** _ , "The fall of the labor share and the rise of superstar firms," 2017.

Barkai, Simcha, "Declining labor and capital shares," *University of Chicago*, 2017.

Bartik, Timothy J, "Who benefits from state and local economic development policies?," 1991.

Benguria, Felipe and Alan M Taylor, "After the Panic: Are Financial Crises Demand or Supply Shocks? Evidence from International Trade," Working Paper 25790, National Bureau of Economic Research April 2019.

Berger, David W, Kyle F Herkenhoff, and Simon Mongey, "Labor Market Power," Technical Report, National Bureau of Economic Research 2019.

Bernard, Andrew B, Teresa C Fort, Valerie Smeets, and Frederic Warzynski, "Heterogeneous Globalization: Offshoring and Reorganization," 2018.

Boehm, Christoph E, Aaron Flaaen, and Nitya Pandalai-Nayar, "Multinationals, offshoring, and the decline of US manufacturing," 2017.

__ , __ , and __ , "Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tōhoku Earthquake," *Review of Economics and Statistics*, 2018, (00).

Brainard, S Lael and David A Riker, "Are US multinationals exporting US jobs?," Technical Report, National bureau of economic research 1997.

Bridgman, Benjamin, "IS LABOR'S LOSS CAPITAL'S GAIN? GROSS VERSUS NET LABOR SHARES," *Macroeconomic Dynamics*, 2018, *22* (08), 2070–2087.

Caballero, Ricardo J, Emmanuel Farhi, and Pierre-Olivier Gourinchas, "Rents, technical change, and risk premia accounting for secular trends in interest rates, returns on capital, earning yields, and factor shares," *American Economic Review*, 2017, *107* (5), 614–20.

Card, David, "Immigrant inflows, native outflows, and the local labor market impacts of higher immigration," *Journal of Labor Economics*, 2001, *19* (1), 22–64.

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi, "Supply chain disruptions: Evidence from the great east japan earthquake," 2016.

Cette, G, L Koehl, and T Philippon, "Labor shares in Some Advanced Economies," Technical Report, Working Paper 2019.

Debreu, Gerard, "Excess demand functions," *Journal of mathematical economics*, 1974, *1* (1), 15–21.

Desai, Mihir A, C Fritz Foley, and James R Hines, "Domestic effects of the foreign activities of US multinationals," *American Economic Journal: Economic Policy*, 2009, *1* (1), 181–203.

Ebenstein, Avraham, Ann Harrison, Margaret McMillan, and Shannon Phillips, "Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys," *The Review of Economics and Statistics*, 2014, *96* (4), 581–595.

Elsby, Michael WL, Bart Hobijn, and Ayşegül Şahin, "The decline of the US labor share," *Brookings Papers on Economic Activity*, 2013, *2013* (2), 1–63.

Feenstra, Robert C and Gordon H Hanson, "Foreign direct investment and relative wages: Evidence from Mexico's maquiladoras," *Journal of international economics*, 1997, *42* (3), 371–393.

Fort, Teresa C, Justin R Pierce, and Peter K Schott, "New perspectives on the decline of us manufacturing employment," *Journal of Economic Perspectives*, 2018, *32* (2), 47–72.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik instruments: What, when, why, and how," Technical Report, National Bureau of Economic Research 2018.

Gouin-Bonenfant, Emilien et al., "Productivity dispersion, between-firm competition and the labor share," 2018.

Gravelle, Jane G, "Tax Havens: International Tax Avoidance and Evasion," 2015.

Greene, William H, *Econometric analysis*, Pearson Education India, 2003.

Greenwald, Daniel L, Martin Lettau, and Sydney C Ludvigson, "How the Wealth Was Won: Factors Shares as Market Fundamentals," Working Paper 25769, National Bureau of Economic Research April 2019.

Handley, Kyle and Nuno Limão, "Policy uncertainty, trade, and welfare: Theory and evidence for china and the united states," *American Economic Review*, 2017, *107* (9), 2731–83.

Haraguchi, Masahiko and Upmanu Lall, "Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making," *International Journal of Disaster Risk Reduction*, 2015, *14*, 256–272.

Harrison, Ann and Margaret McMillan, "Offshoring jobs? Multinationals and US manufacturing employment," *Review of Economics and Statistics*, 2011, *93* (3), 857–875.

Head, Keith and John Ries, "Offshore production and skill upgrading by Japanese manufacturing firms," *Journal of international economics*, 2002, *58* (1), 81–105.

Helpman, Elhanan, Marc J Melitz, and Stephen R Yeaple, "Export versus FDI with heterogeneous firms," *American economic review*, 2004, *94* (1), 300–316.

Hirakata, Naohisa and Yasutaka Koike, "The Labor Share, Capital-Labor Substitution, and Factor Augmenting Technologies," Technical Report, Bank of Japan 2018.

Hubmer, Joachim, "The Race Between Preferences and Technology," Technical Report, MIMEO, Yale University 2018.

Hummels, David, Rasmus Jørgensen, Jakob Munch, and Chong Xiang, "The wage effects of offshoring: Evidence from Danish matched worker-firm data," *American Economic Review*, 2014, *104* (6), 1597–1629.

Johnson, Robert C. and Guillermo Noguera, "Accounting for intermediates: Production sharing and trade in value added," *Journal of International Economics*, 2012, *86* (2), 224 – 236.

_ **and** _ , "A Portrait of Trade in Value-Added over Four Decades," *The Review of Economics and Statistics*, 2017, *99* (5), 896–911.

Kaldor, Nicholas, "Capital accumulation and economic growth," in "The theory of capital," Springer, 1961, pp. 177–222.

Karabarbounis, Loukas and Brent Neiman, "The global decline of the labor share," *The Quarterly journal of economics*, 2013, *129* (1), 61–103.

Kato, Hayato and Toshihiro Okubo, "The Impact of a Natural Disaster on Foreign Direct Investment and Vertical Linkages," 2017.

Kirimura, T, T Nakaya, and K Yano, "Building a spatio-temporal GIS database about boundaries of municipalities: municipality Map Maker for Web," *Theory Appl GIS*, 2011, *19*, 83–92.

Koh, Dongya, Raül Santaeulalia-Llopis, and Yu Zheng, "Labor Share Decline and Intellectual Property Products Capital," 2018.

Kovak, Brian K, Lindsay Oldenski, and Nicholas Sly, "The labor market effects of offshoring by us multinational firms: Evidence from changes in global tax policies," Technical Report, National Bureau of Economic Research 2017.

Loecker, Jan De and Jan Eeckhout, "The rise of market power and the macroeconomic implications," Technical Report, National Bureau of Economic Research 2017.

_ and _ , "Global market power," Technical Report, National Bureau of Economic Research 2018.

Mantel, Rolf R, "On the characterization of aggregate excess demand," *Journal of economic theory*, 1974, *7* (3), 348–353.

Mas-Colell, Andreu, Michael Dennis Whinston, Jerry R Green et al., *Microeconomic theory*, Vol. 1, Oxford university press New York, 1995.

Muendler, Marc-Andreas and Sascha O Becker, "Margins of multinational labor substitution," *The American Economic Review*, 2010, *100* (5), 1999–2030.

Oberfield, Ezra and Devesh Raval, "Micro data and macro technology," Technical Report, National Bureau of Economic Research 2014.

Ottaviano, Gianmarco IP and Giovanni Peri, "Rethinking the effect of immigration on wages," *Journal of the European economic association*, 2012, *10* (1), 152–197.

Pierce, Justin R and Peter K Schott, "The surprisingly swift decline of US manufacturing employment," *American Economic Review*, 2016, *106* (7), 1632–62.

Piketty, Thomas and Gabriel Zucman, "Capital is back: Wealth-income ratios in rich countries 1700–2010," *The Quarterly Journal of Economics*, 2014, *129* (3), 1255–1310.

Ramondo, Natalia and Andrés Rodríguez-Clare, "Trade, multinational production, and the gains from openness," *Journal of Political Economy*, 2013, *121* (2), 273–322.

_ , _ , and Felix Tintelnot, "Multinational production: Data and stylized facts," *American Economic Review*, 2015, *105* (5), 530–36.

Raval, Devesh R, "The micro elasticity of substitution and non-neutral technology," *The RAND Journal of Economics*, 2019, *50* (1), 147–167.

Rognlie, Matthew, "Deciphering the fall and rise in the net capital share: accumulation or scarcity?," *Brookings papers on economic activity*, 2016, *2015* (1), 1–69.

— , "Comment on" Accounting for Factorless Income"," in "NBER Macroeconomics Annual 2018, volume 33," University of Chicago Press, 2018.

Schneider, Dorothee, "The labor share: A review of theory and evidence," Technical Report, SFB 649 discussion paper 2011.

Setzler, Bradley and Felix Tintelnot, "The Effects of Foreign Multinationals on Workers and Firms in the United States," Technical Report, National Bureau of Economic Research 2019.

Slaughter, Matthew J, "Production transfer within multinational enterprises and American wages," *Journal of international Economics*, 2000, *50* (2), 449–472.

Sonnenschein, Hugo, "Market excess demand functions," *Econometrica: Journal of the Econometric Society*, 1972, pp. 549–563.

Steinberg, Joseph et al., "Brexit and the macroeconomic impact of trade policy uncertainty," in "2017 Meeting Papers" number 216 Society for Economic Dynamics 2017.

Sun, Chang, "Multinational production with non-neutral technologies," *Journal of International Economics*, 2020, *123*, 103294.

Tamada, Yoshifumi, Keisuke Hoshikawa, and Tsuruyo Funatsu, *The 2011 Thailand Flood–the record and lessons– (in Japanese)*, Japan External Trade Organization (JETRO) Asian Institute, 2013.

Tolbert, Charles M and Molly Sizer, "US commuting zones and labor market areas: A 1990 update," Technical Report 1996.

Appendix

A Theory Appendix

This appendix provides proofs and extensions of the model described in Section 3.

A.1 Uniqueness of the Equilibrium

A desirable property of a general equilibrium is its uniqueness, as uniqueness guarantees that the equilibrium is robust across shocks and parameter values. Although it is well-known that the uniqueness result is difficult to obtain (Sonnenschein, 1972; Mantel, 1974; Debreu, 1974), our constant returns to scale model allows us to adopt the *generic* uniqueness approach described in Chapter 17 of Mas-Colell et al. (1995). In the explanation below, proposition numbers that begin with "17" are all taken from that chapter.

We begin with the following facts: (i) Under a regularity condition, any equilibrium factor price vector (r, w) is locally isolated (Proposition 17.D.1) and, furthermore, the regularity condition holds generically (Proposition 17.D.5); (ii) If the weak axiom of revealed preference (WARP) is satisfied, then under constant returns to scale technology, the set of equilibrium price vectors (r, w) is convex (Proposition 17.F.2). Note that as our factor demand functions are obtained by solving a cost-minimization problem, so they satisfy WARP. Thus, the set of equilibrium factor price vectors is both locally isolated convex and a singleton. Thus, we may conclude the following:

Proposition 1. *(Generic Uniqueness) The general equilibrium defined in Section 3.1 is generically unique.*

A.2 Equivalence Results

We consider a special case of our model within offshoring and multinational models, beginning the equilibrium analysis from modified versions of Feenstra and Hanson (1997) and Arkolakis et al. (2017) to arrive at equation (6).

A.2.1 Offshoring

First, we propose a modified version of Feenstra and Hanson (1997) in which we do not distinguish between high-skill and low-skill workers but we do distinguish between factor augmenting productivity shocks in the Home country H and the Foreign country F. Each country $c = H, F$ is endowed with (L^c, K^c), and the factor prices are (w^c, r^c). Competitive producers in H and F produce a single numeraire final good q by combining continuum intermediate inputs $z \in [0, 1]$. To produce the intermediate good, producers may use the factors in either H or F. In production place c, the intermediate good z is produced by CES technology[28]

$$x^{c}(z)=\left(\left(\frac{A^{c,L}l^{c}(z)}{a(z)}\right)^{\frac{\sigma-1}{\sigma}}+\left(A^{c,K}k^{c}(z)\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{A.1}$$

where $a(z)$ is increasing and $\sigma<1$. That is, labor and capital are gross complements. The final good q is then costlessly assembled according to the Cobb-Douglas function[29]

$$\ln q=\int_{0}^{1}\alpha(z)\ln x^{c}(z)\,dz. \tag{A.2}$$

There is no cost to trade the output good. Consider for now that world income $E=\overline{E}$ is fixed and spent on the output so that

$$q=\overline{E}. \tag{A.3}$$

The equilibrium is characterized by factor prices $\left(w^{H},r^{H},w^{F},r^{F}\right)$ that solve the market clearing condition. To formally derive such conditions, suppose that foreign labor L^{F} is abundant enough so that

$$\frac{w^{H}}{r^{H}}>\frac{w^{F}}{r^{F}},$$

or H has a comparative advantage in producing the capital-intensive intermediate good. Further assume L^{F} is large so that $\widetilde{w^{H}}>\widetilde{w^{F}}$ where $\widetilde{w^{c}}\equiv w^{c}/A^{c,L}$ and $\widetilde{r^{c}}\equiv r^{c}/A^{c,K}$ are augmented factor prices.[30] We will consider our case of CES output demand and income effects after solving the current simple version.

To solve the model, consider the cost-minimizing factor demand given factor prices $\left(w^{H},r^{H},w^{F},r^{F}\right)$. First, conditional on country $c=H,F$, the unit cost function is

$$c^{c}(z)=\left(\left(a(z)\widetilde{w^{c}}\right)^{1-\sigma}+\left(\widetilde{r^{c}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{A.4}$$

Given the comparative advantage assumption, in equilibrium, there is $z^{*}\in[0,1]$ that satisfies z being produced in the Home country if and only if $z\leq z^{*}$. z^{*} satisfies $c^{H}(z^{*})=c^{F}(z^{*})$, or

$$\left(a(z^{*})\widetilde{w^{H}}\right)^{1-\sigma}+\left(\widetilde{r^{H}}\right)^{1-\sigma}=\left(a(z^{*})\widetilde{w^{F}}\right)^{1-\sigma}+\left(\widetilde{r^{F}}\right)^{1-\sigma}. \tag{A.5}$$

The marginal cost is thus $c(z)\equiv\min_{c}\{c^{c}(z)\}$. Given such z^{*}, by Shepherd's lemma, the factor

[28]Note that this formulation is more general than the nesting of Cobb-Douglas and Leontief production as in Feenstra and Hanson (1997).

[29]Note that the same production function with costless intermediate good trade makes the trade in the final good irrelevant. Specifically, countries do not have an incentive to specialize (or not specialize) in the production of the final good. In this sense, the model is all about intermediate good trade. As we see in equation (A.5), H exports $z<z^{*}$ and imports $z>z^{*}$.

[30]This assumption is not essential, but allows us to proceed without unnecessary complications.

demands are characterized by

$$\widetilde{l^c}(z) = \left(\frac{a(z)\widetilde{w^c}}{c^c(z)}\right)^{-\sigma} a(z)\, x^c(z), \tag{A.6}$$

$$\widetilde{k^c}(z) = \left(\frac{\widetilde{r^c}}{c^c(z)}\right)^{-\sigma} x^c(z) \tag{A.7}$$

for $c = H, F$, where $\widetilde{l^c}(z) \equiv A^{c,L} l^c(z)$ and $\widetilde{k^c}(z) \equiv A^{c,K} k^c(z)$ are the augmented factor demands for variety z in country c. Hence, the market clearing conditions are

$$\widetilde{L^H} = \int_0^{z^*} \widetilde{l^H}(z)\, dz, \tag{A.8}$$

$$\widetilde{K^H} = \int_0^{z^*} \widetilde{k^H}(z)\, dz, \tag{A.9}$$

$$\widetilde{L^F} = \int_{z^*}^{1} \widetilde{l^F}(z)\, dz, \tag{A.10}$$

$$\widetilde{K^F} = \int_{z^*}^{1} \widetilde{k^F}(z)\, dz, \tag{A.11}$$

where $\widetilde{L^c} \equiv A^{c,L} L^c$ and $\widetilde{K^c} \equiv A^{c,K} K^c$ are the augmented endowments for $c = H, F$. To solve $x^c(z)$, by Cobb-Douglas assumption (A.2), we have $p(z)\, x^c(z) = \alpha(z)\, q$, where $p(z)$ is the price of the intermediate good z. Moreover, the perfect competition assumption implies that $p(z)$ is given by the (minimum) marginal cost $c(z)$. Thus, by good market clearing condition (A.3), we have

$$x^c(z) = \frac{\alpha(z)}{c(z)} \overline{E}. \tag{A.12}$$

Thus, the equilibrium is $\left(z^*, \left(\widetilde{w^c}, \widetilde{r^c}\right)_{c\in(H,F)}\right)$ that solves equations (A.5), (A.8), (A.9), (A.10), and (A.11). To study the Home labor share, we still have $LS \equiv w^H L^H / \left(w^H L^H + r^H K^H\right)$ that is to the first order

$$dLS = LS_0 (1 - LS_0) \left(d \ln w^H - d \ln r^H\right).$$

Hence, it remains to study $d \ln w^H$ and $d \ln r^H$. For this purpose, we have log first-order approximations with respect to $d \ln A^{F,L}$ and $d \ln A^{F,K}$ to equations (A.5), (A.8), (A.9), (A.10), and (A.11) as follows:

$$CS^{H,L}(z^*) \left(\sigma_{az} d \ln z^* + d \ln \widetilde{w^H}\right) + CS^{H,K}(z^*)\, d \ln \widetilde{r^H} = CS^{F,L}(z^*) \left(\sigma_{az} d \ln z^* + d \ln \widetilde{w^F}\right) + CS^{F,K}(z^*)\, d \ln \widetilde{r^F}, \tag{A.13}$$

$$0 = \frac{z^* \widetilde{l^H}(z^*)}{\widetilde{L^H}} d \ln z^* - \sigma d \ln \widetilde{w^H} + \int_0^{z^*} \frac{\widetilde{l^H}(z)}{\widetilde{L^H}} \left(\sigma d \ln c^H(z) + d \ln x^H(z)\right) dz,$$

$$0 = \frac{z^* \widetilde{k^H}(z^*)}{\widetilde{K^H}} d \ln z^* - \sigma d \ln \widetilde{r^H} + \int_0^{z^*} \frac{\widetilde{k^H}(z)}{\widetilde{K^H}} \left(\sigma d \ln c^H(z) + d \ln x^H(z)\right) dz,$$

$$d\ln A^{F,L} = -\frac{z^*\widetilde{l^F}(z^*)}{\widetilde{L^F}} d\ln z^* - \sigma d\ln\widetilde{w^F} + \int_{z^*}^1 \frac{\widetilde{l^F}(z)}{\widetilde{L^F}}\left(\sigma d\ln c^F(z) + d\ln x^F(z)\right) dz,$$

$$d\ln A^{F,K} = -\frac{z^*\widetilde{k^F}(z^*)}{\widetilde{K^F}} d\ln z^* - \sigma d\ln\widetilde{r^F} + \int_{z^*}^1 \frac{\widetilde{k^F}(z)}{\widetilde{K^F}}\left(\sigma d\ln c^F(z) + d\ln x^F(z)\right) dz.$$

Note that by equation (A.4), $d\ln c^c(z) = CS^{c,L}(z)\, d\ln\widetilde{w^c} + CS^{c,K}(z)\, d\ln\widetilde{r^c}$ and by equation (A.12), we have

$$d\ln x^c(z) = -d\ln c(z). \tag{A.14}$$

Note also that z is produced in H if and only if $z < z^*$. Hence, the conditions are further reduced to

$$0 = \frac{z^*\widetilde{l^H}(z^*)}{\widetilde{L^H}} d\ln z^* + \left(-\sigma + (\sigma-1)\, ACS^{H,L}(z^*)\right) d\ln\widetilde{w^H} + (\sigma-1)\, ACS^{H,K}(z^*)\, d\ln\widetilde{r^H}, \tag{A.15}$$

$$0 = \frac{z^*\widetilde{k^H}(z^*)}{\widetilde{K^H}} d\ln z^* + (\sigma-1)\, ACS^{H,L}(z^*)\, d\ln\widetilde{w^H} + \left(-\sigma + (\sigma-1)\, ACS^{H,K}(z^*)\right) d\ln\widetilde{r^H}, \tag{A.16}$$

$$d\ln A^{F,L} = -\frac{z^*\widetilde{l^F}(z^*)}{\widetilde{L^H}} d\ln z^* + \left(-\sigma + (\sigma-1)\, ACS^{F,L}(z^*)\right) d\ln\widetilde{w^F} + (\sigma-1)\, ACS^{F,K}(z^*)\, d\ln\widetilde{r^F}, \tag{A.17}$$

$$d\ln A^{F,K} = -\frac{z^*\widetilde{k^F}(z^*)}{\widetilde{K^F}} d\ln z^* + (\sigma-1)\, ACS^{F,L}(z^*)\, d\ln\widetilde{w^F} + \left(-\sigma + (\sigma-1)\, ACS^{F,K}(z^*)\right) d\ln\widetilde{r^F}, \tag{A.18}$$

where

$$ACS^{H,L}(z^*) \equiv \int_0^{z^*} \frac{\widetilde{l^H}(z)}{\widetilde{L^H}} CS^{H,L}(z)\, dz,$$

$$ACS^{H,K}(z^*) \equiv \int_0^{z^*} \frac{\widetilde{k^H}(z)}{\widetilde{K^H}} CS^{H,K}(z)\, dz,$$

$$ACS^{F,L}(z^*) \equiv \int_{z^*}^1 \frac{\widetilde{l^F}(z)}{\widetilde{L^F}} CS^{F,L}(z)\, dz,$$

$$ACS^{F,K}(z^*) \equiv \int_{z^*}^1 \frac{\widetilde{k^F}(z)}{\widetilde{K^F}} CS^{F,K}(z)\, dz$$

are the average cost shares of each factor in each country. Assume for now that $\widetilde{w^H} > \widetilde{w^F}$. We can then show that $CS^{H,L}(z^*) > CS^{F,L}(z^*)$,[31] as we prove below. Also, we will come back to the condition that guarantees $\widetilde{w^H} > \widetilde{w^F}$. By (A.13), we have

$$d\ln z^* = \frac{\left(CS^{F,L}(z^*)\, d\ln\widetilde{w^F} + CS^{F,K}(z^*)\, d\ln\widetilde{r^F}\right) - \left(CS^{H,L}(z^*)\, d\ln\widetilde{w^H} + CS^{H,K}(z^*)\, d\ln\widetilde{r^H}\right)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}}. \tag{A.19}$$

[31] To see this, note that at $z = z^*$ we have $c^H(z^*) = c^F(z^*)$. Hence, it remains to show $\widetilde{w^H}\widetilde{l^H}(z^*) > \widetilde{w^F}\widetilde{l^F}(z^*)$. By substituting the factor demand functions and noting that $c^H(z^*) = c^F(z^*)$ and thus $x^H(z^*) = x^F(z^*)$, the inequality is equivalent with $\left(\widetilde{w^H}\right)^{1-\sigma} > \left(\widetilde{w^F}\right)^{1-\sigma}$. Our assumption $\sigma < 1$ means that this is equivalent to $\widetilde{w^H} > \widetilde{w^F}$.

By substituting equation (A.19) into equations (A.15), (A.16), (A.17), and (A.18), we have

$$
\begin{aligned}
0 = & \underbrace{\left[-\frac{z^* \widetilde{l^H}(z^*)}{\widetilde{L^H}} \frac{CS^{H,L}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}} + \left(-\sigma + (\sigma - 1) ACS^{H,L}(z^*)\right) \right]}_{\equiv \sigma_{\widetilde{l^H}\widetilde{w^H}}} d\ln \widetilde{w^H} \\
& + \underbrace{\left[-\frac{z^* \widetilde{l^H}(z^*)}{\widetilde{L^H}} \frac{z^* \widetilde{l^H}(z^*) CS^{H,K}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}} + (\sigma - 1) ACS^{H,K}(z^*) \right]}_{\equiv \sigma_{\widetilde{l^H}\widetilde{r^H}}} d\ln \widetilde{r^H} \\
& + \underbrace{\frac{z^* \widetilde{l^H}(z^*)}{\widetilde{L^H}} \frac{CS^{F,L}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}}}_{\equiv \sigma_{\widetilde{l^H}\widetilde{w^F}}} d\ln \widetilde{w^F} + \underbrace{\frac{z^* \widetilde{l^H}(z^*)}{\widetilde{L^H}} \frac{CS^{F,K}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}}}_{\equiv \sigma_{\widetilde{l^H}\widetilde{r^F}}} d\ln \widetilde{r^F},
\end{aligned}
$$

$$
\begin{aligned}
0 = & \underbrace{\left[-\frac{z^* \widetilde{k^H}(z^*)}{\widetilde{K^H}} \frac{CS^{H,L}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}} + (\sigma - 1) ACS^{H,L}(z^*) \right]}_{\equiv \sigma_{\widetilde{k^H}\widetilde{w^H}}} d\ln \widetilde{w^H} \\
& + \underbrace{\left[-\frac{z^* \widetilde{k^H}(z^*)}{\widetilde{K^H}} \frac{CS^{H,K}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}} + \left(-\sigma + (\sigma - 1) ACS^{H,K}(z^*)\right) \right]}_{\equiv \sigma_{\widetilde{k^H}\widetilde{r^H}}} d\ln \widetilde{r^H} \\
& + \underbrace{\frac{z^* \widetilde{k^H}(z^*)}{\widetilde{K^H}} \frac{CS^{F,L}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}}}_{\equiv \sigma_{\widetilde{k^H}\widetilde{w^F}}} d\ln \widetilde{w^F} + \underbrace{\frac{z^* \widetilde{k^H}(z^*)}{\widetilde{K^H}} \frac{CS^{F,K}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}}}_{\equiv \sigma_{\widetilde{k^H}\widetilde{r^F}}} d\ln \widetilde{r^F},
\end{aligned}
$$

$$
\begin{aligned}
d\ln A^{F,L} = & \underbrace{\frac{z^* \widetilde{l^F}(z^*)}{\widetilde{L^H}} \frac{CS^{H,L}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}}}_{\equiv \sigma_{\widetilde{l^F}\widetilde{w^H}}} d\ln \widetilde{w^H} + \underbrace{\frac{z^* \widetilde{l^F}(z^*)}{\widetilde{L^H}} \frac{CS^{H,K}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}}}_{\equiv \sigma_{\widetilde{l^F}\widetilde{r^H}}} d\ln \widetilde{r^H} \\
& + \underbrace{\left[-\frac{z^* \widetilde{l^F}(z^*)}{\widetilde{L^H}} \frac{CS^{F,L}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}} + \left(-\sigma + (\sigma - 1) ACS^{F,L}(z^*)\right) \right]}_{\equiv \sigma_{\widetilde{l^F}\widetilde{w^F}}} d\ln \widetilde{w^F} \\
& + \underbrace{\left[-\frac{z^* \widetilde{l^F}(z^*)}{\widetilde{L^H}} \frac{CS^{F,K}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}} + (\sigma - 1) ACS^{F,K}(z^*) \right]}_{\equiv \sigma_{\widetilde{l^F}\widetilde{r^F}}} d\ln \widetilde{r^F},
\end{aligned}
$$

$$d \ln A^{F,K} = \underbrace{\frac{z^* \widetilde{k^F}(z^*)}{\widetilde{K^F}} \frac{CS^{H,L}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}}}_{\equiv \sigma_{\widetilde{k^F}\widetilde{w^H}}} d \ln \widetilde{w^H} + \underbrace{\frac{z^* \widetilde{k^F}(z^*)}{\widetilde{K^F}} \frac{CS^{H,K}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}}}_{\equiv \sigma_{\widetilde{k^F}\widetilde{r^H}}} d \ln \widetilde{r^H},$$

$$\underbrace{\left[-\frac{z^* \widetilde{k^F}(z^*)}{\widetilde{K^F}} \frac{CS^{F,L}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}} + (\sigma - 1) ACS^{F,L}(z^*)\right]}_{\equiv \sigma_{\widetilde{k^F}\widetilde{w^F}}} d \ln \widetilde{w^F}$$

$$\underbrace{\left[-\frac{z^* \widetilde{k^F}(z^*)}{\widetilde{K^F}} \frac{CS^{F,K}(z^*)}{\left(CS^{H,L}(z^*) - CS^{F,L}(z^*)\right)\sigma_{az}} + \left(-\sigma + (\sigma - 1) ACS^{F,K}(z^*)\right)\right]}_{\equiv \sigma_{\widetilde{k^F}\widetilde{r^F}}} d \ln \widetilde{r^F}.$$

Therefore, the elasticity matrix Σ is given as

$$\Sigma \equiv \begin{pmatrix} \sigma_{\widetilde{l^H}\widetilde{w^H}} & \sigma_{\widetilde{l^H}\widetilde{r^H}} & \sigma_{\widetilde{l^H}\widetilde{w^F}} & \sigma_{\widetilde{l^H}\widetilde{r^F}} \\ \sigma_{\widetilde{k^H}\widetilde{w^H}} & \sigma_{\widetilde{k^H}\widetilde{r^H}} & \sigma_{\widetilde{k^H}\widetilde{w^F}} & \sigma_{\widetilde{k^H}\widetilde{r^F}} \\ \sigma_{\widetilde{l^F}\widetilde{w^H}} & \sigma_{\widetilde{l^F}\widetilde{r^H}} & \sigma_{\widetilde{l^F}\widetilde{w^F}} & \sigma_{\widetilde{l^F}\widetilde{r^F}} \\ \sigma_{\widetilde{k^F}\widetilde{w^H}} & \sigma_{\widetilde{k^F}\widetilde{r^H}} & \sigma_{\widetilde{k^F}\widetilde{w^F}} & \sigma_{\widetilde{k^F}\widetilde{r^F}} \end{pmatrix}. \tag{A.20}$$

Now we consider extension cases of non-homogeneous output and income effects. In particular, consideration of non-homogeneous output makes the model more isomorphic to ours. Again, this helps us to think of the heterogeneous firm case and identification given the productivity shocks. Suppose that output is demanded by the following CES demand

$$q = \left(\frac{p}{P}\right)^{-\varepsilon} Q,$$

where P and Q are given exogenously (as H is a small open economy). Then the change in cost structure $d \ln p$ further has a feedback loop through the reduction in output demanded $d \ln q$ with elasticity ε. With this effect taken into consideration in the demand for the intermediate good, equation (A.12) becomes

$$d \ln x^c(z) = -d \ln c(z) - \varepsilon d \ln p.$$

Also, by the perfect competition assumption, $d \ln p = \sum_c \left(ACS^{c,L}(z^*)\, d \ln \widetilde{w^c} + ACS^{c,K}(z^*)\, d \ln \widetilde{r^c}\right)$. With these considerations, we have our expression (6) with Σ defined in equation (A.20) and

$$\sigma_q = \begin{pmatrix} \varepsilon ACS^{H,L}(z^*) \\ \varepsilon ACS^{H,K}(z^*) \\ \varepsilon ACS^{F,L}(z^*) \\ \varepsilon ACS^{F,K}(z^*) \end{pmatrix}.$$

Next, we consider income effects by relaxing the small open economy assumption. This is desirable even when we are willing to assume that Japan is small-open because since the reduction in the cost of multinational production and offshoring are global phenomena and not limited to a particular country such as Japan, it affects world income even if Japan is small-open. To put it differently, only in the case of Japan being small-open *and* an isolated country that experienced a reduction in multinational production cost does the no-income-effect assumption hold. To put it simply, we come back to the homogeneous outcome case and consider the changes in income due to productivity growth. Particularly, suppose instead of equation (A.3) that final demand is given by

$$q = \sum_c \left(w^c L^c + r^c K^c\right).$$

This implies that $d\ln q = \sum_c IS^c \left(LS^c d\ln w^c + (1-LS^c)\, d\ln r^c\right)$, where $IS^c \equiv w^c L^c + r^c K^c / \sum_{c'} \left(w^{c'} L^{c'} + r^{c'} K^{c'}\right)$ is the income share of country c. This again modifies equation (A.14) to

$$\begin{aligned} d\ln x^c(z) &= -d\ln c(z) + d\ln q \\ &= -d\ln c(z) + \sum_c IS^c \left(LS^c d\ln w^c + (1-LS^c)\, d\ln r^c\right). \end{aligned}$$

Hence, the relevant modification to the elasticity matrix (A.20) would accommodate this.

A.2.2 Multinational Production and Export Platforms

Following Arkolakis et al. (2017), we consider a different type of offshoring whereby firms from different source countries may produce a good in a different production country and sell to different destination countries. In particular, we take a special case of Arkolakis et al. (2017) in which is there are two distinct factors, which we interpret as labor and capital. To simplify matters, consider the two country case with H and F. There are no trade costs, whereas there could be an iceberg-type cost for producing in different countries $\gamma^{il} > 1$ for $i \neq l$. In each country, there are two types of factors, labor and capital, with endowment (L^c, K^c), where $c = H, F$.[32] Labor is used for production and capital for innovation. A potential firm in country i can enter the market and create a new variety by paying fixed entry cost $f^{e,i}$ units of capital. When a firm enters, it draws a productivity vector $\boldsymbol{z} \equiv \left(z^H, z^F\right)$ from the multivariate Pareto distribution

$$\Pr\left(Z^H \leq z^H, Z^F \leq z^F\right) = G^i\left(z^H, z^F\right) \equiv 1 - \left(\sum_{l\in\{H,F\}} \left[A^{il}\left(z^l\right)^{-\theta}\right]^{\frac{1}{1-\rho}}\right)^{1-\rho},$$

with support $z^l \geq \left(\widetilde{A^i}\right)^{\theta-1}$ for all l, where $\widetilde{A^i} \equiv \left[\sum_l \left(A^{il}\right)^{(1-\rho)^{-1}}\right]^{1-\rho}$. $\rho \in [0,1)$ is a parameter that governs the correlation between countries, and $\rho = 0$ is the case of uncorrelated Z^H and Z^F while $\rho \to 1$ is the perfect collinear extreme. We assume $A^{il} = A^{e,i} A^{p,l}$ so that $\widetilde{A^i} = \left[\sum_l \left(A^{p,l}\right)^{(1-\rho)^{-1}}\right]^{1-\rho} A^{e,i}$.[33] We call $A^{e,i}$ the quality of innovation in country i and $A^{p,l}$ the productivity in production of country l.

$$\xi^{iln} \equiv \gamma^{il} w^l \tau^{ln}, \tag{A.21}$$

[32] This is a special case of the treatment in Arkolakis et al. (2017); namely, inelastic supply of production and innovation workers, by letting $\kappa \to 1$.

[33] This is without loss of generality, as γ^{il} may have the necessary variation as is clear.

$$\Psi^{in} \equiv \left[\sum_{l'} \left(A^{il'}\left(\xi^{il'n}\right)^{-\theta}\right)^{(1-\rho)^{-1}}\right]^{1-\rho} \tag{A.22}$$

$$\psi^{iln} \equiv \left(\frac{T^{il}\left(\xi^{iln}\right)^{-\theta}}{\Psi^{in}}\right)^{(1-\rho)^{-1}} \tag{A.23}$$

$$X^{iln} = \psi^{iln}\lambda^{E,in}X^{n} \tag{A.24}$$

$$M^{iln} = \frac{\theta-\sigma+1}{\sigma\theta}\frac{X^{iln}}{w^{n}F^{n}}, \tag{A.25}$$

$$\lambda^{E,in} \equiv \frac{\sum_{l} X^{iln}}{X^{n}}. \tag{A.26}$$

$$\lambda^{T,ln} \equiv \sum_{i}\frac{X^{iln}}{X^{n}} = \sum_{i}\psi^{iln}\lambda^{E,in}. \tag{A.27}$$

We now characterize the equilibrium conditions that pin down $\left(w^{H}, r^{H}, w^{F}, r^{F}\right)$ as follows. The labor market equilibrium is given by the payment to workers equalling the sum of the value of labor demand for production and marketing, as

$$\frac{1}{\tilde{\tilde{\sigma}}}\sum_{n}\lambda^{T,ln}X^{n} + \left(1-\eta-\frac{1}{\tilde{\tilde{\sigma}}}\right)X^{l} = w^{l}L^{l} \tag{A.28}$$

for each $l = H, F$. The capital market equilibrium condition is such that the payment to capital equals the value of capital demand for innovation, as

$$\eta\sum_{n}\lambda^{E,in}X^{n} = r^{i}K^{i} \tag{A.29}$$

for each $i = H, F$. Finally, the budget balance condition is

$$w^{i}L^{i} + r^{i}K^{i} + \Delta^{i} = X^{i} \tag{A.30}$$

for each $i = H, F$, where Δ^{i} is the transfer to country i from the ROW.

Consider a multinational production shock to the economy $d\ln\gamma^{HF} < 0$. The log first-order approximations to the system (A.28), (A.29), and (A.30) give

$$LDS^{l}\sum_{n}PS^{ln}\left(d\ln\lambda^{T,ln} + d\ln X^{n}\right) + \left(1-LDS^{l}\right)d\ln X^{l} = d\ln w^{l}, \tag{A.31}$$

$$\sum_{n}IS^{in}\left(d\ln\lambda^{E,in} + d\ln X^{n}\right) = d\ln r^{i}, \tag{A.32}$$

$$LS^{i}d\ln w^{i} + \left(1-LS^{i}\right)d\ln r^{i} = d\ln X^{i}, \tag{A.33}$$

where

$$LDS^l \equiv \frac{\frac{\sigma-1}{\sigma}\sum_n \lambda^{T,ln}X^n}{\frac{\sigma-1}{\sigma}\sum_n \lambda^{T,ln}X^n + \left(1-\eta-\frac{\sigma-1}{\sigma}\right)X^l}, \; PS^{ln} \equiv \frac{\lambda^{T,ln}X^n}{\sum_{n'}\lambda^{T,ln'}X^{n'}}, \; IS^{in} \equiv \frac{\lambda^{E,in}X^n}{\sum_{n'}\lambda^{E,in'}X^{n'}}$$

are the (value) labor demand share in production of each country, the production sales share to country n, and innovation sales share to country n. Substituting equation (A.33) into equations (A.31) and (A.32), we have

$$\sum_n PS^{ln}\left(d\ln\lambda^{T,ln} + LS^n d\ln w^n + (1-LS^n)\,d\ln r^n\right) + LS^l d\ln w^l + \left(1-LS^l\right)d\ln r^l = d\ln w^l, \tag{A.34}$$

$$\sum_n IS^{in}\left(d\ln\lambda^{E,in} + LS^n d\ln w^n + (1-LS^n)\,d\ln r^n\right) = d\ln r^i. \tag{A.35}$$

To study $d\ln\lambda^{T,ln}$ and $d\ln\lambda^{E,in}$, first, by equation (A.27),

$$d\ln\lambda^{T,ln} = \sum_i \frac{\psi^{iln}\lambda^{E,in}}{\sum_{i'}\psi^{i'ln}\lambda^{E,i'n}}\left(d\ln\psi^{iln} + d\ln\lambda^{E,in}\right),$$

which, by equation (A.24), further simplifies to

$$d\ln\lambda^{T,ln} = \sum_i \frac{X^{iln}}{X^n}\left(d\ln\psi^{iln} + d\ln\lambda^{E,in}\right). \tag{A.36}$$

On the other hand, by equation (A.26), we have

$$d\ln\lambda^{E,in} = \left(1-\lambda^{E,in}\right)\left(d\ln M^i + d\ln\Psi^{in}\right) - \lambda^{E,\bar{i}n}\left(d\ln M^{\bar{i}} + d\ln\Psi^{\bar{i}n}\right). \tag{A.37}$$

To further deduce, it remains to know $d\ln\psi^{iln}$, $d\ln M^i$, and $d\ln\Psi^{in}$. By equations (A.21), (A.22), (A.23), and (A.25), they are

$$\begin{aligned} d\ln\psi^{iln} &= \frac{1}{1-\rho}\left(-\theta d\ln\xi^{iln} - d\ln\Psi^{in}\right), \\ &= \frac{1}{1-\rho}\left(-\theta d\ln\left(d\ln w^l + d\ln\gamma^{il}\right) - d\ln\Psi^{in}\right), \end{aligned} \tag{A.38}$$

$$\begin{aligned} d\ln\Psi^{in} &= \sum_{l'}\psi^{il'n}\left(-\theta d\ln\xi^{il'n}\right), \\ &= \sum_{l'}\psi^{il'n}\left(-\theta\left(d\ln w^{l'} + d\ln\gamma^{il'}\right)\right), \end{aligned} \tag{A.39}$$

$$\begin{aligned} d\ln M^i &= \sum_{l',n'}\frac{M^{il'n'}}{M^i}\left(d\ln X^{il'n'} - d\ln w^{n'}\right) \\ &= \sum_{l',n'}\frac{M^{il'n'}}{M^i}\left(d\ln\psi^{il'n'} + d\ln\lambda^{E,in'} + d\ln X^{n'} - d\ln w^{n'}\right). \end{aligned} \tag{A.40}$$

By substituting equations (A.36), (A.37), (A.38), (A.39), and (A.40), into equations (A.34) and (A.35), we obtain an expression for

$$\Sigma \begin{pmatrix} d\ln w^H \\ d\ln r^H \\ d\ln w^F \\ d\ln r^F \end{pmatrix} = b,$$

for a reduced demand elasticity matrix Σ and shock vector b.

A.3 Proof of Equation (13)

The cost minimization problem under the upper nest implies

$$k = \left(a^K\right)^{\sigma-1}\left(\frac{r}{p}\right)^{-\sigma} q, and \tag{A.41}$$

$$l = \left(\frac{w}{p}\right)^{-\sigma} q, \tag{A.42}$$

where $p^X \equiv \left(\left(w/a^L\right)^{1-\lambda} + \left(p^M/a^M\right)^{1-\lambda}\right)^{1/(1-\lambda)}$ is the aggregate wage index and $p \equiv \left(\left(r/a^K\right)^{1-\sigma} + \left(p^X\right)^{1-\sigma}\right)^{1/(1-\sigma)}$ is the marginal cost index. Similarly,

$$l = a^L\left(\frac{w}{p^X}\right)^{-\lambda} l, and \tag{A.43}$$

$$m = a^M\left(\frac{p^M}{p^X}\right)^{-\lambda} l. \tag{A.44}$$

By equating total demand to total supply, we have

$$\begin{aligned}
K &= \left(a^K\right)^{\sigma-1}\left(\frac{r}{p}\right)^{-\sigma} q \Leftrightarrow r = p\left(a^K\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{q}{K}\right)^{\frac{1}{\sigma}}, \\
X &= \left(\frac{p^X}{p}\right)^{-\sigma} q \Leftrightarrow p^X = p\left(\frac{q}{X}\right)^{\frac{1}{\sigma}}, \\
L &= \left(a^H\right)^{\lambda-1}\left(\frac{w}{p^X}\right)^{-\lambda} X \Leftrightarrow w = p^X\left(a^H\right)^{\frac{\lambda-1}{\lambda}}\left(\frac{X}{L^H}\right)^{\frac{1}{\lambda}}, \\
M &= \left(a^M\right)^{\lambda-1}\left(\frac{p^M}{p^X}\right)^{-\lambda} X \Leftrightarrow p^M = p^X\left(a^M\right)^{\frac{\lambda-1}{\lambda}}\left(\frac{X}{M}\right)^{\frac{1}{\lambda}}.
\end{aligned}$$

By substituting these expressions,

$$
\begin{aligned}
LS &\equiv \frac{wL}{wL+rK} \\
&= \frac{w\left(a^{L}\right)^{\frac{\lambda-1}{\lambda}}\left(\frac{X}{L}\right)^{\frac{1}{\lambda}}L}{w\left(a^{L}\right)^{\frac{\lambda-1}{\lambda}}\left(\frac{X}{L}\right)^{\frac{1}{\lambda}}L+c\left(a^{K}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{q}{K}\right)^{\frac{1}{\sigma}}K} \\
&= \frac{c\left(\frac{q}{L}\right)^{\frac{1}{\sigma}}\left(a^{L}\right)^{\frac{\lambda-1}{\lambda}}\left(\frac{X}{L}\right)^{\frac{1}{\lambda}}L}{c\left(\frac{q}{X}\right)^{\frac{1}{\sigma}}\left(a^{L}\right)^{\frac{\lambda-1}{\lambda}}\left(\frac{X}{L}\right)^{\frac{1}{\lambda}}L+c\left(a^{K}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{q}{K}\right)^{\frac{1}{\sigma}}K} \\
&= \frac{\left(a^{L}L\right)^{1-\lambda^{-1}}X^{\lambda^{-1}-\sigma^{-1}}}{\left(a^{L}L\right)^{1-\lambda^{-1}}X^{\lambda^{-1}-\sigma^{-1}}+\left(a^{K}K\right)^{1-\sigma^{-1}}}.
\end{aligned}
$$

A.4 Proof of Equations (15) and (16)

We prove the effect of the shock with the following property: The shock decreases only the foreign augmentation $d\ln a^{M}<0$ but not capital and labor $d\ln a^{K}=d\ln a^{L}=0$, and hits only an infinitesimal set of firms so that factor prices are not affected. Note that perfect competition implies the price is the marginal cost. Consider the following overall marginal cost function

$$
\begin{aligned}
p &= \left(\left(\frac{r}{a^{K}}\right)^{1-\sigma}+\left(p^{X}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \\
&= \left(\left(\frac{r}{a^{K}}\right)^{1-\sigma}+\left(\left(\frac{w}{a^{L}}\right)^{1-\lambda}+\left(\frac{p^{M}}{a^{M}}\right)^{1-\lambda}\right)^{\frac{1-\sigma}{1-\lambda}}\right)^{\frac{1}{1-\sigma}}.
\end{aligned}
$$

Then the (first-order) elasticity of the cost with respect to log foreign factor-augmenting productivity $d\ln A^{F}$ is

$$d\ln p=-CS_{0}^{M}d\ln a^{M},$$

where $CS^{M}\equiv p^{M}m/\left(rk+wl+p^{M}m\right)$ is the share of foreign labor cost in the overall cost. In addition, by equation (1) we have $d\ln q=-\varepsilon d\ln p$. This in turn reduces the factor demand $d\ln x=d\ln q$ according to aggregate labor demand (A.42). Lower-nest labor demands (A.43) and (A.44) imply that $d\ln l=d\ln x$ and $d\ln m=(\lambda-1)\,d\ln a^{M}+d\ln x$. In a nutshell, we arrive at equations (15) and (16).

A.5 Elasticity Matrix under Nested CES

Under the homogeneous nested CES, by factor demand functions (A.41), (A.42), (A.43), and (A.44), we may obtain that the reduced elasticity matrix

$$
\Sigma\equiv\begin{pmatrix}
-\sigma+(\sigma-\varepsilon)\,CS^{K} & (\sigma-\varepsilon)\,CS^{L} & (\sigma-\varepsilon)\,CS^{M} \\
(\sigma-\varepsilon)\,CS^{K} & -\lambda+(\lambda-\sigma)\,WS^{L}+(\sigma-\varepsilon)\,CS^{L} & (\lambda-\sigma)\,WS^{M}+(\sigma-\varepsilon)\,CS^{M} \\
(\sigma-\varepsilon)\,CS^{K} & (\lambda-\sigma)\,WS^{L}+(\sigma-\varepsilon)\,CS^{L} & -\lambda+(\lambda-\sigma)\,WS^{M}+(\sigma-\varepsilon)\,CS^{M}
\end{pmatrix}.
$$

A.6 Proof of Equation (26)

Next, we consider rich heterogeneity in factor augmenting productivities. The production function is

$$q_i = \left(\left(a_i^K k_i\right)^{1-\sigma^{-1}} + x_i^{1-\sigma^{-1}}\right)^{\left(1-\sigma^{-1}\right)^{-1}}, and$$
$$x_i = \left(\left(a_i^L l_i\right)^{1-\lambda^{-1}} + \left(a_i^M m_i\right)^{1-\lambda^{-1}}\right)^{\left(1-\lambda^{-1}\right)^{-1}}.$$

We assume that Assumption 1 is satisfied for the purpose of the matrix inversion exercise below. For simplicity, assume additionally that the competitive environment features constant markups such as in perfect competition or monopolistic competition. The factor supply (K, L, M) and total demand Q are fixed.[34] Thus, the following factor market clearing conditions determine the market wages (r, w, p^M).

$$K = \int_0^1 k_i di, L = \int_0^1 l_i di, M = \int_0^1 m_i di. \tag{A.45}$$

Unless otherwise noted, the integrals below are with respect to each firm and so from 0 to 1, which are omitted to keep the notation concise.

The cost-minimizing factor demands of firm i are

$$k_i = \left(a_i^K\right)^{\sigma-1}\left(\frac{r}{p_i}\right)^{-\sigma} q_i, x_i = \left(\frac{p_i^X}{p_i}\right)^{-\sigma} q_i, l_i = \left(a_i^L\right)^{\lambda-1}\left(\frac{w_i}{p_i^X}\right)^{-\lambda} x_i, m_i = \left(a_i^F\right)^{\lambda-1}\left(\frac{p_i^M}{p_i^X}\right)^{-\lambda} x_i,$$

where the marginal cost and aggregate labor-foreign input cost index are

$$p_i = \left(\left(\frac{r}{a_i^K}\right)^{1-\sigma} + \left(p_i^X\right)^{1-\sigma}\right)^{(1-\sigma)^{-1}}, p_i^X = \left(\left(\frac{w}{a_i^L}\right)^{1-\lambda} + \left(\frac{p^M}{a_i^M}\right)^{1-\lambda}\right)^{(1-\lambda)^{-1}}. \tag{A.46}$$

Substituting these into conditions (A.45), we have

$$K = \int \left(a_i^K\right)^{\sigma-1}\left(\frac{r}{p_i}\right)^{-\sigma}\left(\frac{p_i}{P}\right)^{-\varepsilon} Qdi, \tag{A.47}$$
$$L = \int \left(a_i^L\right)^{\lambda-1}\left(\frac{w}{p_i^X}\right)^{-\lambda}\left(\frac{p_i^X}{p_i}\right)^{\sigma}\left(\frac{p_i}{P}\right)^{-\varepsilon} Qdi, \tag{A.48}$$
$$M = \int \left(a_i^M\right)^{\lambda-1}\left(\frac{p^M}{p_i^X}\right)^{-\lambda}\left(\frac{p_i^X}{p_i}\right)^{\sigma}\left(\frac{p_i}{P}\right)^{-\varepsilon} Qdi. \tag{A.49}$$

Since the system involves integrals of non-linear equations of unknowns (r, w, p^M), the closed-form

[34]Note that the fixed total demand Q means that Q is independent of the income of factors. This further implies that the treatment of the economic profits of firms is immaterial because so long as their shares enter as incomes. An assumption that justifies this would be that the Home country is a small-open *exporter* of the goods each Home firm produces. In this case, the factor income of the Home country is negligible relative to the World income, which makes Q virtually fixed. We will come back to this issue when we analyze the general equilibrium.

solution is hardly tractable. We thus rely on our first order approximation obtained in (6). Therefore, it suffices to know the log first-order approximation on w and r. The log first-order approximations with respect to a^M to the system (A.47), (A.48), and (A.49) are

$$
\begin{aligned}
0 &= \int \frac{rk_i}{rK}\left(-\sigma d\ln r + (\sigma-\varepsilon)\, d\ln p_i\right) di, \\
0 &= \int \frac{wl_i}{wL}\left(-\lambda d\ln w + (\lambda-\sigma)\, d\ln p_i^X + (\sigma-\varepsilon)\, d\ln p_i\right) di, \\
0 &= \int \frac{p^M m_i}{p^M M}\left((\lambda-1)\, d\ln a^M - \lambda d\ln p^M + (\lambda-\sigma)\, d\ln p_i^X + (\sigma-\varepsilon)\, d\ln p_i\right) di,
\end{aligned}
$$

where, by equations (A.46) and cost-minimizing demand functions,

$$
\begin{aligned}
d\ln p_i &= \frac{rk_i}{p_i q_i} d\ln r + \frac{p_i^X x_i}{p_i q_i} d\ln w_i, \mathit{and} \\
d\ln w_i &= \frac{wl_i}{p_i^X x_i} d\ln w^H + \frac{p^M m_i}{p_i^X x_i} d\ln w^F.
\end{aligned}
$$

With slight abuse of notation, for $Z = K, L, M$ and $y = k, l, m$, write CS_y^Z as the employment of factor y-weighted average of payment share to factor Z. For instance, with the home labor (l) employment as the weight, the weighted average of the capital (K) payment share is $CS_l^K \equiv \int \frac{wl_i}{wL}\frac{rk_i}{p_i q_i} di$. Accordingly, for $Z = L, M$ and $y = l, m$, write WS_y^Z as the employment of factor y-weighted average of wage payment share to factor Z.[35] With these notations, we can summarize the first-order approximation as the linear algebraic problem $Az = b$, where

$$
A \equiv \begin{pmatrix}
(\sigma-\varepsilon)\, CS_k^K - \sigma & (\sigma-\varepsilon)\, CS_k^L & (\sigma-\varepsilon)\, CS_k^M \\
(\sigma-\varepsilon)\, CS_l^K & (\lambda-\sigma)\, WS_l^L + (\sigma-\varepsilon)\, CS_l^L - \lambda & (\lambda-\sigma)\, WS_l^M + (\sigma-\varepsilon)\, CS_l^M \\
(\sigma-\varepsilon)\, CS_m^K & (\lambda-\sigma)\, WS_m^L + (\sigma-\varepsilon)\, CS_m^L & (\lambda-\sigma)\, WS_m^M + (\sigma-\varepsilon)\, CS_m^M - \lambda
\end{pmatrix}, \tag{A.50}
$$

$$
z \equiv \begin{pmatrix} d\ln r \\ d\ln w \\ d\ln p^M \end{pmatrix},
$$

$$
b \equiv \begin{pmatrix}
(\sigma-\varepsilon)\, CS_k^M \\
(\lambda-\sigma)\, WS_l^M + (\sigma-\varepsilon)\, CS_l^M \\
(\lambda-\sigma)\, WS_l^M + (\sigma-\varepsilon)\, CS_l^M - \lambda - (\lambda-1)
\end{pmatrix} d\ln a^M. \tag{A.51}
$$

Hence, if A is non-singular, z can be solved as $z = A^{-1}b$ and the log first-order approximation of labor share (6) can be solved accordingly. Indeed, equation (6) shows that only $x_2 - x_1$ is our variable of interest.

[35] Note the similarity of the definition to the one used in the homogeneous case in equation (14). WS_y^X is the version that accommodates heterogeneity and contains the homogeneous case as a special case–with homogeneous firms, $WS_y^X = WS^X$ for any y, and WS^F coincides with the one in equation (14).

To proceed, note that

$$z_2 - z_1 = \sum_{j=1}^{3} \left(a_{2j}^{-1} - a_{1j}^{-1} \right) b_j,$$

where a_{ij}^{-1} is (i, j)-element of inverse matrix A^{-1}. According to the formula of inverting 3×3 matrices, we have

$$\begin{aligned}
z_2 - z_1 \propto & \left\{ (a_{31} + a_{32})\, a_{23} - (a_{21} + a_{22})\, a_{33} \right\} b_1 \\
& + \left\{ (a_{11} + a_{12})\, a_{33} - (a_{31} + a_{32})\, a_{13} \right\} b_2 \\
& + \left\{ (a_{21} + a_{22})\, a_{13} - (a_{11} + a_{12})\, a_{23} \right\} b_3 \\
= & \left(a_{11} + a_{12} \right) \left(a_{33} b_2 - a_{23} b_3 \right) + \left(a_{21} + a_{22} \right) \left(a_{13} b_3 - a_{33} b_1 \right) \\
& \left(a_{31} + a_{32} \right) \left(a_{23} b_1 - a_{13} b_2 \right).
\end{aligned}$$

Note that from equations (A.50) and (A.51), we have $a_{13} = b_1, a_{23} = b_2$, and $a_{33} = b_3 + (\lambda - 1)$. Therefore, $a_{33} b_2 - a_{23} b_3 = [b_3 + (\lambda - 1)]\, b_2 - b_2 b_3 = (\lambda - 1)\, b_2$, $a_{13} b_3 - a_{33} b_1 = b_1 b_3 - [b_3 + (\lambda - 1)]\, b_1 = -(\lambda - 1)\, b_1$, and $a_{23} b_1 - a_{13} b_2 = b_2 b_1 - b_1 b_2 = 0$. Using these facts, we further deduce that

$$z_2 - z_1 \propto (a_{11} + a_{12})\, b_2 + (a_{21} + a_{22})\, b_1.$$

Substituting the elements in expressions (A.50) and (A.51), we finally have expression (26).

A.7 Proof of Equations (27) and (28)

Here, we prove only equation (27), as (28) follows the same logic. First, recall that the quantity-conditional factor demand cross derivatives $\partial \widetilde{k}_i / \partial \widetilde{p_i^M}|_{q_i}$ and $\partial \widetilde{m}_i / \partial \widetilde{r}_i|_{q_i}$ are equal because (i) due to Shephard's lemma, factor demands are the partial derivative of the (quantity-conditional) cost function and (ii) the Hessian matrix is symmetric due to Young's theorem. Thus we have

$$\sigma_{\widetilde{m}\widetilde{r},i}|_{q_i} \equiv \frac{\widetilde{r}_i}{\widetilde{m}_i} \frac{\partial \widetilde{m}_i}{\partial \widetilde{r}_i}|_{q_i} = \frac{\widetilde{r}_i}{\widetilde{m}_i} \frac{\partial \widetilde{k}_i}{\partial \widetilde{p_i^M}}|_{q_i} = \frac{r k_i}{p^M m_i} \sigma_{\widetilde{k}\widetilde{p^M},i}|_{q_i},$$

where the last equality follows by definition $\sigma_{\widetilde{k}\widetilde{p^M},i}|_{q_i} \equiv \left(\widetilde{p_i^M} / \widetilde{k}_i \right) \left(\partial \widetilde{k}_i / \partial \widetilde{p_i^M}|_{q_i} \right)$ and the definitions of factor augmentation notations (tilde). By rearranging, we have

$$CS_i^M \sigma_{\widetilde{m}\widetilde{r},i}|_{q_i} = CS_i^K \sigma_{\widetilde{k}\widetilde{p^M},i}|_{q_i}. \tag{A.52}$$

Finally, we have

$$\begin{aligned}
\sigma_{\widetilde{m}\widetilde{r},i} &\equiv \sigma_{\widetilde{m}\widetilde{r},i}|_{q_i} + \sigma_{qp} \frac{\partial \ln \widetilde{p}_i}{\partial \ln \widetilde{r}_i} \\
&= \sigma_{\widetilde{m}\widetilde{r},i}|_{q_i} + \sigma_{qp} CS_i^K,
\end{aligned}$$

where the last equality again follows Shepard's lemma. Similarly, we have $\sigma_{\widetilde{k}\widetilde{p^M},i} = \sigma_{\widetilde{k}\widetilde{p^M},i}|_{q_i} + \sigma_{qp}CS_i^M$. Hence, we have

$$CS_i^M\sigma_{\widetilde{m}\widetilde{r},i} = CS_i^M\sigma_{\widetilde{m}\widetilde{r},i}|_{q_i} + CS_i^M\sigma_{qp}CS_i^K = CS_i^K\sigma_{\widetilde{k}\widetilde{p^M},i}|_{q_i} + CS_i^K\sigma_{qp}CS_i^M = CS_i^K\sigma_{\widetilde{k}\widetilde{p^M},i},$$

where the second equality holds by equation (A.52).

A.8 Properties of the Factor Demand Elasticity Matrix

Generalizing the results in Section A.7, we may establish the following result regarding off-diagonal elements of the (quantity-controlled and -uncontrolled) elasticity matrix. We further establish additional results below.

Proposition 2. *(i) (Off-diagonal elements) For any $f, g \in \{k, l, m\}$ with $f \neq g$,*

$$CS_i^f\sigma_{\widetilde{f}\widetilde{g},i}|_{q_i} = CS_i^g\sigma_{\widetilde{g}\widetilde{f},i}|_{q_i},$$

$$CS_i^f\sigma_{\widetilde{f}\widetilde{g},i} = CS_i^g\sigma_{\widetilde{g}\widetilde{f},i}.$$

(ii) (Singularity) $\Sigma_i|_{q_i}$ is singular.

Proof. (i) is a generalization of other factor-factor price pairs of the arguments in Section A.7. To show (ii), recall that by zero-th order homogeneity of the cost-minimizing factor demand functions, Euler's theorem implies that

$$\frac{\partial\widetilde{k}_i}{\partial\widetilde{r}_i}|_{q_i}\widetilde{r}_i + \frac{\partial\widetilde{k}_i}{\partial\widetilde{w}_i}|_{q_i}\widetilde{w}_i + \frac{\partial\widetilde{k}_i}{\partial\widetilde{p_i^M}}|_{q_i}\widetilde{p_i^M} = 0.$$

Hence, we have

$$\sigma_{\widetilde{k}\widetilde{r},i}|_{q_i} + \sigma_{\widetilde{k}\widetilde{w},i}|_{q_i} + \sigma_{\widetilde{k}\widetilde{p^M},i}|_{q_i} = \frac{1}{\widetilde{k}_i}\left(\frac{\partial\widetilde{k}_i}{\partial\widetilde{r}_i}|_{q_i}\widetilde{r}_i + \frac{\partial\widetilde{k}_i}{\partial\widetilde{w}_i}|_{q_i}\widetilde{w}_i + \frac{\partial\widetilde{k}_i}{\partial\widetilde{p_i^M}}|_{q_i}\widetilde{p_i^M}\right) = 0.$$

Similar arguments apply for augmented-factor demand functions $\widetilde{l}_i$ and $\widetilde{m}_i$, so we have

$$\left(\Sigma_i|_{q_i}\right)\mathbf{1} = 0.$$

Hence, $\Sigma_i|_{q_i}$ is singular. □

B Empirical Appendix

B.1 MNEs and Labor Share, Cross Country

This section describes the construction of Figure 1 and some further results from it. To see the first pass evidence that multinational activities have an impact on labor share, we take the cross country variation in the change of outward multinational activities and the change in labor share using labor share data from Karabarbounis and Neiman (2013) and assembling data on multinational activities from UNCTAD. We calculate the level and change in outward multinational activities as follows. For the level, we take a snap-shot (1996-2000 average) of net outward multinational sales, taking a five-year average to control the noise in the raw data. For the change, we obtain the difference in net outward multinational sales between the 1991-1995 average and the 1996-2000 average.

Figure 1 shows the results in the form of a correlation plot. To allow for a lagged response in the labor share to multinational intensity changes, we take the change in the labor share between 1995 and 2007. The left panel shows the results for the level of outward multinational sales and the right panel shows the change. We fit the correlation by the weighted regression by country size measured by the base-year GDP. The number of countries in both plots is 36, and even with such a small sample, we see a remarkably significant negative relationship both in the level of multinational intensity and the change. Both regression slope coefficients are significantly negative at the two-sided 95 percent level.

An interpretation of this negative relationship is that the outward multinational activities substitute labor in the home country more than capital. Hence, the demand for labor in the home country decreases more than proportionately to the decrease in the demand for capital. The theory is detailed in Section 3.

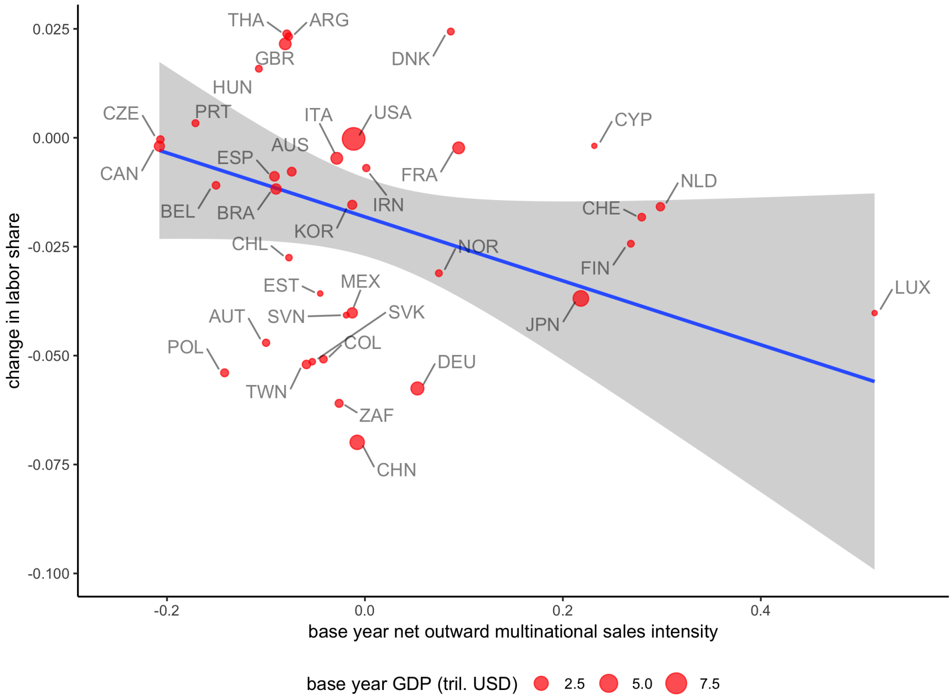
Figure B.1 shows a plot of the levels of net multinational sales (1991-1995) and the changes in labor share (1991-2000). Again, the countries that have higher multinational sales have relatively larger decreases in labor share in the next 10 years.

B.2 Thailand's Gross Export and Import Trends

Figure B.2 shows the trend in Thailand's exports and imports using data from Comtrade. Recalling that the floods occurred in 2011, exports and imports show a roughly parallel trend before the floods, but after 2011, export growth falters and the trend breaks from that of imports. This is consistent with our interpretation that the flooding hit the supply-side of the economy heavily, given that several large-scale manufacturing industrial parks were inundated. Also, this is consistent with Benguria and Taylor (2019), who present a method for identifying demand and supply shocks from gross export and import data in the context of financial crises. They claim that "firm deleveraging shocks are mainly supply shocks and contract exports," while leaving imports largely unchanged.

Next, we provide an overview of Thailand's economic policies. Thailand began international liberalization ahead of other Southeast Asian countries, being one of the original member countries of the *Association of Southeast Asian Nations* (ASEAN) and entering GATT in 1982. In the early 2000's, it formed FTAs with several large economies (India in 2003, the U.S. in 2004, Australia and Japan in 2005). This is in addition to some major internal and external FTAs made by ASEAN. The internal FTA among member countries went into effect in 1993, and by 2003, internal tariffs had been driven down to below five percent. External FTAs with other large economies include one with China in 2003. Given this history, over the period of our analysis from 2007 to 2016, we do not see a large

Figure B.1: Net Outward Multinational Sales and Labor Share



Source: Karabarbounis Neiman (2014) and UNCTAD.
Note: The horizontal axis is the 1991-1995 average sum of bilateral net outward multinational sales. The vertical axis is the change in labor share from 1991 to 2000. Singapore was dropped because it had an outlier value for the outward multinational sales measure.

degree of institutional internationalization, as much of this had occurred beforehand.[36] The gross trade trends shown in Figure B.2 are consistent with this fact, as the drivers behind the changes in trade trends were external business cycles (e.g., the global great recession after 2008) or political upheaval (e.g., a coup d'etat in 2014) rather than large trade policy changes.

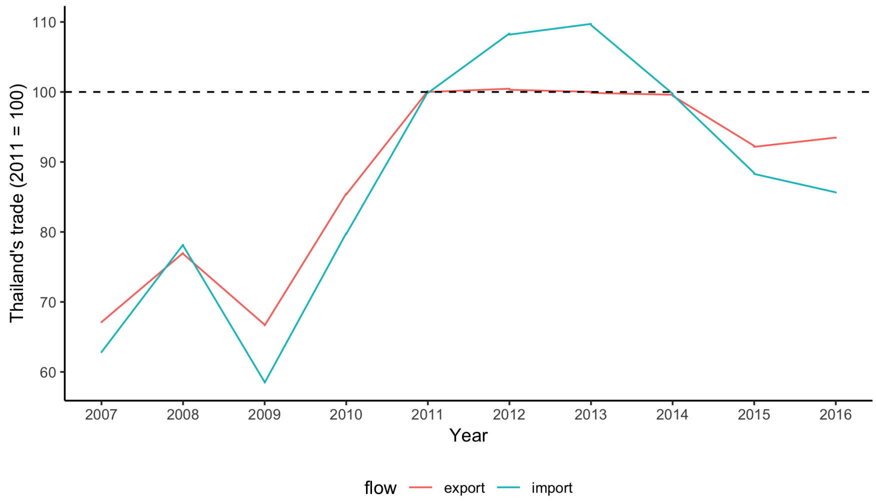
B.3 Discussion of Data Sources

B.3.1 Country-level Analysis from BSOBA

Throughout the main sections, we maintained the assumption of an aggregated rest of the world (ROW). Although this simplifies the analysis greatly, there are at least two reasons why we believe this may not be consistent with empirical findings. First, ample empirical evidence suggests that the motivation for MNE investment is different for high-income and low-income countries (see, e.g., Harrison and McMillan, 2011). Second, to the extent that our natural experiment involves a local natural disaster, a model in which the factors in the affected area can be separated from factors in other regions would be more realistic. To move in this direction, this section discusses several country-level data. By doing so, we provide the motivation for the future development of multi-country analyses.

[36]Several exceptions include the ASEAN-South Korea FTA that reduced the tariff between South Korea and Thailand in 2010 and the Chile-Thailand FTA that went into effect in 2015.

Figure B.2: Trend of Thailand's Trade



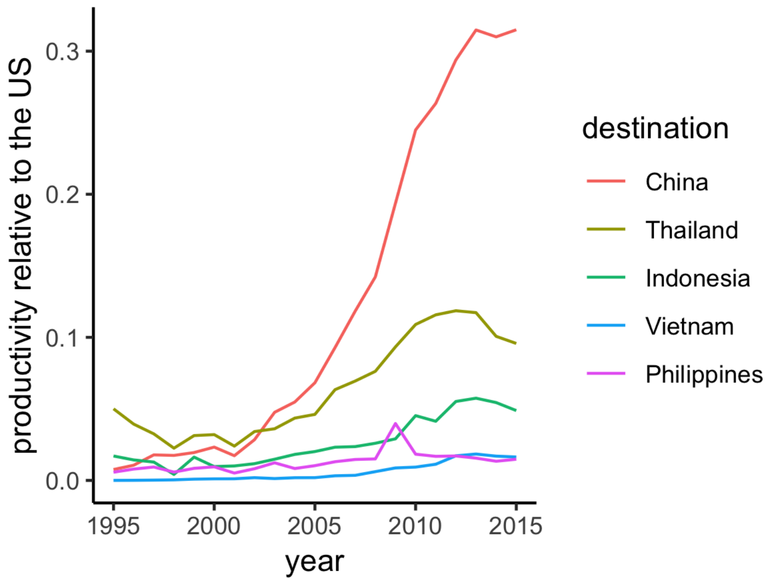
Source: Comtrade

Our major data source for MNEs is BSOBA which, as described in Section 2.1, contains the universe of offshore plants owned by headquarter firms located and registered in Japan, covering both private and public firms. As each plant-level observation has the country-level location, total employment and total labor compensation, we may aggregate the country-level average wage and labor productivity measure. These variables are analyzed in detail below.

Productivity Growth in Each Destination Country Applying the model inversion (25) for each destination country, Figure B.3 shows the results for Japan's five most intensive MNE destination countries measured by size of total employment, taking the U.S. as the base country in equation (25). Therefore, observed productivity growth relative to the base country shows the relative augmentation of factors in these developing economies.

Broader Country-level Wage Trends–Evidence from PWT Figure B.4 shows country-level wages generated from *Penn World Table* (PWT) data. Each line indicates the country-level average wage, where wage is calculated as per-capita average labor compensation. To highlight the differences between developed and developing countries, blue lines indicate OECD countries and red lines non-OECD countries. Since our empirical application focuses on Thailand, it is highlighted in bold. Several points can be taken from the figure. First, there is significant wage variation across countries. In particular, OECD countries on average have historically paid higher wages than their non-OECD counterparts. This in itself might indicate that the reasons behind multinational activities differ, which would make a theory based on multiple countries more realistic. For example, Harrison and McMillan (2011) point out that cost changes in high-income and low-income countries result in different effects in home-country employment, so future research should take this into consideration. Second, average wages have grown in many countries, in both OECD and non-OECD countries alike. This may make it more difficult to derive conclusions about the desirability for multinational firms

Figure B.3: Country-level Measured Productivity



to hire foreign workers based on differences in labor costs. Our approach is therefore to invert the factor demand to obtain the implied factor-augmenting productivity shocks, as detailed in Section 5.1. Third, our natural experiment shock in Thailand in 2011 did not appear to change the average wage drastically. This might be due to the fact that the flood shock was local and short-lived, which might not be well-captured in coarse country-year aggregate data. We thus employ microdata set out in Section 2.1 to study the exogenous negative foreign factor productivity shock.

Comparison of BSOBA and PWT In this section, we check the differences in the aggregate (average) wage measures from PWT and BSOBA, our primary source of data on multinational production. Note that PWT aggregate wage is calculated from the total labor cost and total employment in each country. Thus, a wage difference emerges if Japanese-parented subsidiaries hire a different type of worker than the typical firm in each country. Figure B.5 shows the comparison of BSOBA and PWT for a selected set of nine countries chosen by their ranking in terms of total employment by Japanese subsidiaries at the end of FY2015. From the Figure, one can see that BSOBA and PWT show a similar trend for each country overall. This suggests that Japanese subsidiary firms hire workers from a similar labor market as other firms in each country. However, there are several interesting deviations from this pattern, particularly in high-income countries such as the U.K. and the U.S. This might reflect the fact that the subsidiaries in these countries focus on high-value added activities such as finance, which might cause the hiring structure of Japanese subsidiaries there to be different from that of other firms. We also show in Table B.1 the results of a regression of the PWT wage on the BSOBA wage with and without fixed effects to confirm that the goodness of fit is remarkably high for cross-section-cross-year data.

Figure B.4: Offshore Labor Cost in Thailand and Other Countries

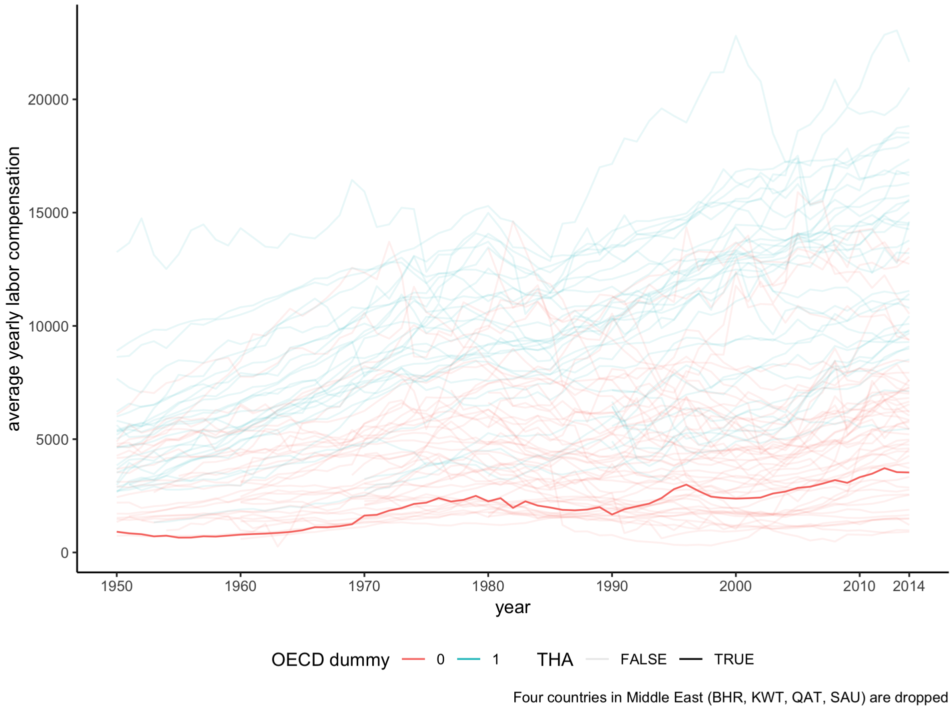


Table B.1: Discrepancies between SOBA and PWT

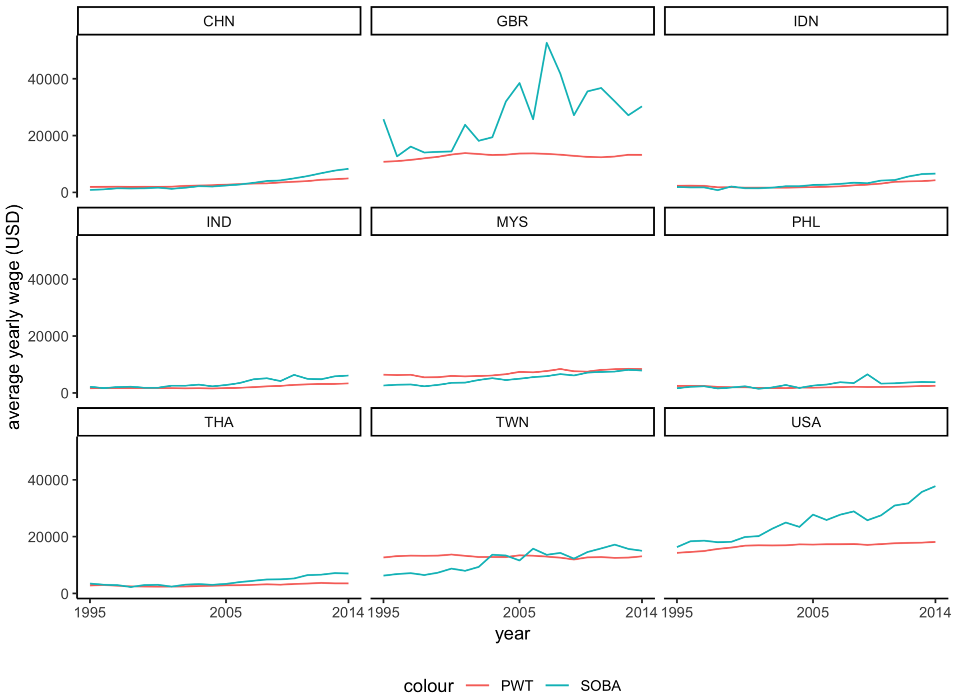
	All	All	Top 9	Top 9
	(1)	(2)	(3)	(4)
PR	0.332***	0.038***	0.772***	0.409***
	(0.014)	(0.007)	(0.028)	(0.045)
Country FE		YES		YES
Year FE		YES		YES
Observations	1,350	1,350	180	180
R^2	0.300	0.950	0.805	0.983
Notes:	*** p<0.01, ** p<0.05, * p<0.1			

B.3.2 Data-linking strategy

We match the BSJBSA and BSOBA datasets in the following way. First, for each firm, we pick up from both BSOBA and TSR the firm name, the headquarter address and phone number for each year. To match the datasets using this information, we first need to deal with a problem of spelling variation. Due to language translation, there are several potential spelling variations that refer to the same company or address, so we prepare a spelling variation table and applied it to the data to obtain a variation-proof dataset.[37] In addition, to further improve the precision of the addresses, we geocode the written address to the layered system of all Japanese addresses using the CSV Geocoding Service

[37]The spelling variation table is available upon request.

Figure B.5: Comparison of BSOBA and PWT



offered by the University of Tokyo Center for Spatial Information Science.[38] The layers are defined as follows. 1 and 2: "todofuken" (prefecture), 3: city, 4: district in large cities, 5 and 6: coarse street address, and 7: fine street address.

Using the obtained data for each year, we conduct the following matching. To break the potential multiple matches within and across years, for each match in each year we assign a match score that measures the quality of the match. The match score is defined as follows: a firm name match receive a score of 1,000, a firm phone number match receive 100, a firm address match before geocoding receive 10, and a firm address match after geocoding at the layer of $l = 2, \ldots, 7$ received l.[39] We considered the match successful if the match score is strictly larger than 1,000. In other words, this means that we require the following two criteria. First, the firm names have to match between the two datasets up to any spelling variation. Second, either the address or the phone number have to match. If there are multiple successful matches, we pick the one with the highest match score. Then we compare the matching results across years and use the results with the highest score. This procedure results in a match rate of 93.0% from all firm IDs in BSOBA to firm IDs in TSR.

We match BSJBSA and TSR data by a similar method except that we have BSJBSA data from the year of 1995. The resulting match rate for all firm IDs in BSJBSA in year 2007-2016 is 88.9%. Figure B.6 provides a schematic diagram that summarizes the data-linking strategy set out above.

[38] http://newspat.csis.u-tokyo.ac.jp/geocode/ (in Japanese, accessed on July 27, 2018)

[39] We did not assign any points for the match at the level of todofuken because it is too coarse.

Figure B.6: Schematic Data-linking Strategy

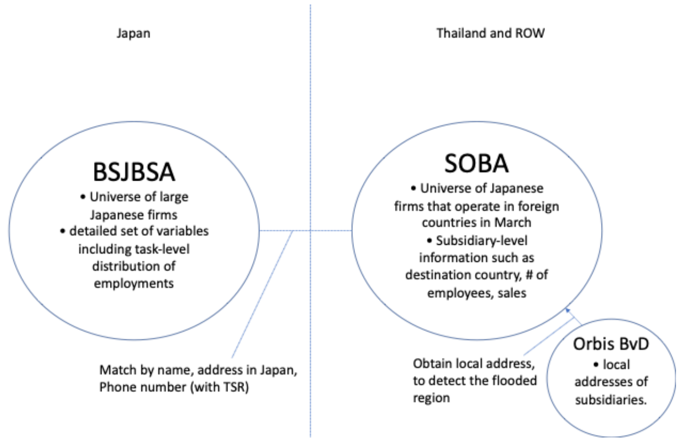
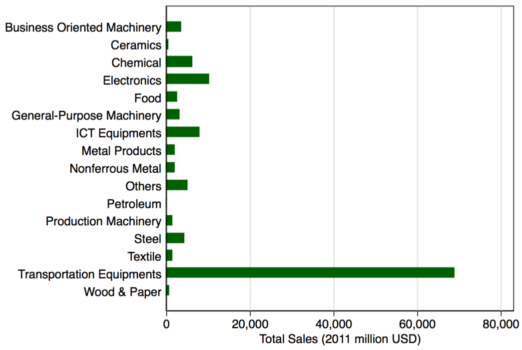
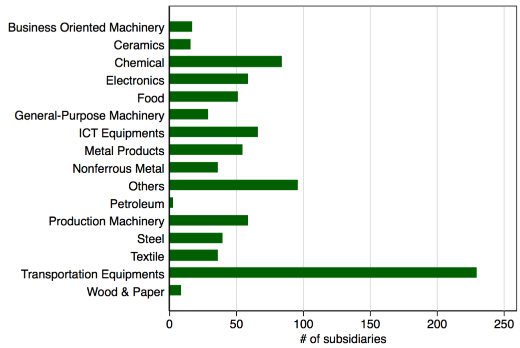


Figure B.7: Industry Distribution of the Treated Subsidiaries of Japanese firms, 2011

(a) Total Sales



(b) Number of Subsidiaries



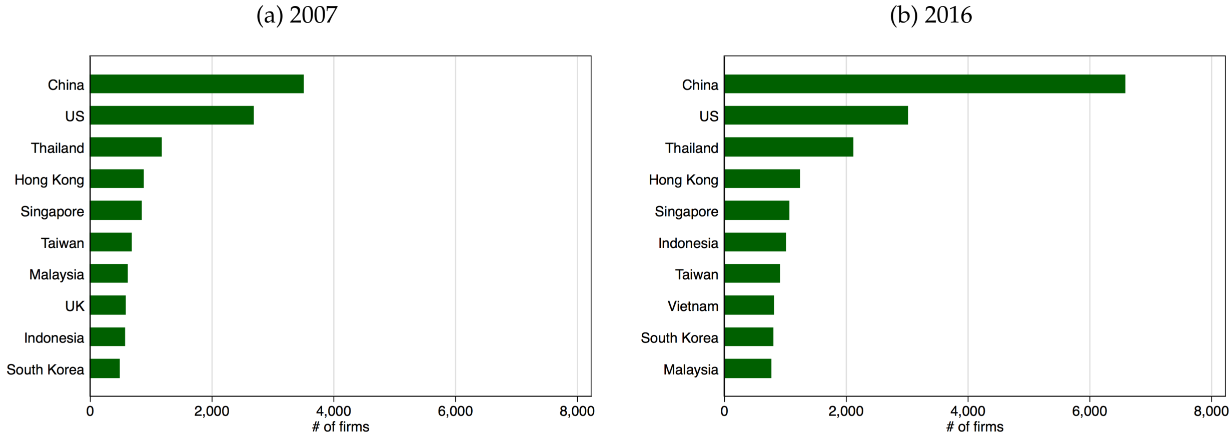
B.3.3 Overview of Japanese Subsidiaries in Thailand

Using the datasets described above, we here show statistics about production in the flooded region. First, to understand the industry clustering patterns in detail, Figure B.7 shows the industry distribution of Japanese subsidiaries in the flooded region in Thailand by sales in 2011. As mentioned earlier, most of the subsidiaries in the flooded region produced Transportation Equipment, including automobiles, whether measured by total sales or number of local subsidiaries. The second and third largest sectors were Electronics and ICT Equipment when measured by total sales. Transportation Equipment dominates other industries in terms of total sales because the unit value is high, but the difference is slightly less dramatic in terms of the number of subsidiaries.

B.3.4 Destination Countries of Japanese MNEs

To further support our empirical analysis, we discuss here the strong relationship with respect to foreign direct investment (FDI) from Japan to Thailand. In 2011, Japan was the largest country investing in Thailand, while Thailand was the third largest destination country for Japanese FDI. Therefore, the flooding in Thailand was not only a local shock but also had a non-negligible impact on the Japanese MNEs and their employment as well.

Figure B.8: Top 10 Countries in which Japanese Firms Have Subsidiaries



To confirm the importance of the Japan-Thailand relationship, Figure B.8 shows the top 10 countries in which Japanese firms had subsidiaries in 2007 and 2016. During these 10 years, the ranking of the top five countries did not change (China, U.S., Thailand, Hong Kong, and Singapore), which indicates the stable economic relationship between these countries and Japanese firms. The number of Japanese firms with links to Thailand actually grew during this period.

B.3.5 Balancing Analysis

To check the similarity between the firms that experienced and did not experience flooding, we conduct several balancing tests. Figure B.9 shows the industry distribution of subsidiary manufacturing firms for the group of parent firms that invested in 2011 in the flooded region in Thailand (labeled Thai) and other regions of Thailand and the ROW (labeled Others).

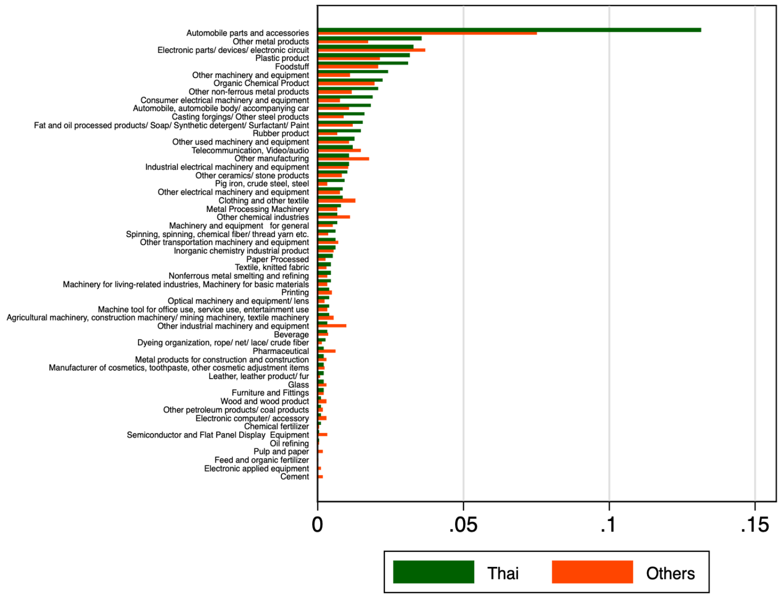
Qualitatively, industries that had many firms in the flooded region of Thailand are likely to also have had a higher number of firms in other countries, but the flooded region had relatively more "Automobile parts and accessories" industry firms relative to other countries.

Figure B.10 shows the estimated distribution of the size of subsidiary firms of the parent firms that invested in the flooded region of Thailand versus other regions. We measure the size by log sales in 2011, and the estimation is a kernel density estimation with an Epanechinikov kernel. At the top of the distribution, the densities of the flooded group (labeled Thai) and the other group (labeled Others) are similar, while at the bottom of the distribution, the Thailand group dominates the Others group. The Kolmogorov-Smirnov test rejects the null hypothesis that the distribution of the two groups is the same.

B.3.6 Other Trends

Complementing the relative aggregate trend analysis in Section 4.1.1, the left and right panels of Figure B.11 show the trends in investment and sales. The red vertical line indicates 2011, the year of the floods. Interestingly, the investment trend in the flooded region and the rest of the world

Figure B.9: Industry Distributions, Flooded Region of Thailand vs Other Regions



follows a parallel path before the flood, but the trend breaks sharply after the flood. Intuitively, this is reasonable because plants in the damaged area would have needed to substantially increase investment to repair flood damage. On the other hand, the sales trend in the right panel does not show a parallel pattern even before the flood.

B.3.7 Choice of Treatment Groups

As described in Section 4.1.1, the flood severely affected *Ayutthaya* and *Pathum Thani* provinces. However, it is important to acknowledge these particular provinces because Thailand overall was relatively unaffected in terms of employment or number of subsidiaries of Japanese MNEs after the flood, as seen in Figure B.12, which shows the trends in employment and number of Japanese subsidiaries inside and outside of Thailand instead of only in the flooded provinces. One can see that the impact on total Thai employment and number of subsidiaries is not as stark as when we compare the flooded provinces versus the rest of the world in Figure 8. Therefore, in our main analysis, we take these two heavily flooded provinces as the shocked regions and construct the IV based on that idea. Note again that, for this purpose, it is critical to link our BSOBA data, which only contains the country information of each Japanese MNE overseas factory, to Orbis BvD that contains specific factory addresses.

B.4 Calibration Details

B.4.1 Estimation of σ

Following recent developments in estimating capital-labor elasticities (Oberfield and Raval, 2014; Raval, 2019), we estimate σ using the regression equation (20). Our coefficient of interest is b_1 since

Figure B.10: Sales Distributions, Flooded Region of Thailand vs Others

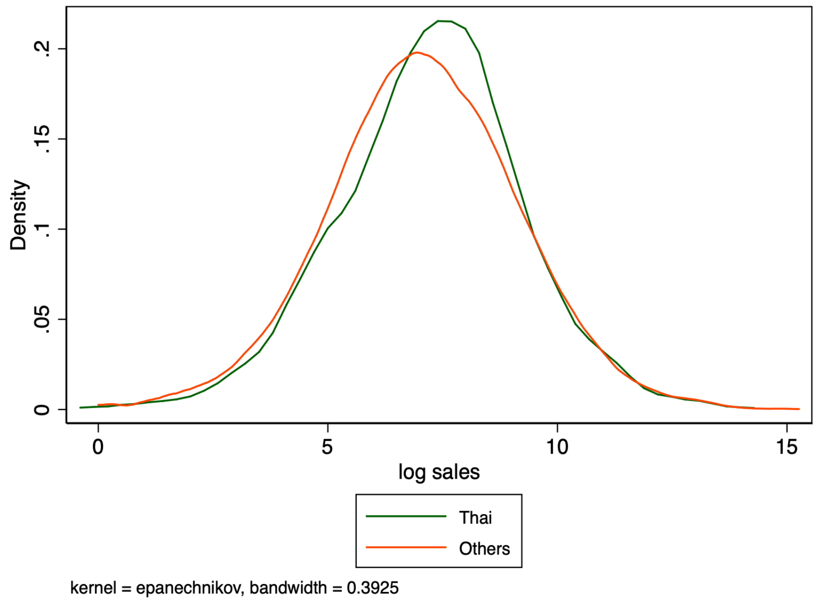
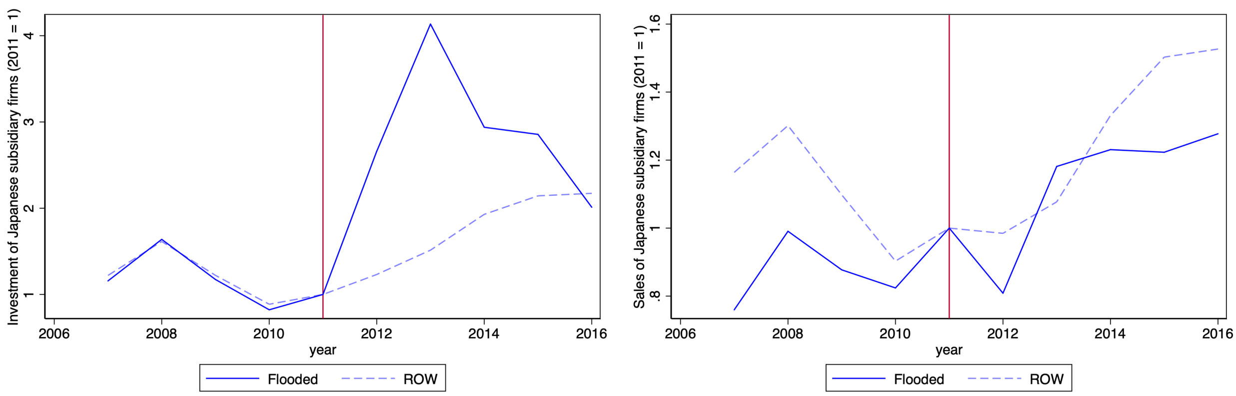


Figure B.11: Relative Trends in Investment and Sales of Japanese MNEs



(a) Investment

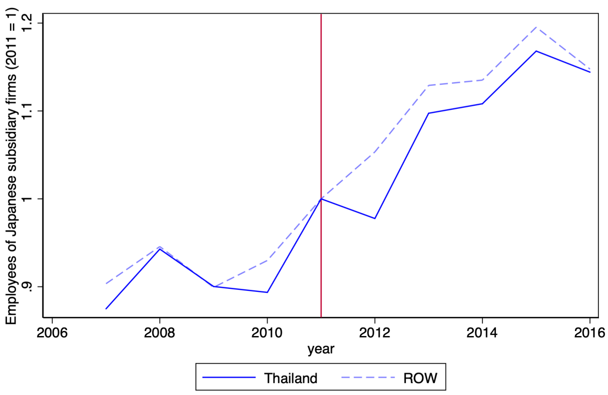
(b) Sales

$\sigma = b_1 + 1$.

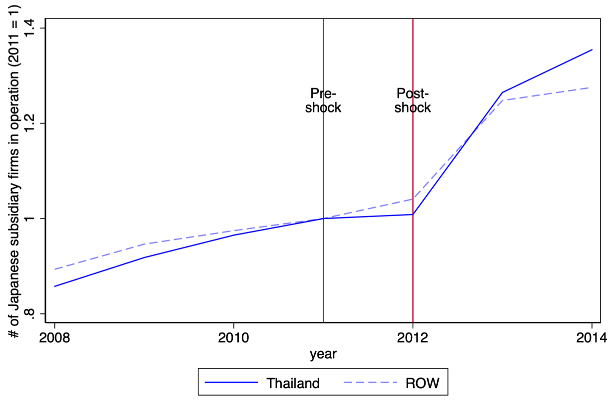
To obtain the factor payment ratio $(rk/wl)_i$, we use the annual *Census of Manufacture* (CoM) survey. For our purposes, we use the initial stock of tangible assets in the next year survey. To obtain the total payment to workers, we use the variable total payroll for all workers, which includes both full-time and part-time workers. Since we can obtain the rental rate of capital at the industry level, it drops with the industry-fixed effect in specification (20). Finally, CoM also offers municipality, 4-digit industry, and multiplant status variables. The multiplant status includes three values: no other plants or headquarter office; no other plant but a headquarter office; has other offices. We include the fixed effect for all of these values in specification (20).

For the local wage, we use the municipality-level wage taken from the long-run economic database of the Japan Cabinet Office. The long-run trend data offers the taxpayer-per-capita tax-

Figure B.12: Trends in Employment and Japanese MNE Subsidiaries, Thailand versus ROW



(a) Total employment



(b) Count of subsidiaries

able income from 1975 to 2013.[40] The municipality unit is as of the last day of April 2014. We convert the municipality code in each analysis year to the one as of April 2014 using *Municipality Map Maker* (Kirimura et al., 2011).

To control the endogeneity in equation (20), we use a shift-share instrument (Bartik, 1991; Goldsmith-Pinkham et al., 2018). Specifically, estimation equation (20) may be biased with the existence of labor-augmenting productivity shocks to locality $m(i)$. If $m(i)$ receives a positive shock, then $w_{m(i)}$ increases and $(rK/wL)_i$ decreases, so β would be negatively biased. To obtain the exogenous shifter that changes $w_{m(i)}$ but not $(rK/wL)_i$ without the influence through $w_{m(i)}$, we take the average of national growth in employment weighted by the base-year employment share of non-manufacturing industries. In particular, from the Employment Status Survey (ESS), we take the ten year growth in employment in industry n as $g_{n,t} = \ln(L_{n,t}/L_{n,t-10})/10$. We then take the base-year industry-n share of employment $\omega_{m,n,t-10}$ in municipality m, and calculate our shift-share instrument by

$$z_{j,t} = \sum_n \omega_{m,n,t-10} g_{n,t}.$$

Table B.2 shows the results of regression (20) for 1997 since it is the nearest year to that of the ESS survey.

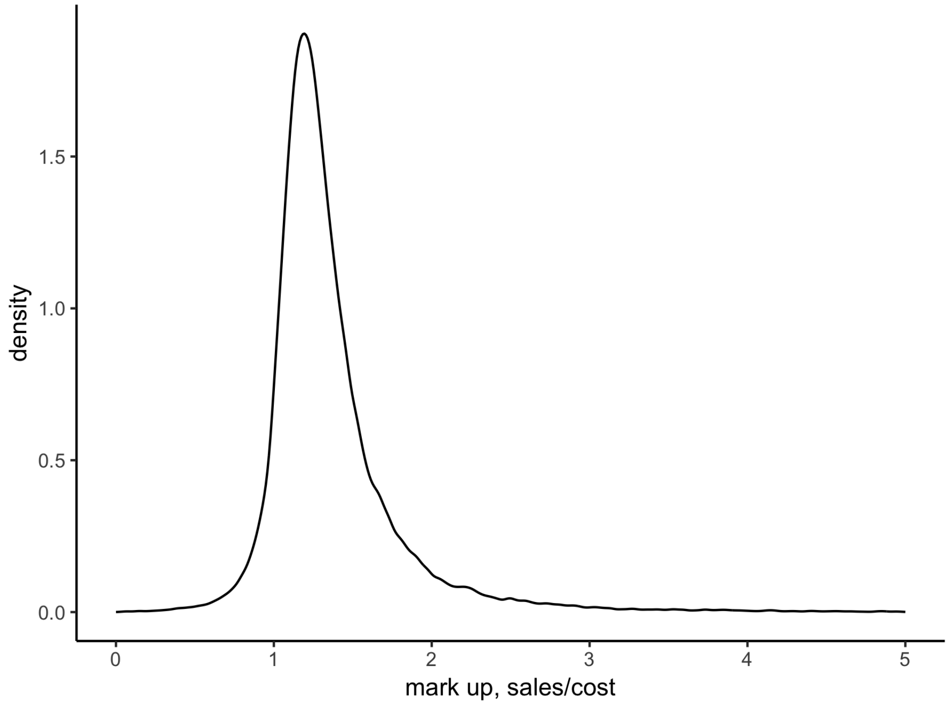
[40]The primary data source of this dataset is the *Survey of Municipality Taxation* administered by Ministry of Internal Affairs and Communications, Japan.

Table B.2: Estimates of $\sigma - 1$

	OLS, CO	OLS, BSWS, all	OLS, BSWS, manuf.	IV, CO	IV, BSWS, all	IV, BSWS, manuf.
$\log(w_{m(i)})$	-0.60^{***}	-0.20^{***}	-0.13^{***}	-1.15^{***}	-1.24^{***}	-0.88^{***}
	(0.05)	(0.04)	(0.03)	(0.18)	(0.18)	(0.13)
Num. obs.	51477	51477	51477	51477	51477	51477

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. CO indicates that the wage data is from the Cabinet Office. BSWS indicates that the wage data is from the Basic Survey of Wage Structures. ”BSWS, all” indicates that the wage variable is taken from all industries, while ”BSWS, manuf.” indicates that the wage variable is taken from manufacturing industries. See the text for detail. All regressions include industry FE and multiunit status indicator. Standard errors are clustered at municipality level.

Figure B.13: Distribution of Measured Markup m



Source: Census of Manufacture, 2011. Estimates are obtained by inverting the markup, following Oberfield and Raval (2014). The markup is defined as sales divided by the sum of costs from capital, labor, and materials.

Comparison to the Literature The central estimate of Oberfield and Raval (2014) was around 0.7. However, this value includes industry-level heterogeneity in substitutability and the caused reallocation mechanism. Oberfield and Raval (2014) reports that plant-level elasticity estimates range from 0.4-0.7 depending on the industry, which is closer to our value. Incorporating heterogeneity into the model is our high-priority next research step.

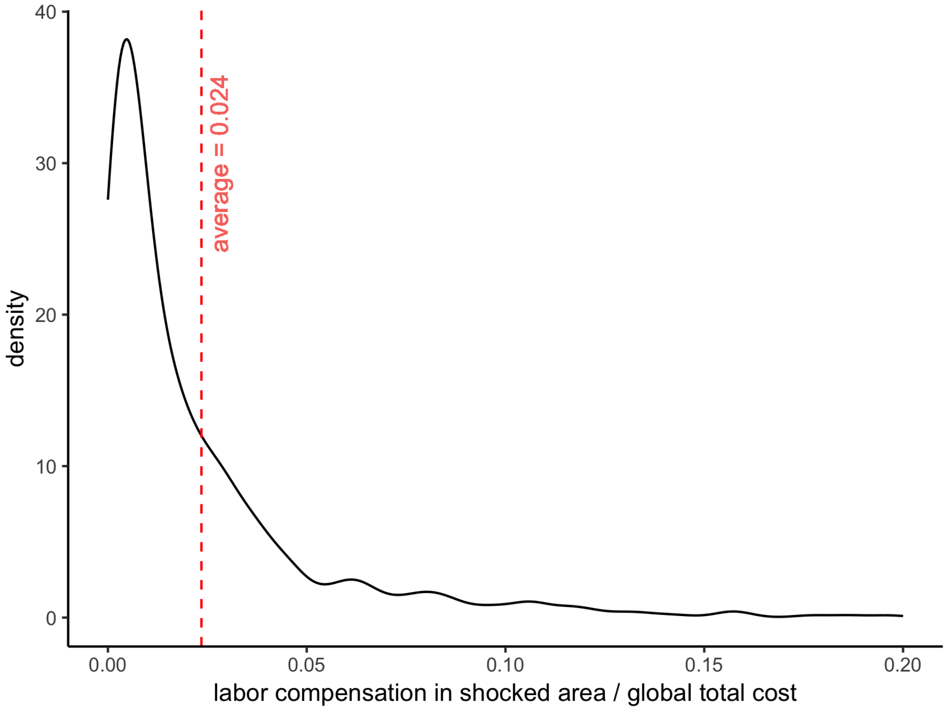
Moreover, the capital-labor substitution parameters at micro and macro-level estimates sometimes disagree. In fact, although microdata-based findings by ourselves and Oberfield and Raval (2014) both point to gross-complementary capital and labor, the macro estimates often indicate that they are gross substitutes (Karabarbounis and Neiman, 2013; Hubmer, 2018). Note that these macro estimates typically rely on U.S. data. In Japan, even at the macro level, Hirakata and Koike (2018) show that the capital-labor elasticity is below one, which is qualitatively consistent with our findings.

B.4.2 Detailed Results regarding ε and CS^M

Figure B.13 shows the distribution of measured markups, which exhibits a spike at a value slightly larger than one and a longer tail on the right side than the left. Our estimate $\varepsilon = 4$ is based on the peak value of measured markup $m = 4/3$, which is standard in the literature (Oberfield and Raval, 2014).

To calculate CS^M at the firm level, global total cost is calculated as the sum of domestic cost and multinational cost. The domestic cost is the sum of the following items: advertising expense, information processing communication cost, mobile real estate rent, packing and transportation costs,

Figure B.14: Share of Foreign Labor Cost in Total Cost CS^M



Note: Global total cost is calculated by the sum of domestic cost and multinational cost, where domestic cost is the sum of the following items: advertising expense, information processing communication cost, mobile real estate rent, packing and transportation costs, total payroll, depreciation expense, welfare expense, taxes, interest expense, and lease payments. The international cost is the sum of each subsidiary's total cost, which is total sales minus total purchases of intermediate goods.

total payroll, depreciation expense, welfare expense, taxes, interest expense, and lease payments. The international cost is the sum of each subsidiary's total costs, which is its total sales minus the total purchase of intermediate goods.

B.5 Delta Method for $se\left(\widehat{\lambda}\right)$

This section derives the standard error estimate of our estimator of λ obtained by

$$\widehat{b_{IV}} = \frac{\left(\sigma - \widehat{\lambda}\right) WS^F + (\varepsilon - \sigma)\, CS^F}{\widehat{\lambda} - 1 + \left(\sigma - \widehat{\lambda}\right) WS^F + (\varepsilon - \sigma)\, CS^F}$$

$$\Leftrightarrow \widehat{\lambda} = \frac{\widehat{b_{IV}}\left(1 - \sigma WS^F + (\sigma - \varepsilon)\, CS^F\right) + \sigma WS^F - (\sigma - \varepsilon)\, CS^F}{\widehat{b_{IV}}\left(1 - WS^F\right) + WS^F}.$$

Recall that a standard argument holds for our standard two-stage least square estimate $\widehat{b}$. Hence, it satisfies $\sqrt{n}\left(\widehat{b} - b_0\right) \to_d N\left(0, \Sigma\right)$ so, by the delta method, we have

$$\sqrt{n}\left(\widehat{\lambda} - \lambda_0\right) \to_d N\left(0, \left(\frac{\varepsilon s_0^F}{b_0^2}\right)^2 \Sigma\right).$$

Thus, in our case, $se\left(\widehat{\lambda}\right) = \left(\varepsilon s_0^F / \widehat{b}^2\right) \sqrt{\widehat{\Sigma}} = \left(4 \times 0.024 / \left(0.19\right)^2\right) \times 0.05 \approx 0.13$. Given our point estimate $\widehat{\lambda} = 1.4$, we can test if $H_0 : \lambda \leq 1$; namely, that home labor and foreign labor are gross complements. As the standard t-value is $t = 0.40/0.13 \approx 3.08$., we reject H_0 at the 0.1 percent level of significance.

B.6 Robustness Checks

B.6.1 Alternative Extensive-Margin Instrument

We consider the following instrumental variable:

$$Z_{it}^{EXT} = \mathbf{1}\left\{ L_{i,2011}^{treated} > 0 \cap t \geq 2012 \right\}. \tag{B.1}$$

The idea is to take the extensive margin of the shock, meaning that a firm located in the flooded region changes employment relative to those in other regions. Table B.3 shows the results and, notably, the estimate for $\widehat{b}_{IV}$ in column 3 here (0.212) is remarkably similar to the 0.192 in column 3 of Table 2. As there is no statistical difference between these two estimates, our result is robust to the choice of IV.

It is also worth noting the reasons underlying the similar estimates. In columns 4 and 5 of Table B.3, we find significantly smaller first stage and reduced-form estimates than the corresponding values in Table 2. This is because we define the shock Z_{it}^{EXT} at the extensive margin taking the binary value of zero or one, which has a larger variance than $Z_{it} \in [0, 1]$ in equation (22), and this larger variance in the regressor results in smaller estimates in columns 4 and 5. This signifies our choice of target reduced-form parameter (18); since we do not know the exact size of the flood shock, we do not have a precise measure of its size. Therefore, arbitrary definitions of the shocks such as (22) or (B.1) would result in quantitatively different estimates of equations (15) and (16), recalling that they are *proportionally* corresponding to columns 4 and 5 up to the choice of the shock measure or IV. Our choice of the target parameter (18), however, does not depend on such a choice. Specifically, as can be seen in the 2SLS formula, the variance of the instrument does not affect the estimator, but the *relative* covariance of the regressand and regressor does. Therefore, our 2SLS produces stable and robust estimates.

B.6.2 Different Control Groups

In our main specification, we consider only MNEs in our sample, a choice that is justified because MNE and non-MNE firms differ substantially, and also because the inclusion of fixed effects in regression equations (23) and (24) makes the variation in the IV for firms that are never MNEs irrelevant since then $Z_{it} = 0$ for any t by definition (22), which is absorbed by the fixed effect. However, to ensure that the home employment trend did not differ significantly between MNEs and non-MNEs, Table B.4 shows the reduced form of 2SLS (23) and (24) with different control groups. Formally, the specification is

$$\ln\left(l_{it}^{JPN}\right) = a_i^{robustness} + a_t^{robustness} + b^{robustness} Z_{it} + e_{it}^{robustness},$$

Table B.3: Extensive Margin Estimates

VARIABLES	(1) $\ln l_{it}^{JPN}$	(2) $\ln l_{it}^{JPN}$	(3) $\ln l_{it}^{JPN}$	(4) $\ln l_{it}^{ROW}$	(5) $\ln l_{it}^{JPN}$
$\ln l_{ft}^{ROW}$	0.284***	0.0271***	0.212**		
	(0.00394)	(0.00435)	(0.0921)		
Z_{ft}				-0.321***	-0.0681**
				(0.0854)	(0.0291)
Observations	22,795	22,795	22,795	22,795	22,795
Model	OLS	FE	2SLS	2SLS-1st	2SLS-reduced
Firm FE	-	YES	YES	YES	YES
Year FE	-	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

with different samples and different IV definitions.

Columns 1-4 show the results including all firms in Japan. Then, since our data is an unbalanced panel, we select firms that are observed throughout the period 2007-2016 to construct a balanced panel, and columns 5-8 show these results. Columns 1 and 2 show the results based on the IV Z_{it}^{EXT} defined in equation (B.1) (labeled "extensive"), and columns 3 and 4 show Z_{it} in equation (22) (labeled "intensive"). Note that both of these IVs leverage the shock induced by the 2011 Thailand Floods, though the precise definition differs. Column 1 defines the flooded region as Ayutthaya and Pathum Thani provinces, which is our preferred definition (labeled "Flooded"), while column 2 defines the flooded area as all of Thailand (labeled "Thailand"). The other columns show the results based on the specifications following this basic structure. The table shows that a robust result is obtained irrespective of the choice of sample and IV definition; that is, the flood-affected firms *reduced* employment in the home country, Japan.

Table B.4: Different Reduced Form Specifications

VARIABLES	(1) Extensive Flooded	(2) Extensive Thailand	(3) Intensive Flooded	(4) Intensive Thailand	(5) Extensive Flooded	(6) Extensive Thailand	(7) Intensive Flooded	(8) Intensive Thailand
shock	-0.0497***	-0.0159***	-0.172***	-0.127***	-0.0490***	-0.00747	-0.249***	-0.101***
	(0.0126)	(0.00585)	(0.0667)	(0.0242)	(0.0139)	(0.00612)	(0.0774)	(0.0248)
Observations	185,703	185,703	185,703	185,703	91,690	91,690	91,690	91,690
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Balanced panel?					YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Indeed, it is crucial to have the IV defined according to the flood-induced variation, despite minor differences in definitions between equations (22) and (B.1). In Section B.7.1, we see that another widely-used IV definition, the Bartik instrument, does not work in our context, which highlights our choice based on the natural experiment and its power of identification.

B.6.3 The 2011 Tohoku Earthquake

As another check of the robustness of our results, we now consider the potential impact on our results of the 2011 Tohoku Earthquake, another severe natural disaster that affected Japanese industry that year. It's impact on the country was so profound that it remains in the minds of Japanese today almost a decade later. Carvalho et al. (2016) summarizes the event as follows: "On March 11, 2011, a magnitude 9.0 earthquake occurred off the northeast coast of Japan. This was the largest earthquake in the history of Japan and the fifth largest in the world since 1900. The earthquake brought a three-fold impact on the residents of northeast Japan: (i) the main earthquake and its aftershocks, directly responsible for much of the material damage that ensued; (ii) the resulting tsunami, which flooded 561 square kilometers of the northeast coastline; and (iii) the failure of the Fukushima Dai-ichi Nuclear Power Plant that led to the evacuation of 99,000 residents of the Fukushima prefecture."

Since our data is annual and the flooding in Thailand began about four months after the earthquake in Japan, we want to ensure that our results using the Thai Floods as a natural experiment are not qualitatively affected by the co-ocurrence of the Tohoku earthquake that same year. There are two ways to address this concern. First, our specifications (23) and (24) include the fixed effects of firms, which means that we are leveraging the variation within a firm across years, not the differences between firms that may or may not have experienced the earthquake. Second, in order to further mitigate any concern that the existence of flooded firms in the main sample still biases the fixed effect estimator, we conduct the following robustness check exercise. We drop firms located in the four most severely hit prefectures in Japan–Aomori, Iwate, Miyagi, and Fukushima (called "damaged prefectures" below). These damaged prefectures include 36 municipalities that were designated as disaster areas by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) of Japan after the earthquake, and this is also used by Carvalho et al. (2016), which an interested reader may refer to for the rationale.[41]

Table B.5 shows the results of the 2SLS regression based on equations (23) and (24) for the sample that omits firms in the damaged prefectures. We do not find any statistically significant difference in the estimates between the two samples, which is expected given the similar samples considered. Further, because the 2011 Tohoku Earthquake hit the more rural northeast regions of Japan most severely while firms that intensively engage in FDI and multinational activities are skewed to large cities such as the Tokyo and Osaka metropolitan areas, dropping the firms that suffered from the

[41] Although the propagation of the shock due to the input-output linkages makes it not trivial to measure the exact impact of the earthquake on each firm, we view our choice as a conservative test for the existence of an earthquake effect on our estimator. Namely, since the firms located in the defined four prefectures suffered most from the earthquake, if there are any confounding effects of the earthquake on our estimator, dropping such firms should substantially alter the estimate. Thus, if we find no difference between our full sample and the sample omitting these four prefectures, this indicates that any potential earthquake effects are not significant.

Table B.5: Specification Without Earthquake-hit Firms

VARIABLES	(1) $\ln l_{it}^{JPN}$	(2) $\ln l_{it}^{JPN}$	(3) $\ln l_{it}^{JPN}$	(4) $\ln l_{it}^{ROW}$	(5) $\ln l_{it}^{JPN}$
$\ln l_{it}^{ROW}$	0.448***	0.0601***	0.192***		
	(0.00684)	(0.0107)	(0.0502)		
Z_{it}				-0.730***	-0.140***
				(0.108)	(0.0368)
Observations	5,551	5,551	5,551	5,551	5,551
Model	OLS	FE	2SLS	2SLS-1st	2SLS-reduced
Firm FE	-	YES	YES	YES	YES
Year FE	-	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

earthquake did not substantially alter our original estimation sample of multinational firms. Consequently, we find similar estimates in Tables 2 and B.5, which indicates that the effect of the 2011 Tohoku Earthquake on our estimate is limited at most.

B.6.4 Other Measures of Foreign Factors

In our main empirical specification, we use foreign labor employment as the measure of the foreign factor due to the data limitation that other factor employment quantities are difficult to measure and not readily available. However, our model shows that the foreign factor is more general than just labor employment. For example, the foreign factor may contain foreign capital and land that produce additional value added to the output of the MNE from country H. To capture this feature of the model, we now consider the value added measure by subtracting the value of all intermediate good purchases from the total sales of each subsidiary. We then aggregate these subsidiary-level sales for each MNE to construct the MNE-level foreign value added measure VA_{it}^{ROW}. Then we conduct the regression with specification

$$\ln\left(l_{it}^{JPN}\right) = a_i^{VA} + a_t^{VA} + b^{VA}\ln\left(VA_{it}^{ROW}\right) + e_{it}^{VA}. \tag{B.2}$$

As an additional check, we also substitute a raw sales measure for the value added measure. Here, we construct the flood shock-based IV as in the main text, but with our value added measure instead:

$$Z_{it}^{VA} = \frac{VA_{i,2011}^{flooded}}{VA_{i,2011}^{JPN} + VA_{i,2011}^{ROW}} \times \mathbf{1}\left\{t \geq 2012\right\}. \tag{B.3}$$

Since both IVs (22) and (B.3) satisfy the standard requirements for IVs under our maintained assumption that the flood was an unexpected augmentation shock to the MNEs located in the damaged region, we conduct the robustness exercise based on both definitions.

Tables B.6 and B.7 show the results from our VA-based regressor specification (B.2) using our

Table B.6: VA-based Regressor with IV (22)

VARIABLES	(1) $\ln VA_{it}^{ROW}$	(2) $\ln l_{it}^{JPN}$	(3) $\ln l_{it}^{JPN}$	(4) $\ln sales_{it}^{ROW}$	(5) $\ln l_{it}^{JPN}$
Z_{it}	-0.762***	-0.132***		-0.549***	
	(0.105)	(0.0374)		(0.0849)	
$\ln(VA_{it}^{ROW})$			0.173***		
			(0.0494)		
$\ln(sales_{it}^{ROW})$					0.240***
					(0.0685)
Observations	5,460	5,460	5,460	5,460	5,460
Model	2SLS-1st	2SLS-reduced	2SLS	2SLS-1st	2SLS
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

preferred IV (22) and the IV defined by equation (B.3), respectively. Both tables share the same structure; Columns 1-3 show the results using VA_{it}^{ROW} as the regressor, while columns 4 and 5 use the raw sales measure. Columns 1 and 4 show the first stage results to check the relevance of the IV, and column 2 shows the reduced form relating the IV to the outcome variable. Note that the value added and crude sales regressors share the same reduced form. Finally, columns 3 and 5 show the 2SLS results, and particularly worth mentioning is that they are all qualitatively similar *no matter what regressors and IVs were used*. Therefore, we view our preferred result reported in Table 2 as robust to the choice both of variables for foreign factor employment and IVs.

B.6.5 Long-difference Specification

Our main empirical specification (23) and (24) is meant to identify the medium- to long-run elasticity for five years after the flood. Another way to approach this is to conduct a long-difference specification by taking the difference between variables after the flood and before:

$$\Delta \ln\left(l_i^{JPN}\right) = a^{LD} + b^{LD} \Delta \ln\left(l_i^{ROW}\right) + \Delta e_i^{LD},$$

where the time difference Δ takes the difference between the 2012-2016 average after the flood and the 2007-2011 average before the flood. We instrument the regression with the long-difference IV

$$\Delta Z_i = \frac{l_{i,2011}^{flooded}}{l_{i,2011}^{JPN} + l_{i,2011}^{ROW}}.$$

The results are shown in Table B.8, with column 1 the 2SLS first stage, column 2 the 2SLS reduced form, and column 3 the 2SLS result. Although the sample size reduced significantly due to time-averaging, the qualitative result of the regressions remain the same as in Table 2: strong first-stage

Table B.7: VA-based Regressor with IV (B.3)

VARIABLES	(1) $\ln VA_{it}^{ROW}$	(2) $\ln l_{it}^{JPN}$	(3) $\ln l_{it}^{JPN}$	(4) $\ln sales_{it}^{ROW}$	(5) $\ln l_{it}^{JPN}$
Z_{it}^{VA}	-0.957***	-0.144*		-0.791***	
	(0.210)	(0.0749)		(0.173)	
$\ln(VA_{it}^{ROW})$			0.173***		
			(0.0494)		
$\ln(sales_{it}^{ROW})$					0.183**
					(0.0846)
Observations	5,460	5,460	5,460	5,460	5,460
Model	2SLS-1st	2SLS-reduced	2SLS	2SLS-1st	2SLS
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.8: Long-difference Specification

VARIABLES	(1) $\Delta \ln l_i^{ROW}$	(2) $\ln \Delta l_i^{JPN}$	(3) $\ln \Delta l_i^{JPN}$
ΔZ_i	-0.731***	-0.121**	
	(0.159)	(0.0570)	
$\Delta \ln l_i^{ROW}$			0.165**
			(0.0787)
Observations	674	674	674
Model	2SLS-1st	2SLS-reduced	2SLS

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

correlation (column 1), weaker but significant negative correlation in the reduced form (column 2), and the positively significant 2SLS estimate (column 3) which is not significantly different from the preferred 2SLS estimate (column 3 of Table 2).

B.7 Further Empirical Results

Next, we conduct several extension exercises of the linear regression results discussed in Section 4.2.2.

B.7.1 Shift-share-type Instrument and Identifying the Substitution Elasticity

Hummels et al. (2014) considers a type of offshoring whereby a firm does not hire foreign factors directly but imports the intermediate good instead of producing it in the home country, which we call *output offshoring*. Our concern, however, is multinational firms' foreign employment, or *factor* *offshoring*. The firm-level specification of Hummels et al. (2014) is

$$\ln l_{it} = a_i^{HJMX} + a_t^{HJMX} + b^{HJMX} \ln m_{it} + e_{it}^{HJMX},$$

where l_{it} is firm f's employment in year t and m_{it} is the value of offshoring, measured by the value of imports.[42] They address the endogenous offshoring value by adopting the shift-share instrument at the country and product level,

$$I_{it} = \sum_{c,k} s_{ick} I_{ckt},$$

where s_{ick} is the pre-sample year (1994) share of the country c-product k pair in total material imports of firm f, and I_{ckt} is a world export shifter such as world export supply or transport costs of country c, product k, in year t.

Analogously, in our *factor offshoring* framework, the relevant regression is

$$\ln l_{it}^{JPN} = a_i^{FO} + a_t^{FO} + b^{FO} \ln l_{it}^{ROW} + e_{ft}^{FO}, \tag{B.4}$$

where l_{it}^{ROW} is employment of offshore workers and the instrument is

$$I_{it}^{ROW} = \sum_{c} s_{ic}^{O} L_{ct}^{ROW},$$

where s_c^O is the pre-sample year (in our case, 2007) share of offshore employment in country c of firm i, and $emp_{ct}^{O,-JPN}$ is the stock of workers at subsidiaries of multinational firms excluding those in Japan. However, as we do not find a relevant measure for L_{ct}^{ROW}, we need a proxy for that.

Note that Desai et al. (2009) takes the GDP growth rate in each country as the instrumental variable, based on the idea that "national economic growth is associated with productivity gains that correspond to declining real input costs" (p. 186). A problem that one can imagine with this proxy is that the GDP growth rate does not necessarily reflect the offshorability or availability of offshore factors in the destination country. For example, the GDP growth rate might not reflect political instability (Pierce and Schott, 2016). If a country has high growth but high political instability that makes employment difficult for multinational firms, then GDP growth might overstate the actual ability to offshore in the country. Moreover, the Desai et al. (2009) measure is the GDP growth rate rather than the level of GDP, whereas Hummels et al. (2014) take world trade value levels to construct the instrumental variable. With these cautions in mind, we calculate the instrumental variable as follows:

$$\tilde{I}_{it}^{ROW} = \sum_{c} s_{ic}^{O} g_{ct},$$

where g_{ct} is the GDP growth rate of country c from year $t-1$ to year t.

While Hummels et al. (2014) find a statistically significant substitution of home labor with the foreign imported intermediate input, in contrast, we do not find a similar substitution result (Table

[42]More specifically, this corresponds to the row named "log employment," with point coefficient 0.044 in Table 3, Column 2 ofHummels et al. (2014).

Table B.9: Results with GDP Growth-based Bartik Instruments

VARIABLES	(1) OLS	(2) FE	(3) 2SLS	(4) 2SLS first stage	(5) 2SLS reduced form
Log Subsidiary Employment	0.304***	0.0314***	0.0770		
	(0.00364)	(0.00245)	(0.0896)		
Shift-share Shock				0.435***	0.0335
				(0.123)	(0.0388)
Observations	20,317	20,317	20,317	20,317	20,317
Firm FE		YES	YES	YES	YES
Year FE		YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B.9). This highlights the difficulty in using a Bartik-type instrument to identify the effect of factor-usage offshorability on home employment, as we emphasized in the beginning of Section 4.

B.7.2 Long-run Impact on Foreign Employment

In our main specification (23) and (24), we consider the average long-run, but not time-varying, impacts. As we saw in Figure 8, the flood had long-lasting effects on employment in Thailand, so to see if this is true at the firm-level of those affected by the flood, we consider the following event-study regression:

$$y_{it} = a_i^{ES} + a_t^{ES} + \sum_{\tau \neq 2011} b_\tau^{ES} \frac{l_{i,2011}^{flooded}}{l_{i,2011}^{JPN} + l_{i,2011}^{ROW}} \times \mathbf{1}\{t = \tau\} + e_{it}^{ES}. \tag{B.5}$$

Figure B.15 shows the event-study plots of b_t^{ES},which confirm that the effect of the flood persisted for at least five years in terms of foreign employment.

We next turn to the long-run effect on Home employment. Namely, we take log employment in Japan as y_{it} and run regression (B.5), with the results shown in Figure B.16. Consistent with the reduced form results of our main specification in Table 2, we find significantly negative effects four years after the flood at the 5 percent significance level. We can also confirm that the pre-trends are balanced since no coefficient before the year of the flood is statistically significantly different from zero. In 2016, the coefficient is negative but only marginally different from zero (significant only at the 10 percent level). This reversion to zero may imply recovery from the flood for the firms that were severely hit. However, even in the Home country (Japan), the recovery in terms of employment took at least five years after the flood. In a nutshell, the event-study analysis supports our interpretation of the shock as having a medium-run impact on worldwide factor employment by affected firms.

Figure B.15: Results of Event Study Regression on Foreign Employment

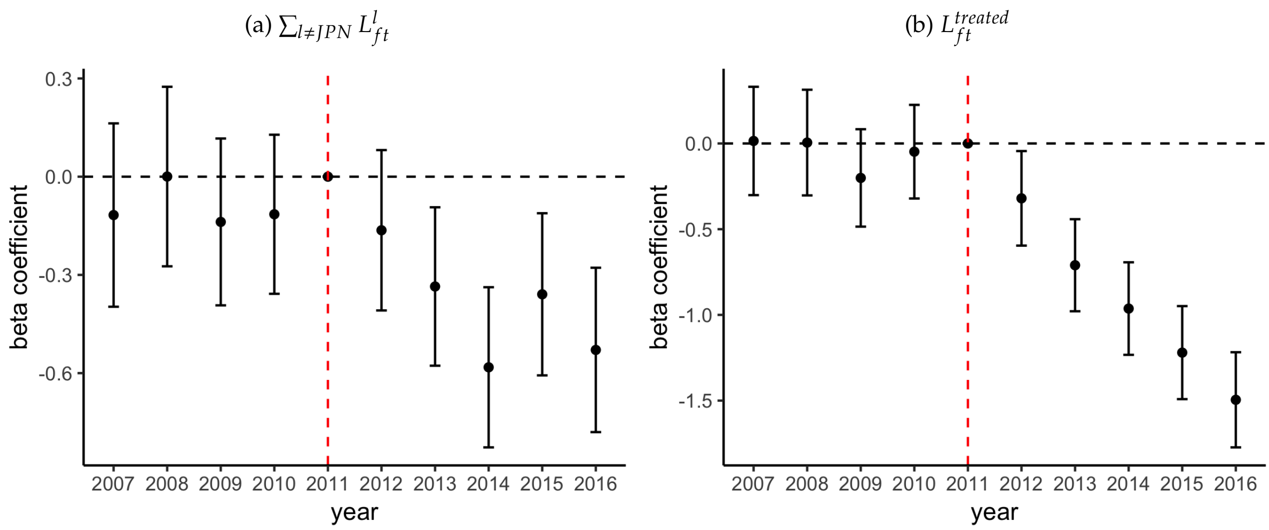
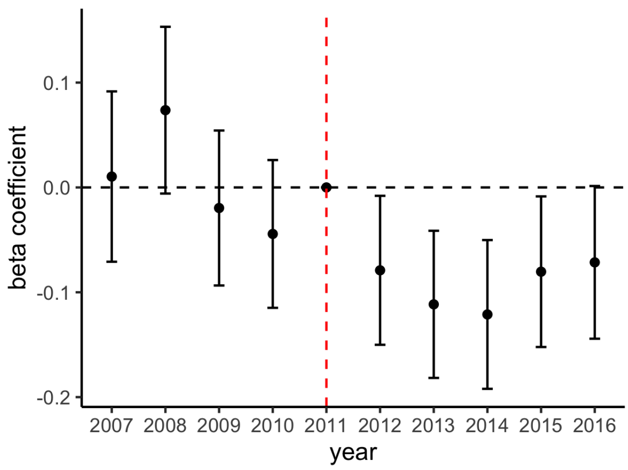


Figure B.16: Results of Event Study Regression on Home Employment

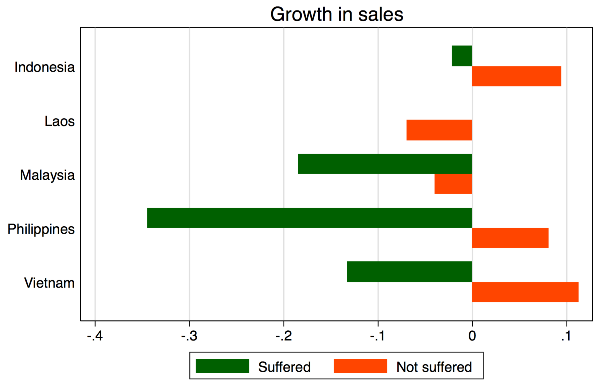


B.7.3 Third Country Substitution

Where do subsidiaries substitute production after the flood? To answer this in a brief manner, we can observe the sales growth of subsidiaries in nearby countries (Indonesia, Laos, Malaysia, Philippines, and Vietnam) between 2011 and 2012 for those firms affected and unaffected by the flooding. If production substitution occurred in nearby countries, then the MNEs affected by the floods would increase sales in nearby countries relative to unaffected MNEs. Figure B.17 shows the sales growth rates of foreign subsidiaries in each country near Thailand for those MNEs with subsidiaries in Thailand (labeled as "suffered") and those without (labeled as "not suffered"). As one can see, for all countries except Laos, there is no relative increase in sales for firms hit by the flooding. Therefore, on average, production substitution to nearby countries did not occur very strongly, which supports the validity of our main analysis of production substitution between Japan and Thailand.

To more formally and systematically study the substitution after the flood, we conduct the same regression specification as in the main text with a modified coefficient notation to indicate Third

Figure B.17: Growth in Sales Across Firms Located in Thailand in 2011 or Not



Country Substitution (TCS):

$$y_{it} = a_i^{TCS} + a_t^{TCS} + b^{TCS} Z_{it} + e_{it}^{TCS}, \tag{B.6}$$

and also with the outcome variable about operations in third countries. Specifically, we take as an outcome variable log employment in Southeast Asian countries other than Thailand (Myanmar, Malaysia, Singapore, Indonesia, Phillipines, Cambodia, Laos, with notation emp_{it}^{SEA}), log employment in the world other than in Thailand and Japan (emp_{it}^{World}), log sales in Southeast Asian countries other than Thailand ($sales_{it}^{SEA}$), and log sales in the world other than in Thailand and Japan ($sales_{it}^{World}$). To best control any unobserved subsidiary heterogeneity, we restrict the sample to subsidiaries located in Thailand, and compare the headquarters that have subsidiaries in the flooded regions versus those that do not, using our IV Z_{it}. If third country substitution were significant, we would observe the positive coefficient $b^{TCS} > 0$.

Table B.10 shows the results of regression (B.6), and throughout columns 1-4, we do not find positive substitution from the flooded regions to non-flooded third countries. Perhaps surprisingly, we do find some strong *negative* effects on third country employment and sales. In fact, this is consistent with our interpretation that the flood decreased overall productivity of the affected MNEs, so that they decreased factor employment and sales *everywhere* in the world, including third countries and Japan. Recall that this productivity effect could be seen in our main regression result 2.

B.7.4 Regression by Industries

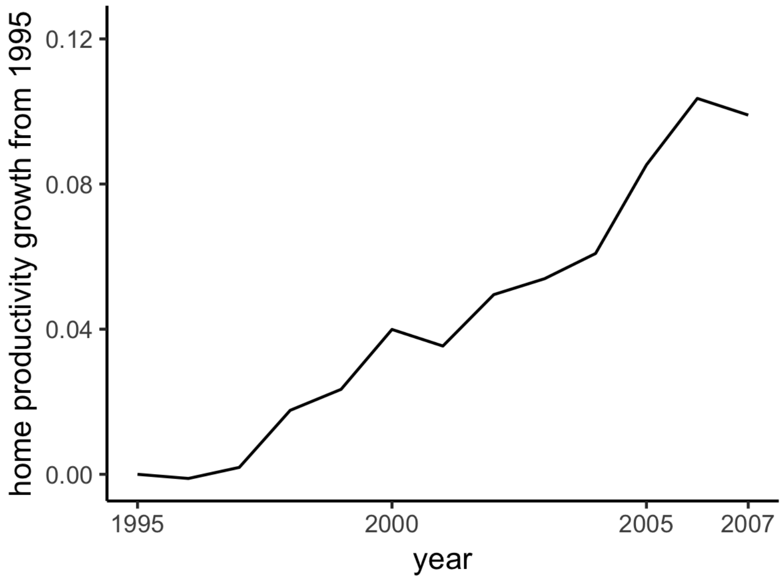
Table B.11 shows the results of the headquarter industry-regression for specification (22) and (B.1), with panel B.11a showing the 2SLS results and B.12b and B.12c showing the corresponding first stage and reduced-form regressions. In each panel, column 1 refers to the aggregated manufacturing sector and columns 2-6 the Chemical, Metal, General Machinery, Electronic Machinery, and Automobile industries, respectively.

Table B.10: Third Country Substitution

VARIABLES	(1) $\ln emp_{it}^{SEA}$	(2) $\ln emp_{it}^{World}$	(3) $\ln sales_{it}^{SEA}$	(4) $\ln sales_{it}^{World}$
Z_{it}	0.443	-1.039***	-0.600**	-0.951***
	(0.354)	(0.270)	(0.253)	(0.184)
Observations	2,434	5,549	2,364	5,489
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure C.1: Evolution of $d \ln a^L$



C Quantification Appendix

C.1 Calibration Details

C.1.1 Home Labor Productivity Growth since 1995

Figure C.1 shows the evolution of $d \ln a_t^L \approx \ln a_t^L - \ln a_{1995}^L$, with the base year 1995. Although labor productivity in Japan has grown somewhat since 1995, it is less than the foreign productivity growth shown in the left panel of Figure 9, with foreign factor productivity growing by more than three log points from 1995 to 2007 while labor productivity in Japan grew only by 0.1 log point. This is consistent with our interpretation of foreign factor augmentation; that is, that over the period, other countries grew relatively more quickly than Japan due to relatively faster technological growth and several international trade liberalization events such as China's entry into the WTO.

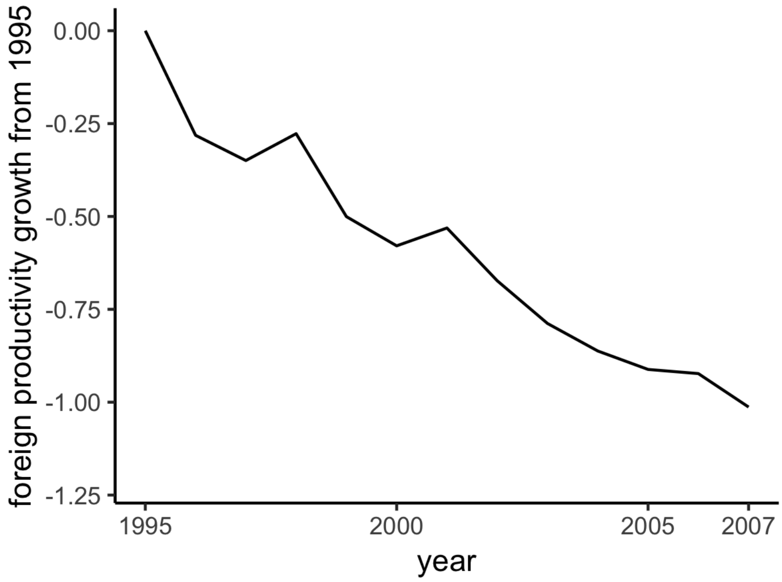


Figure C.2: Implied a^M Trend When $\lambda = \sigma = 0.2$

C.1.2 Factor-bias and Implied Factor Augmentation

Here we provide additional suggestive evidence that λ is likely to be greater than one, which indicates that foreign factor augmentation is foreign factor-*biased* technological change. Note that relative aggregate employment L^F/L^H and wages w^F/w^H increased over the period of interest. Then $\lambda < 1$ would imply that our model inversion

$$\frac{a_t^M}{a_t^L} = \left(\frac{M_t}{L_t}\right)^{\frac{1}{\lambda-1}} \left(\frac{p_t^M}{w_t}\right)^{\frac{\lambda}{\lambda-1}}$$

means *decreasing* relative foreign productivity. As a numerical example, Figure C.2 shows $d\ln\left(a_t^M/a_t^L\right) = d\ln a_t^M - d\ln a_t^L$ when $\lambda = 0.2\,(=\sigma)$. Therefore, $\lambda < 1$ would imply observed relative foreign factor *compression* over the period 1995-2007.

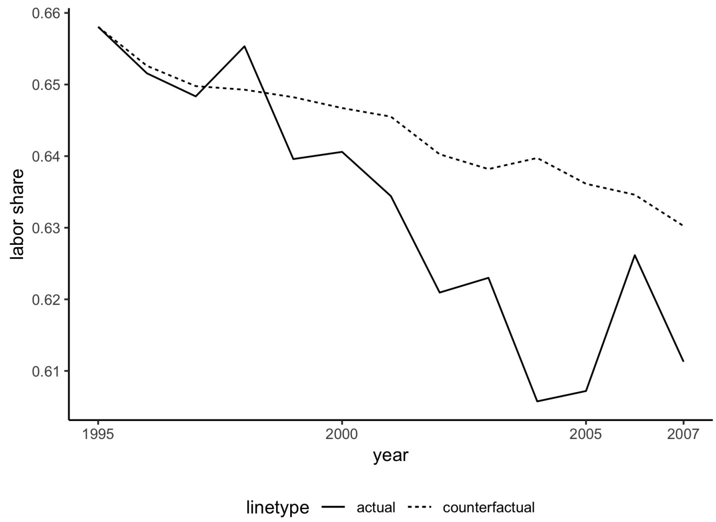
C.1.3 Sensitivity to Parameters

Our numerical results in Section 5.1 are sensitive to parameter values λ and σ, as we show some implied counterfactual results for different values in Figure C.3.

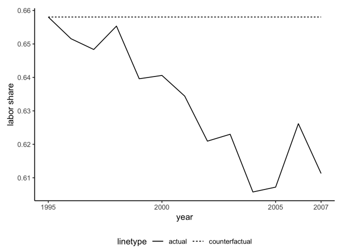
C.2 Implications of a More Recent Trend, 1995-2015

The 2008SNA from the Japan Cabinet Office provides System of National Accounts (SNA) data for 1994-2015. The 2008SNA introduced many modifications to the previous SNAs, among them the capitalization of Research and Development (R&D) expenditures which, for our purposes, bumps up value added and drives down labor share.

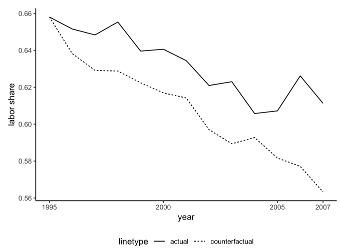
Figure C.3: Sensitivity Analysis to Parameter Values λ and σ



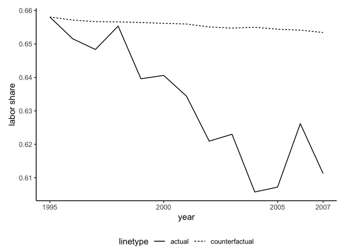
(a) (Preferred Calibration) $\lambda = 1.4, \sigma = 0.2$



(b) $\lambda = \sigma = 0.2$



(c) $\lambda \to 1, \sigma = 0.2$

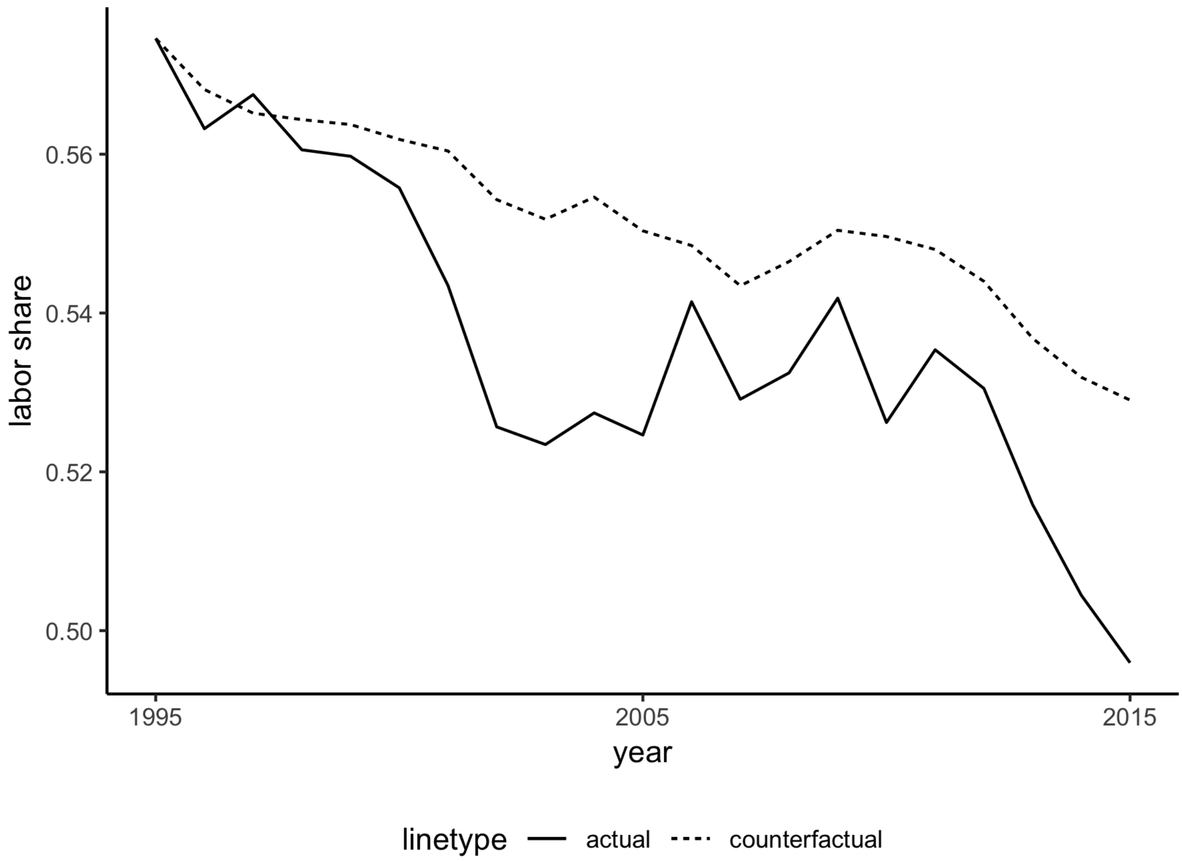


(d) $\lambda = 1.4, \sigma = 0.7$

Another qualification regarding the use of the more recent trend is the Great Recession that began in 2008 which empirically shows a halt in the reduction in labor share in the mid 2000s that is consistent with a widely found fact that labor share is countercyclical (Schneider, 2011). Since our focus is the structural change in foreign factor augmentation, we do not emphasize this period, but as described below, our mechanism of *relative* factor substitution of labor might help to explain this countercyclicality.

Figure C.4 shows the actual and counterfactual labor share trends derived by the same exercise as in Figure 10b. As mentioned above, while labor share has generally been decreasing, there was a halt in the decline in the mid 2000s to early 2010s. Remarkably, the counterfactual trend shows a similar pattern of an overall decline that paused during the Great Recession. To understand this, recall that an important factor driving the changes in the counterfactual trend is the observed foreign factor augmentation (e.g., equation (25)), which is backed out by relative foreign employment and wages. To the extent that during the Great Recession globalization halted and MNE multinational activities stalled, the measured foreign factor augmentation process slowed down and even reversed, which is consistent with the slow-down and increase in counterfactual labor share seen in Figure C.4. Although we do not centralize this hypothesis in the current paper, a more thorough examination of the validity of attributing the countercyclicality in labor share to the countercyclicality of globaliza-

Figure C.4: Actual and Counterfactual Labor Shares, 1995-2015



tion would be a promising future research project. Finally, from the quantitative analysis, we find that during period 1995-2015, 57.9 percent of the decrease in the labor share may be explained by increased productivity of foreign factors.

C.3 Standard Errors of the Method of Moments Estimator

To find the standard errors of the method of moments estimator given by (9), we refer to Greene (2003), Section 13.2.2, and conclude that

$$\sqrt{n}\left(\widehat{\sigma}-\sigma_0\right) \rightarrow_d N\left(0, \left[\Gamma\left(\sigma_0\right)\right]^{-1} \Phi \left[\Gamma\left(\sigma_0\right)\right]^{-1}\right) \tag{C.1}$$

under a set of regularity conditions, where n is the sample size, $\sigma \equiv \left(\sigma_{\widetilde{kp^M}}, \sigma_{\widetilde{lp^M}}\right)'$ is the vector of target parameters, σ_0 is the true value and $\widehat{\sigma}$ is the estimator implied by the sample analog of equation (9). Furthermore, the 2×2 matrices $\Gamma\left(\sigma\right)$ and Φ's are such that

$$\sqrt{n}\left(\frac{1}{n}\sum_i Z_i \boldsymbol{a}_i\left(\sigma_0\right)\right) \rightarrow_d N\left(0, \Phi\right),$$

$$\frac{1}{n}\sum_i Z_i \nabla_\sigma \boldsymbol{a}_i\left(\sigma\right) \rightarrow_p \Gamma\left(\sigma\right),$$

for any σ, where n is the effective sample size after removal of fixed effects, $\boldsymbol{a}_i(\sigma) = \left(d\ln a_i^K(\sigma), d\ln a_i^L(\sigma)\right)'$ and the dependence on σ is given by equations (10), (11), and Assumption 2. To learn more about $\nabla_\sigma \boldsymbol{a}_i(\sigma)$, recall that the derivative of the inverse matrix is given by

$$\frac{\partial}{\partial\sigma_{\widetilde{kp^M}}}\left(I+\Sigma_i(\sigma)\right)^{-1} = -\left(I+\Sigma_i(\sigma)\right)^{-1}\mathbf{0}_{(1,3)}\left(I+\Sigma_i(\sigma)\right)^{-1}$$

where $\mathbf{0}_{(i,j)}$ is the 3×3 matrix filled with one in its (i,j) element and zeros elsewhere. Note also that

$$\begin{aligned} 0 = \frac{\partial}{\partial\sigma_{\widetilde{kp^M}}}I &= \frac{\partial}{\partial\sigma_{\widetilde{kp^M}}}\left[\left(I+\Sigma_i(\sigma)\right)\left(I+\Sigma_i(\sigma)\right)^{-1}\right] \\ &= \left[\frac{\partial}{\partial\sigma_{\widetilde{kp^M}}}\left(I+\Sigma_i(\sigma)\right)\right]\left(I+\Sigma_i(\sigma)\right)^{-1} + \left(I+\Sigma_i(\sigma)\right)\left[\frac{\partial}{\partial\sigma_{\widetilde{kp^M}}}\left(I+\Sigma_i(\sigma)\right)^{-1}\right]. \end{aligned}$$

Using these, we may solve

$$\nabla_\sigma \boldsymbol{a}_i(\sigma) = \left(\frac{\partial}{\partial\sigma_{\widetilde{kp^M}}}\boldsymbol{a}_i(\sigma), \frac{\partial}{\partial\sigma_{\widetilde{lp^M}}}\boldsymbol{a}_i(\sigma)\right)$$

and

$$\begin{aligned} \frac{\partial}{\partial\sigma_{\widetilde{kp^M}}}\boldsymbol{a}_i(\sigma) &= I_{-(3,\cdot)}\left(I+\Sigma_i(\sigma)\right)^{-1}\mathbf{0}_{(1,3)}\left(I+\Sigma_i(\sigma)\right)^{-1}\boldsymbol{p}_i, \\ \frac{\partial}{\partial\sigma_{\widetilde{lp^M}}}\boldsymbol{a}_i(\sigma) &= I_{-(3,\cdot)}\left(I+\Sigma_i(\sigma)\right)^{-1}\mathbf{0}_{(2,3)}\left(I+\Sigma_i(\sigma)\right)^{-1}\boldsymbol{p}_i, \end{aligned}$$

where

$$I_{-(3,\cdot)} \equiv \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}, \; \boldsymbol{p}_i = \begin{pmatrix} d\ln(rk_i) \\ d\ln(wl_i) \\ d\ln\left(p^M m_i\right) \end{pmatrix}.$$

To estimate Φ and $\Gamma(\sigma)$, we use their sample analogs $\widehat{\Phi}$ and $\widehat{\Gamma}(\sigma)$

$$\widehat{\Phi}_{j_1,j_2} = \frac{1}{n-1}\sum_i Z_i^2 d\ln a_i^{j_1}(\widehat{\sigma})\, d\ln a_i^{j_2}(\widehat{\sigma}),$$

$$\widehat{\Gamma}(\sigma) = \frac{1}{n}\sum_i Z_i \nabla_\sigma \boldsymbol{a}_i(\sigma),$$

where $j_1, j_2 \in \{K, L\}$. We evaluate $\widehat{\Gamma}$ at the estimated parameter value $\sigma = \widehat{\sigma}$, and then estimate the finite approximation of the asymmetric distribution of the estimator (C.1) by

$$\frac{1}{n}\left[\widehat{\Gamma}(\widehat{\sigma})\right]^{-1}\widehat{\Phi}\left[\widehat{\Gamma}(\widehat{\sigma})\right]^{-1}.$$

Table B.11: Industry-level Regression

(a) 2SLS

VARIABLES	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Log Subsidiary Employment	0.120**	-0.00447	0.168***	0.0774	-0.184	0.507*
	(0.0501)	(0.610)	(0.0486)	(0.0694)	(0.162)	(0.292)
Observations	3,704	773	540	563	521	915
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry	manuf	chem	metal	machine	elec	auto

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) 1st	(2) 1st	(3) 1st	(4) 1st	(5) 1st	(6) 1st
Thai Flood Shock	-0.730***	-0.152	-1.655***	-2.223**	-0.655***	-0.303**
	(0.169)	(0.173)	(0.358)	(1.101)	(0.161)	(0.132)
Observations	3,704	773	540	563	521	915
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry	manuf	chem	metal	machine	elec	auto

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) First Stage

VARIABLES	(1) reduced	(2) reduced	(3) reduced	(4) reduced	(5) reduced	(6) reduced
Thai Flood Shock	-0.0874**	0.000677	-0.277***	-0.172	0.120	-0.154**
	(0.0428)	(0.0923)	(0.0594)	(0.225)	(0.105)	(0.0700)
Observations	3,704	773	540	563	521	915
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry	manuf	chem	metal	machine	elec	auto

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(c) Reduced Form