Trade Wars with FDI Diversion[*]

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Abstract

I study the impacts of trade policies on trade and welfare by connecting foreign direct investment (FDI) to trade, as highlighted by the China-US trade war. Using the Trump tariffs, I show that countries with greater potential to substitute for Chinese exports to the US also experience higher FDI growth, which I term as FDI diversion. Such FDI diversion accounts for, on average, 29% of a country's production capacity adjustments in response to the Trump tariffs. I document the large heterogeneity of FDI responses that can be partly explained by observable country characteristics. I build a multi-country general equilibrium model with two main features and quantitatively evaluate the Trump tariffs. First, FDI diversion due to trade policies leads to profit shifting and changes the producers' productivity distribution, bringing large aggregate and distributional welfare implications. Second, heterogeneous bilateral FDI elasticities are important to account for the pattern of FDI diversion and the quantitative effects of the Trump tariffs.

1 Introduction

One of the classic questions in international economics concerns the impacts of trade policies on trade and welfare. Recent literature, partly revived by the China-US trade war, focuses primarily on trade diversion – the substitution of goods exports across countries (e.g. Fajgelbaum et al. (2021)). However, the China-US trade war also highlights the connection between changes in trade patterns and significant movements of productive capital. A showcase example of this is Vietnam, which is often portrayed as a winner from the China-US trade war. This is not only because it exports a lot more to the US replacing Chinese exports, but also because it attracts a large amount of foreign direct investment (FDI). This paper studies the role of FDI as well as country-specific characteristics related to FDI when analyzing trade policies.

The analysis proceeds in three steps. First, I present evidence that establishes a connection between the Trump tariffs, trade, and FDI. Then I develop a general equilibrium framework where trade shocks lead to both trade and FDI diversion. Finally, I use this framework to illustrate the mechanisms through which FDI affects trade and welfare, and show the quantitative significance of these mechanisms for understanding the Trump tariffs.

I begin by showing that countries with greater potential to substitute for China's exports to the US experienced higher inward FDI growth following the China-US trade war. Taking Vietnam as an example, its constructed measure of this potential, which I refer to as the "trade diversion index" in this paper, is approximately at the 95th percentile of my sample. Consequently, the inward FDI stocks for Vietnam is around 8% higher two years after the trade war than countries with a trade diversion index around zero, such as Russia.

Next, I assess how important FDI is for the export growth in response to the Trump tariffs. First, I estimate the causal impacts of the Trump tariffs on a country's export growth to the US, which could come from both domestic capital investment and FDI adjustment. Next, I calculate the relative importance of domestic capital investment and FDI adjustment for export growth in response to the Trump tariffs. I show that, on average, the growth in FDI in the two years following the trade war accounts for approximately 29% of the changes in a country's production capacity, and thus the changes in its export.

Having established the causal link between trade policies and FDI diversion, I proceed to document the large variance of bilateral FDI investment changes. Importantly, there are systemic deviations in bilateral FDI investment relative to a simple gravity benchmark. For example, from 2017 to 2019, French FDI investment in Mexico grew much more than its investment in Vietnam, whereas Taiwan's FDI investment in Vietnam grew much more than its investment in Mexico. Conditional on the change in each FDI source country's total outward FDI investment and on each FDI receiver country's total inward FDI investment, there are some systematic changes in bilateral FDI flows. I call this heterogeneous bilateral FDI elasticity.

I show that part of the FDI responsiveness, beyond simply the level of FDI, is systematically related to observable country-pair characteristics, rather than being solely attributable to idiosyncratic bilateral shocks. For example, FDI investment responses between geographically closer countries are systematically larger, after controlling for the receiver country's total inward FDI change and the source country's total outward FDI change. I show that standard FDI models in the existing literature are inadequate for generating heterogeneous FDI responses. I argue that accounting for such heterogeneity is quantitatively important when assessing the implications for trade and welfare.

With these empirical findings in mind, I build a multi-country general equilibrium model that captures the connections between trade and FDI, along with heterogeneous FDI elasticities. There are two simple departures from the literature. First, I think of FDI as domestic producers operating their firms in foreign countries, earning profits and bringing know-how with them. Tariff shocks that lead to trade diversion concurrently alter the producers' values of operation in different production locations. The producers adjust their optimal production location, resulting in FDI diversion. When FDI diversion happens, the profit shifting – where producers repatriate profits to domestic owners – and the changing composition of producers' productivity often yield opposite effects on a country's labor wages and producer profits, thus generating large distributional implications.

Secondly, I apply a recently developed method to study trade elasticity heterogeneity (Lind and Ramondo (2023)) and adapt it to my FDI problem. This approach provides a tractable yet flexible method to capture the empirically observed hetero-

geneity in FDI response. The heterogeneity of the FDI diversion elasticity greatly changes the pattern of FDI responses, and thus the aggregate and distributional welfare implications of trade policies.

I calibrate my model to a world economy of fourteen economies and three sectors with the year before the China-US trade war as the original equilibrium. I perfectly match the country expenditures, bilateral trade shares, and FDI investment shares across countries. I use a standard gravity regression with fixed effects to recover parameters governing trade elasticities, and use indirect inference to calibrate the parameters that govern the magnitude and heterogeneity of FDI elasticities.

There are three bilateral country characteristics that I find to be correlated with the magnitude of FDI responses, which I use for calibration. The first is bilateral distance, a standard gravity variable traditionally impacting the level of trade flows and FDI in the literature. Here, it also affects FDI responsiveness. When two countries are geographically closer, the FDI elasticity with respect to the value of operation is larger. The second is the source country's GDP per capita, reflecting its development level. More developed countries' FDI investments are systematically more responsive in the data. The final one is a measure of comparative advantage similarity using the correlation between countries' export portfolios across industries. When two economies share similar comparative advantages, such as Vietnam and China, the FDI response is systematically larger. While I do not claim that these are the only factors influencing bilateral FDI elasticities, this calibration procedure captures some observable systematic patterns of heterogeneous FDI elasticities in a reduced-form way. This, in turn, quantitatively improves the model's predictions about FDI diversion. Accounting for such country characteristics is especially important for understanding the implications of the China-US trade war on countries like Vietnam.

Next, I perform a counterfactual analysis, subjecting the original equilibrium to the Trump tariffs. This reveals the varying impacts on countries in terms of trade, FDI stocks, as well as aggregate and distributional welfare.

The majority of economies increase their exports to the US, substituting for Chinese exports. The contribution of FDI to export growth is particularly important for economies such as Mexico, Vietnam, Malaysia, but less so for economies like Japan, Korea, Germany and France, and Taiwan. The relative contributions of FDI

and domestic production capacity hinge on the significance of foreign producers for the exporting country and the extent of FDI diversion. For example, in Mexico, foreign producers constitute a substantial portion of the manufacturing sector's production capacity, and Mexico also has large increase in inward FDI stocks.

China experiences a large decrease in its inward FDI stock as it becomes a less favorable location for exports, while its outward FDI investment increases. These FDI changes are highly heterogeneous. Japan and Korea experience a much more pronounced percentage drop in their FDI in China, whereas the decrease is less significant for Germany and France, owing to the difference in bilateral FDI elasticities. Similarly, Chinese outward FDI growth in economies like Vietnam, Japan, Korea, Malaysia, and Taiwan are much larger than the investment growth in economies like the US, or Mexico. In comparison, a model assuming homogeneous FDI elasticity would predict much more uniform changes in bilateral FDI in and out of China.

On the other hand, economies with substantial exports to the US, such as Mexico and Vietnam, in general attract more FDI. As most of the expenditure in the US is domestically sourced, the US itself is a major FDI receiver country. However, Canada, who also exports a lot to the US, receives little increase in FDI due to its low bilateral elasticities with the major FDI outflow countries.

FDI diversion not only changes the aggregate real consumption implications for each country, but also impacts the distribution of income within each country. In a trade-only model, economies that substitute more for Chinese exports benefit from higher wage rates and domestic profits. In my model, these economies also attract more FDI, further amplifying wage gains. FDI diversion turns the United States' net losses (as in the trade-only model in the literature, e.g., Fajgelbaum et al. (2020)) into net gains due to increased wages. However, FDI diversion doesn't have the same positive effect on domestic profits since profits generated by foreign producers are remitted to their home countries. In fact, when foreign producers are more productive than domestic producers, as in the cases of Mexico and Vietnam, FDI diversion can increase production costs, potentially resulting in losses for domestic producers.

The welfare implications depend on the general equilibrium income effects and a country's FDI network. The Trump tariffs make the world economy poorer, with economies that are close to China suffering the most. The income effects are further

amplified by FDI diversion. Economies like the UK, which have significantly invested in production locations that benefitted from the Trump tariffs, stand to gain as profits from their inframarginal FDI increase. Conversely, economies, such as Japan, Korea, and Taiwan, which invested more in production locations adversely affected by the Trump tariffs, experience negative effects.

Related Literature

My paper contributes to the vast literature on the impact of trade policies. The recent China-US trade tension has rekindled interests in this classic question, with a focus on the price effects of trade policies, including Amiti, Redding and Weinstein (2020); Fajgelbaum et al. (2020); Flaaen, Hortaçsu and Tintelnot (2020); Fajgelbaum et al. (2021); Cavallo et al. (2021). Waugh (2019) goes beyond price effects by looking at employment and consumption implications. Some papers study the trade war implications by allowing for additional elements, such as labor and firms reallocations domestically in Caliendo and Parro (2019) and firm-to-firm supply relationships in Grossman, Helpman and Redding (2023).

My paper highlights the importance of large movements of FDI during the China-US trade war, which are frequently featured in media headlines and are of considerable policy concern, e.g. IMF (2023). My paper offers a general equilibrium model that directly links FDI to trade and production fundamentals, and studies the implications of the trade war. Furthermore, I provide empirical evidence on how different countries respond to trade shocks in terms of FDI, whereas the existing literature tends to concentrate on individual countries, e.g. McCaig, Pavcnik and Wong (2022).

My treatment of FDI is closely related to the literature on multinational production (as reviewed Antràs and Yeaple (2014); Bernard et al. (2018)). The classic view on horizontal versus vertical FDI focuses on the substitutability and complementarity between trade and FDI between the source and receiver countries (e.g. Helpman (1984); Helpman, Melitz and Yeaple (2004); Ramondo and Rodriguez-Clare (2013); Irarrazabal, Moxnes and Opromolla (2013); Arkolakis et al. (2018)). In this paper, I emphasize the producer's choice of FDI location across all potential receiver countries. The optimal location for a producer serves as an export platform (e.g. Ramondo and Rodriguez-Clare (2013); Tintelnot (2017)). Compared to these papers, as profits are send back to foreign owners, FDI in my model affects profit sharing

and the producers' productivity distribution in a country. As a result, FDI diversion can have varying implications on wages, domestic profits, and foreign profits due to profit shifting and changes in producers' productivity distributions, leading to large distributional effects.

Another important contribution on my treatment of FDI is to recognize the large heterogeneous responses of FDI across source countries to a common shock to the receiver country, which cannot be accounted for in most FDI models in the literature. Recent literature develops various method to study heterogeneous trade elasticities through flexible demand systems (e.g. Adao, Costinot and Donaldson (2017); Fajgelbaum et al. (2021); Lind and Ramondo (2023), also Farrokhi and Pellegrina (2023) on technology choice elasticity). I apply the generalized extreme value distribution method from Lind and Ramondo (2023) to my FDI problem, offering a tractable yet flexible enough method to generate heterogeneous FDI elasticities governed by data. I show through quantitative counterfactuals that such heterogeneity has large implications on both FDI diversion patterns and welfare implications.

My paper also relates to the large international macroeconomics literature on global capital allocations and country imbalances, including Portes and Rey (2005); Eaton et al. (2016); Alvarez (2017); Alessandria, Choi and Lu (2017); Reyes-Heroles (2017); Anderson, Larch and Yotov (2019); Ravikumar, Santacreu and Sposi (2019); Li, Nie and Wang (2020); Davis, Valente and van Wincoop (2021); Kleinman et al. (2022); Hu (2023).

2 Empirical Evidence

This section makes two empirical analyses of global FDI changes. The first analysis provides evidence that trade policy shocks, such as the Trump tariffs, generate FDI responses across different countries. This results in what I refer to as FDI diversion.

This concept of FDI diversion with respect to trade and other external shocks is supported by a lot of anecdotal evidence. For example, European integration has led to significant relative capital formation and reallocation across economies within Europe, such as in Spain, Portugal, and Estonia following their accession to EU membership (see Baldwin and Wyplosz (2022)). There have also been numerous

concerns that China's integration into the world economy has diverted investment away from other developing economies.

While many research studies employ shocks like bilateral trade and investment agreements to empirically analyze FDI responses (e.g. McCaig, Pavcnik and Wong (2022)), these studies typically focus on a single country, rather than providing evidence on FDI diversion across countries. More importantly, the magnitude of shocks is hard to compare across different investment agreements. In contrast, the shock of the Trump tariffs complements these empirical studies by offering a large enough shock that has the potential to affect many countries to varying degrees that can be measured quantitatively.

After introducing the data, I construct a trade diversion index that captures a country's potential to substitute for Chinese exports in meeting US demand as a result of the Trump tariffs. I then show that countries with higher trade diversion indexes have larger inward FDI growth, and that this FDI growth plays a significant role in driving countries' export growth.

The second analysis offers suggestive evidence of the heterogeneous responses of FDI from different source countries to a change of FDI attractiveness in a receiver country that is common to these source countries. During the China-US trade war, some countries are often regarded as winners as their export and FDI growth are particularly salient, such as Vietnam and Mexico. I show that there are large variances across bilateral FDI changes for the same FDI receiving country, and exhibits systematic deviations from a standard FDI gravity model. Importantly, part of these deviations are systematically correlated with observable country characteristics. This empirical exercise highlights the need to deviate from existing benchmarks to understand the FDI and welfare implications of the China-US trade war for various countries.

2.1 FDI Data

I use two sources of FDI data. The first is the official data collected and published by governments and international agencies. I start with the OECD International direct investment database, which offers both country-level FDI aggregates, and FDI

by partner country or by industry.[1]

The OECD database is limited in terms of countries available. It is more complete when one side of the country-pair is an OECD country, while less so when neither is (e.g. China and Vietnam). Thus, in addition to the OECD database, I use the Coordinated Direct Investment Survey (CDIS) complied by the International Monetary Fund (IMF), which offers bilateral FDI positions for many more countries than the OECD database.[2] For certain important economies not fully covered by the international databases, I manually collected data from national statistical offices. For aggregate inward FDI stocks still missing values, I further use UNCTADstat's foreign direct investment data on inward and outward stocks.[3] The official FDI data thus offers unilateral inward FDI positions for most countries, and bilateral FDI positions to a limited number of countries, from 2013 to 2021.

The second type of FDI data is a micro-level database called fDi Markets offered by Financial Times, which tracks crossborder greenfield investments globally[4] The fDi Markets database has two main advantages. First, it provides information on the industry of each project, allowing me to construct FDI information at a much more granular industry level, broadly at the three-digit NAICS 2012 level. Second, the

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[1]FDI data are based on statistics provided by 38 OECD member countries. The data is public and can be accessed from here: `https://stats.oecd.org/index.aspx?DataSetCode=FDI_FLOW_PARTNER`. The definition for FDI is: "FDI statistics cover all entities in an FDI relationship. An FDI relationship is established when an investor in one country acquires 10% or more of the voting power in a business enterprise in another country. The 10 percent criteria is used to establish that the direct investor has a significant degree of influence over the operations of the direct investment enterprise."

One major problem to use FDI data for economic analysis is the complex financing structure of firms making these investments, including the use of special purpose entities (SPEs) to channel investments. My objective in analyzing FDI data is to capture how much actual production capacity is deployed in a receiver country and ultimately owned by a source country. In the OECD database, each reporting country would report different measures of FDI values. The domestic entity related to the FDI investments can be divided into either SPEs or non-SPEs, and the counterpart country can be measured by immediate or ultimate destination. I prioritize using the receiver country's reported non-SPEs entities' FDI from an ultimate source country whenever the information is available. When non-SPEs entity or ultimate source country FDI is not available, I will use the total (SPEs and non-SPEs) or immediate source country data. When the reporting country's information is not available, I will use the mirror data from other reporting countries.

[2]I again prioritize over the reporting country's inward FDI position, and fill in using other information when missing.

[3]See `https://unctadstat.unctad.org/wds/TableViewer/tableView.aspx?ReportId=96740`.

[4]The dataset is at the project level and details are available since 2003.

database exclusively records greenfield investments, and thus the complex financing structures (like SPEs) behind official FDI data are less of a concern. However, it is important to note that these advantages also result in a different definition of FDI compared to the official data. The FDI projects recorded through news and business agencies might vary in quality and coverage across countries. Moreover, FDI investments made through mergers and acquisitions are not included. I use the fDi Markets database as an independent and complementary source of information to empirically study FDI diversion. I will show that despite their different construction criteria, both the fDi Markets database and the official FDI data tell a consistent story. To construct the dataset for my empirical analysis, I first extract all FDI projects from the database for a list of countries, with each country serving as either the source or receiver. I then map all projects to their respective sectors, and aggregate the projects to the source-destination-sector-year level to serve as a measure of bilateral FDI investment. Three variables are used as proxies for FDI investments: the number of projects, the estimated number of jobs created, and the estimated amount of capital invested, all cumulatively over the years.

2.2 Construction of the Trump Tariffs Trade Diversion Index

In 2018 and 2019, the United States imposed tariffs increase on China that covered about $350 billion in trade flows. The Trump tariffs have been used to study trade diversion in the literature. Similar to Fajgelbaum et al. (2021), I assume that the product-level variations in tariff increases by the US on Chinese exports are not correlated with countries' specialization in goods produced. Given that I do not have FDI data at the product level, I construct a trade diversion index at both the country and sector levels, by using variation from the Trump tariffs across goods and countries' trade shares. This index is intended to capture the relative potential each country has to substitute for Chinese exports in meeting US demand.[5] Using this trade diversion index, I test and gauge the impact of the Trump tariffs on FDI

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[5]My construction of the trade diversion index follows a shift-share design, with the tariff variations across products being the shift, and trade share being the share. To identify the effect of this index on inward FDI stocks, the shifters need to be mean-independent of the shares, the potential outcomes (inward FDI stock growth for each country in absence of the Trump tariffs), and the treatment effects per unit of shifters on each country (see Proposition 1 in Adão, Kolesár and Morales (2019)).

diversion.

I take the HS 6-digit level tariff increases imposed by the US on China from Fajgelbaum et al. (2020).[6] I then use BACI trade flow data to construct weights for the tariff increases.[7] Intuitively, countries that specialize in goods hit by a larger tariff increase from the US on Chinese exports are likely to experience a larger increase in diverted export demand. This potential increase is likely to be stronger if the US is a larger market for that good and for this country. Finally, the diverted export demand is likely to be greater if China was a prominent exporter of this good to the US. Thus, using the BACI trade value data from 2017 (and I suppress the t subscript below), for each good ν, I calculate country i's export revenue share, $r_i(\nu)$, country i's export revenue share from the US, $r_{\text{US},i}(\nu)$, and the US import share from China, $\pi_{\text{US},\text{CN}}(\nu)$.[8]

Denoting the US tariff increase on China for good ν by $\Delta\tau_{\text{US},\text{CN}}(\nu)$, the trade diversion index for country i is defined as:

$$\text{DI}_i = \sum_\nu r_i(\nu)\, r_{\text{US},i}(\nu)\, \pi_{\text{US},\text{CN}}(\nu)\, \Delta\tau_{\text{US},\text{CN}}(\nu). \tag{1}$$

When analyzing sector-level FDI responses, I define a similar country-sector level index, DI_i^s, by aggregating over all goods within a sector s.

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[6]The authors extend the data through the end of 2019. The tariff changes are rescaled in proportion to their duration within a 24-month interval.

[7]BACI provides data on bilateral trade flow data for 200 countries at the product level (5000 products). Products correspond to the "Harmonized System" nomenclature (6 digit code). See `http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37`.

[8]Let $\text{EX}_{hit}(\nu)$ be the export value from country i to h for a good ν in year t, then the three weights are calculated as

$$r_i(\nu) = \frac{\sum_h \text{EX}_{h,i}(\nu)}{\sum_\nu \sum_h \text{EX}_{h,i}(\nu)},$$

$$r_{\text{US},i}(\nu) = \frac{\text{EX}_{\text{US},i}(\nu)}{\sum_h \text{EX}_{h,i}(\nu)},$$

$$\pi_{\text{US},\text{CN}}(\nu) = \frac{\text{EX}_{\text{US},\text{CN}}(\nu)}{\sum_i \text{EX}_{\text{US},i}(\nu)}.$$

2.3 FDI Diversion: Event Study Design

I employ an event-study specification, using the Trump tariffs implemented in 2018 as an exogenous shock. Specifically, the baseline specification uses country-level FDI data and runs the following regression

$$\ln \mathrm{FDK}_{it} = \mathrm{FE}_i + \mathrm{FE}_t + \sum_{t'=2013, t' \neq 2017}^{2021} \vartheta_{t'} \mathbb{1}_{t'} \times \mathrm{DI}_i + u_{it}, \tag{2}$$

where FDK_{it} is the inward FDI stock for country i at time t, and $\mathbb{1}_{t'}$ is the time dummy for year t'.

Figure 1 plots the coefficients $\vartheta_{t'}$, providing the baseline evidence on how FDI responds to the constructed trade diversion index. Given that the coefficients for post-years are approximately 20, and the 95th percentile trade diversion index is around 0.004 (which is Vietnam), it can be inferred that the Trump tariffs led to a relative increase of roughly 8% in Vietnam's inward FDI stock compared to a country with a near-zero trade diversion index, such as Russia. Appendix A.1 presents four different specifications of a similar regression, employing exchange-rate-adjusted FDI values, constructing the trade diversion index at the ISIC 2-digit level tariff changes[9], using bilateral FDI stocks, and directly using the observed export growth as the explanatory variable instead of the trade diversion index. Across these robustness checks, I find a consistent positive effect of the trade diversion index on the inward FDI stock growth.

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[9]This captures the idea that a country may be an ideal production location for a certain good, attracting FDI inflows not solely by specializing in that specific good, but also by being proficient in producing similar goods. For example, when dining tables are tariffed by the US, Vietnam doesn't need to be a better location solely based on its export of dining tables. If it specializes in furniture production, it could adjust its production capacity accordingly, making it a likely destination for increased FDI.
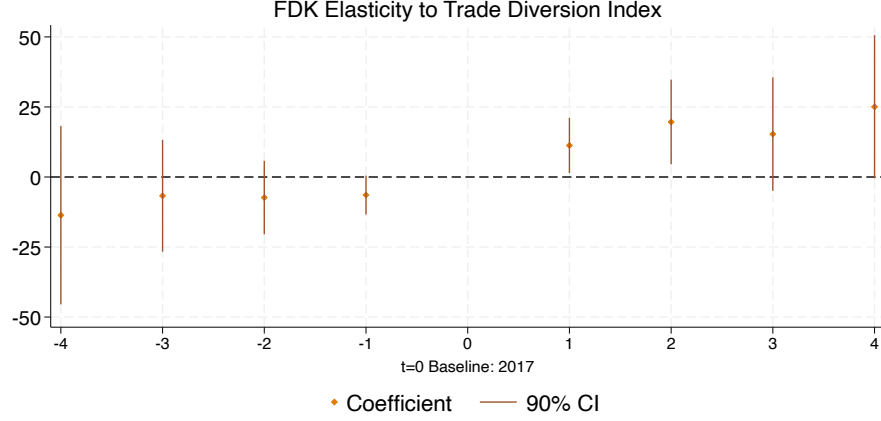
FDK Elasticity to Trade Diversion Index

Notes: The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. I constrain the sample to include those countries with the largest inward FDI stocks in 2017, while excluding those typically considered tax heavens. This results in 117 countries included in the regression (2). The trade diversion index is constructed using equation (1), with ν at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 1: FDI Diversion and Trade Diversion Index

Figure 2 presents a similar result from a regression at the sectoral level, using fDi Markets data. I control for the receiver-country-year, source-country-year, and sector-year fixed effects. The dependent variable is the cumulative estimated number of jobs created.[10] Appendix A.2 shows for the other two dependent variables used to measure FDI investments, which are the cumulative number of projects and the cumulative estimated value of capital invested. All of these results point to the same conclusion as the exercise using official FDI data.

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[10]More specifically, the regression is

$$\ln J_{sit} = FE_{it} + FE_{st} + FE_{si} + \sum_{t'=2013, t'\neq 2017}^{2021} \vartheta_{t'} \mathbb{1}_{t'} \times DI_{si} + u_{sit}.$$
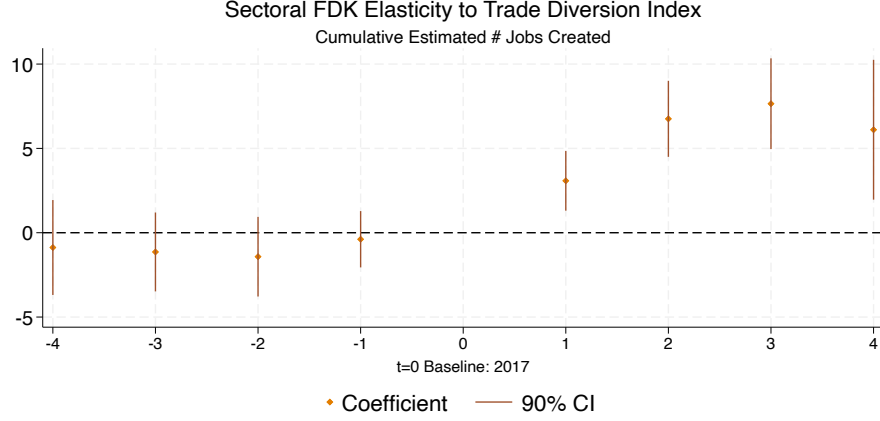
Sectoral FDK Elasticity to Trade Diversion Index

Cumulative Estimated # Jobs Created

Notes: The FDI data used are the fDi Markets database measure of greenfield FDI investments. The dependent variable is the cumulative estimated number of jobs created by these projects, aggregated at the source-receiver-sector level. The sectors are broadly categorized according to the NAICS 2012 3-digit level. I constrain the sample include those receiver-sector pairs with at least 10 projects before 2017, and service sectors are excluded. This results in a sample of 31 receiver countries and 24 sectors. The regression controls for the receiver-year, receiver-sector, and sector-year fixed effects. The trade diversion index is constructed similarly to equation (1) at the country-sector level, with ν at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.
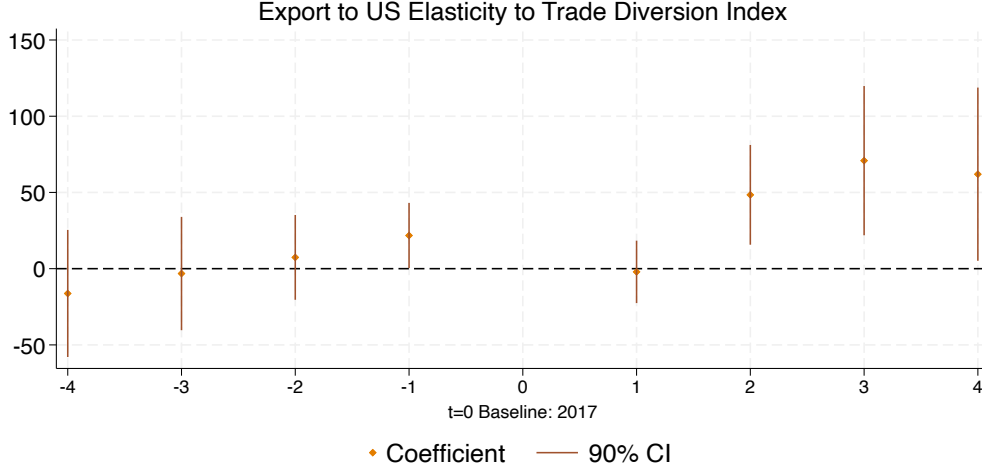
Figure 2: Sectoral FDI Diversion and Trade Diversion Index

2.4 Contribution of FDI Diversion to Export Growth

The FDI diversion resulting from the Trump tariffs by itself is interesting and could have many impacts on a country beyond the scope of this paper (e.g., technology diffusion), but one aspect is of particular importance, namely trade. Supporting evidence for a positive correlation between export and FDI growth can be found in Appendix A.3, which features binscatter plots illustrating this relationship.

Complementary to existing findings in the literature (e.g., Fajgelbaum et al. (2021)), I show that the trade diversion index constructed above predicts relative export growth. Figure 3 presents the results of regression (3), which is analogous to (2) with the log of export to the US for each country $\ln \mathrm{EX}_{\mathrm{US},i,t}$ as the dependent variable.

$$\ln \mathrm{EX}_{\mathrm{US},i,t} = \mathrm{FE}_i + \mathrm{FE}_t + \sum_{t'=2013, t' \neq 2017}^{2021} \vartheta_{t'}^{\mathrm{EX,DI}} \mathbb{1}_{t'} \times \mathrm{DI}_i + u_{it}. \tag{3}$$

14

Export to US Elasticity to Trade Diversion Index

Figure 3: Trade Diversion: Export (to US) Elasticity to Trade Diversion Index

Appendix A.3 shows a similar result to Figure 3 with the dependent variable being the log of a country's total export excluding China.

The impacts of the trade diversion index on relative export growth to the US may result from a combination of expanded domestic production capacity and increased production capacity through FDI. The next logical inquiry is to assess FDI's contributions to a country's export growth. I assume that the contributions of per unit increasing in domestic and FDI production capacity on export growth are identical.[11] In this case, a simple calculation of FDI's contribution to export growth uses the responses of both FDK and the domestic capitals to the trade diversion index, and the share of FDK to the domestic capitals.

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[11] For example, in a world where domestic and foreign producers share identical export portfolios from a common exporting location, and constant returns to scale in production.

	FDK	Domestic Capital
	(1)	(2)
DI	26.029**	19.567*
	(11.536)	(11.265)
R2 adj.	.04	.02
# of Obs.	99	94

Notes: The dependent variables are FDK growth and domestic capital stocks growth from 2017 to 2019 at the country level. The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. The domestic capital stocks data used are from the IMF Investment and Capital Stock Dataset (2021 version), which does not have data after 2019. I constrain the sample to include those countries with the largest inward FDI stocks in 2017, while excluding those typically considered tax heavens. I drop countries whose measured FDK is larger than the domestic capital stocks. I further winsorize the growth of domestic capitals at the 2.5th and 97.5th percentiles, and drop Mexico and Canada. I exclude Mexico and Canada because they have the largest trade diversion indexes. If I include these two countries, the estimates and standard errors for both columns become 17.96 (8.13) and 8.95 (7.92). This results in 99 countries included in column (1) and 94 countries in column (2). The trade diversion index is constructed using equation (1), with ν at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1: FDK and Domestic Capital Stocks Elasticities on Trade Diversion Index

In the sample from column (1), the mean ratio of FDK to the aggregate of FDK and domestic capital stocks is 23.6%. Thus, the subsequent ratio quantifies an average proportion of a country's total production capacity growth attributable to FDK from 2017 to 2019, as a response to the Trump tariffs.

$$\frac{26.03 \times 23.6\%}{26.03 \times 23.6\% + 19.57 \times (1 - 23.6\%)} \approx 29.1\%.$$

To be clear, I do not suggest that in a world without FDI movements, the export growth to the US on average for a country due to the Trump tariffs would be 27% lower. In such a world, domestic producers might increase their operation more, and price might adjust differently. It is also important to note that while both domestic and FDI production can contribute to a country's export growth, their implications for economic welfare are distinct, as will be discussed in the later quantitative analysis.

2.5 The Hererogeneity of Bilateral FDI Change

When a receiver country becomes a more attractive location for production and attracts FDI, do all source countries increase their FDI investments in that country proportionally? Figure 4 shows an example for two economies that are much talked-

about as winners from the US-China trade war, Vietnam and Mexico. The figure shows the growth of bilateral FDI stocks from two source economies, France and Taiwan, into Vietnam and Mexico, from 2017 to 2019.

France and Taiwan could have totally different incentives to adjust their total outward FDI investments, but the point here is that they seem to redirect their investment into different receiver countries. France increased FDI investments much more into Mexico than Vietnam, while Taiwan increased much more into Vietnam than Mexico.

Figure 4: Bilatral FDI Growth for Vietnam and Mexico from 2017 to 2019

Such heterogeneous changes could be purely due to idiosyncratic factors. For example, two economies might sign a new treaty regarding FDI investments, or could be subject to unexpected political tensions. However, such heterogeneous changes are inconsistent with a world where the receiver economy experiences a shock that is common to all source countries, and the FDI investment responses are homogeneous across these source economies. In such a world, France should have either increased more in both Vietnam and Mexico, or less in both.

Regression (4) looks for systematic factors that can explain the observed heterogeneity in FDI responses across different country pairs:

$$\mathrm{d}\ln\mathrm{FDI}_{ij} = \mathrm{FE}_i + \mathrm{FE}_j + \boldsymbol{Z}_{ij}\tilde{\boldsymbol{\psi}} + (\mathrm{d}\ln\mathrm{FDI}_i \cdot \boldsymbol{Z}_{ij})\,\boldsymbol{\psi} + u_{ij}, \tag{4}$$

where $\boldsymbol{Z}_{ij}$ represents a vector of observable bilateral country characteristics. The fixed effect FE_i captures all common factors that affect the bilateral inward FDI investments into country i, and FE_j captures the changes of the source country's incentives for overall FDI investments. The receiver country's total inward FDI change, $\mathrm{d}\ln\mathrm{FDI}_i$, serves as a proxy for the change in the receiver country's attractiveness for FDI. Therefore, the interaction coefficients, $\boldsymbol{\psi}$, reflect how these observed country characteristics correlate with the magnitude of bilateral FDI responses. Table 2 reports results for coefficients $\boldsymbol{\psi}$.

	Outcome: $\mathrm{d}\ln\mathrm{FDI}_{ij}$
$\mathrm{d}\ln\mathrm{FDI}_i \times \ln\left(\mathrm{Dist}_{ij}\right)$	-0.284**
	(0.122)
$\mathrm{d}\ln\mathrm{FDI}_i \times \ln\left(\mathrm{GDPpc}_j\right)$	0.156**
	(0.065)
$\mathrm{d}\ln\mathrm{FDI}_i \times \mathrm{ComparaAdv}_{ij}$	0.599**
	(0.283)
R^2	0.105
# of Obs.	2735

Notes: The FDI data used are official bilateral FDI stocks from the OECD, IMF CDIS. The dependent variable is the bilateral FDI growth from 2017 to 2019. The sample is limited to source countries with a sufficient number of investment destinations, resulting in 34 source countries and 199 receiver countries being included in the regression. Distance between countries is obtained from the CEPII Gravity Database (version 202211). GDP per capita data is sourced from the World Bank's World Development Indicators (WDI). Comparative advantage similarity is calculated based on BACI trade values from the year 2017. Standard errors in parentheses are clustered at the receiver country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Country Characteristics and the Magnitude of Bilateral FDI Responses

The first variable, $\ln\left(\mathrm{Dist}_{ij}\right)$,[12] is a standard gravity variable commonly used in predicting bilateral trade values. The estimates suggest that distance is negatively correlated with bilateral FDI *responses* given the receiver's and source country's unilateral FDI change. $\ln\left(\mathrm{GDPpc}_j\right)$ is the log of the source country's GDP per capita, which serves as a proxy for the general level of development of the source country. The positive coefficient suggests that a more developed source country tends to have systematically larger FDI investment response to a receiver country that attracts more FDI. Finally, the variable $\mathrm{ComparaAdv}_{ij}$ is a measure of comparative advan-

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[12]Distance is the log of population-weighted distance between most populated cities of two countries (harmonic mean).

tage similarity, calculated as the correlation between two countries' export shares across industries, which correlates with a larger magnitude of FDI responses.

I will show later that standard stochastic assumptions on FDI location choices fail to generate heterogeneous FDI elasticities across source countries in response to a common shock to a receiver country.[13] One of the main contributions of this paper is the application of a simple method to generate endogenous heterogeneous FDI elasticities across country pairs in a tractable way. This approach is also flexible enough to utilize empirical results from Table 2 to regulate the model's FDI elasticity heterogeneity.

3 Model

I study a world economy that consists of N countries and S sectors. The model is static. Each country j is endowed with exogenous inelastically-supplied efficiency units of labor L_j and an aggregate firm productivity level z_j. For each country and sector, there is a fixed unit mass of producers indexed by ω. Each producer has a technology to produce a differentiated variety. Each ω is constrained to operate in one production country i, and sells its variety to all potential importing countries h.[14]

I first outline the demand system that combines all varieties for the consumption of the representative household. I then specify the production technology and how producers make their production and location choices. Subsequent to defining the equilibrium, I analyze how shocks lead to FDI diversion, and how to apply the tools of Lind and Ramondo (2023) that allows for heterogeneous FDI elasticities across country pairs.

I discuss three model simplifying assumptions and their implications at the end of this section. First, I discuss the implications of dynamic transitions and extend the model to a dynamic version. Second, I discuss how the assumption that producers are restricted to one production location affects the elasticity of FDI diversion. Third,

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[13]For example, the model from Irarrazabal, Moxnes and Opromolla (2013) and the model from Ramondo and Rodriguez-Clare (2013) with no correlation across productivity draws across receiver countries and no headquarter inputs.

[14]I assume that there is a large enough span-of-control cost such that no producers operate in multiple locations. I will index the source country (where the producers are from) by j, the production country by i, and the importing country by h.

I offer some thoughts on the extension of the model to incorporate heterogeneity in both trade and FDI elasticities.

3.1 Demand & Household

For an importing country h and sector s, there is a producer of the sectoral composite good Q_h^s who supplies it at cost by purchasing and combining all tradable varieties. Let M_{ij}^s denote the set of varieties owned by producers from country j produced in country i in sector s. These tradable varieties are subject to two types of frictions between the production (or exporting) country i and importing country h: (i) iceberg trade costs d_{hi}^s, and (ii) one plus the ad-valorem tariff, denoted by τ_{hi}^s. More specifically,

$$Q_h^s = \left(\sum_{j=1}^{N} \sum_{i=1}^{N} \int_{M_{ij}^s} \left(q_{hij}^s(\omega) \right)^{\frac{\epsilon^s - 1}{\epsilon^s}} \, d\omega \right)^{\frac{\epsilon^s}{\epsilon^s - 1}},$$

where $q_{hij}^s(\omega)$ is the quantity of variety ω in sector s imported by h, produced in i, and owned by a producer from j (including domestically produced varieties when $h = i$). ϵ^s is the sector-specific elasticity of substitution across varieties. The demand for a variety owned by a producer ω from j, operating in i and s is given by

$$q_{hij}^s(\omega) = \left(\frac{p_{hij}^s(\omega)}{P_h^s} \right)^{-\epsilon^s} Q_h^s,$$

following the CES demand system, where P_h^s is the associated price index of the sectoral composite good

$$P_h^s = \left(\sum_{j=1}^{N} \sum_{i=1}^{N} \int_{M_{ij}^s} p_{hij}^s(\omega)^{1-\epsilon^s} \, d\omega \right)^{\frac{1}{1-\epsilon^s}}.$$

The sectoral composites are then purchased and aggregated into the final good for household's consumption

$$Q_h = \prod_{s=1}^{S} (Q_h^s)^{\phi_h^s}, \text{ s.t. } \sum_s \phi_h^s = 1,$$

where ϕ_h^s is the exogenous expenditure share for the sectoral composites. The corresponding final good price index is P_h.

The representative household consumes the final good, and the expenditure $P_h C_h$ equals the household's total income

$$w_h L_h + D_h + T_h - \Gamma_h.$$

The right-hand-side represents the household's total income, which includes labor income (with wage rate w_h) and other incomes that are taken as given, including (i) the aggregate domestic producers' profits D_h, as all firms are ultimately owned by the domestic household, (ii) government-collected tariff revenue T_h, and (iii) an exogenous country-level transfer Γ_h. The transfer could represent reserves or other mechanisms that affect the country's balance of payments but are not endogenously captured within the model.

3.2   Production

Each producer gets a productivity draw for each potential production location. Based on the outcomes of these draws and the respective values of operation in each location, the producer then decides where to establish its firm. Conditional on the production location choice, the producer solves its optimal production and pricing problem.

Let $\mathbf{a}_j^s(\omega) = \left\{ a_{ij}^s(\omega) \right\}_{i=1}^N$ be the random vector of productivity draws that a producer ω from j in sector s receives across all potential production locations i. I will suppress the superscript s and the argument ω that indicates individual producer with the understanding that the following set-up applies independently and symmetrically across all producers and sectors.

I assume that the vector $\{a_{ij}\}_{i=1}^N$ follows a max-stable multivariate Fréchet distribution characterized by a shape parameter θ, scale parameter z_j and a correlation

function G^j,[15]

$$\mathbb{F}_{ij}(\mathbf{a}_j) \equiv \mathbb{P}\left(a_{1j} \leq a_1, a_{2j} \leq a_2, \ldots, a_{Nj} \leq a_N\right) = e^{-z_j G^j\left(a_1^{-\theta}, a_2^{-\theta}, \ldots, a_N^{-\theta}\right)}.$$

The correlation function G^j allows for a flexible structure for the dependence of productivity draws across different production locations i for producers from a source country j. This flexibility is crucial for generating heterogeneous FDI elasticities across country pairs. To fix ideas, the common assumption in the literature is that productivity draws are independent across countries, as in Eaton and Kortum (2002), which corresponds to an additive correlation function $G^j\left(a_1^{-\theta}, a_2^{-\theta}, \ldots, a_N^{-\theta}\right) = \sum_i a_i^{-\theta}$. In this case, a deviation to the attractiveness of location i as an FDI receiver country results in the same responsiveness from different source countries j, inconsistent with the empirical evidence. I will discuss later the specific form of the correlation function G^j and its implications, focusing on the heterogeneous FDI elasticity across country pairs.

Consider a producer from j in sector s, operating in i with an individual productivity a. Conditional on this productivity, the producer uses a constant returns to scale technology and a single factor of production, namely labor, to produce

$$q_{ij}^s(a) = \frac{a^{\frac{1}{\sigma^s-1}}}{\kappa_{ij}^s} l_{ij}^s(a),$$

where $q_{ij}^s(a)$ is the quantity of output, $l_{ij}^s(a)$ is the amount of labor hired from country i, and κ_{ij}^s is the bilateral foreign operation friction that is normalized to one when the producer operates in its home country ($i = j$).

Given the production technology and CES demand, each producer determines the price at which it sells its variety to importing country h, denoted as $p_{hij}^s(a)$, and the quantity of labor to hire $l_{ij}^s(a)$, subject to the constraint that the total output produced must equal the total quantities sold, taking into account trade costs: $\sum_{h=1}^N d_{hi}^s q_{hij}^s(a) = q_{ij}^s(a)$.

It is important to note that I abstract from fixed costs of exporting, and fixed costs of operation by assuming a fixed mass of producers for each source country and

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[15]For an introduction of this class of generalized extreme value distributions, see Lind and Ramondo (2023).

sector, and that each producer is constrained to operate in only one location. These fixed costs are important for understanding the different margins of adjustments of trade and FDI as highlighted by Melitz (2003) for export and Tintelnot (2017) for FDI. However, I will argue in more detail at the end of this section that abstracting from them gains tractability for the model, and my calibration method matches the country-level aggregate FDI diversion elasticity as in the data.

3.3 Market Clearing and Equilibrium

Let π_{hi}^s be the import share of goods that are shipped from i to importer h in sector s. Let D_{ij}^s be the aggregate profits earned by producers from j who operate in i and sector s. Denote $D_j \equiv \sum_i \sum_s D_{ij}^s, \mathcal{D}_j \equiv \sum_i \sum_s D_{ji}^s$ to be country j's total inward and outward profits. In this static framework, where actual capital is not explicitly modeled, profits serve as a proxy for FDI.

The goods market clearing condition is

$$Y_i = \sum_h \sum_s \frac{\pi_{hi}^s}{\tau_{hi}^s} X_h^s,$$

where $Y_i \equiv w_i L_i + \mathcal{D}_i$ is the total value of output in country i.

The net export for country j is Net Export$_j \equiv Y_j - X_j$, and the net income is Net Income$_j \equiv D_j - \mathcal{D}_j$. The budget constraint for each country must be satisfied:

$$\text{Net Export}_j + \text{Net Income}_j + T_j - \Gamma_j = 0.$$

An equilibrium is a set of prices (good prices, wages) and allocations (consumptions, producer allocations) given a set of fundamentals (productivities, labor endowments, trade costs, tariffs, foreign operation frictions, and distributions of idiosyncratic productivity draws) such that households and producers optimize, the distributions of producers are consistent with these decisions, goods markets clear, and country budget constraints hold.

3.4 Solution to the Producer's Problem

I solve the producer's problem in two steps. First, I solve the producer's optimal pricing and production problem, given the choice of production location. This gives us the value of operation in each location. Second, producers decide on the location of production, taking into account the values of operation in each location and the random productivity draws.

For a producer from j in sector s, operating in i, and selling to country h, the optimal price $p^s_{hij}(a)$ is set as a mark-up over marginal cost. The mark-up is given by the sector-specific elasticity of substitution, $\frac{\epsilon^s}{\epsilon^s-1}$. The marginal cost depends on the trade costs, tariffs, bilateral operation frictions, the wage rate in the production location, and the producer's productivity. The optimal price is given by:

$$p^s_{hij}(a) = \frac{\epsilon^s}{\epsilon^s - 1} \frac{d^s_{hi} \tau^s_{hi} w_i}{a^{\frac{1}{\epsilon^s-1}} / \kappa^s_{ij}}.$$

The profit from selling to all importing countries h is

$$v^s_{ij}(a) \equiv \frac{1}{\epsilon^s - 1} A^s_i w_i^{1-\epsilon^s} \frac{a}{\kappa^s_{ij}{}^{\epsilon^s-1}},$$

where $A^s_i = \sum_h (d^s_{hi})^{-\epsilon^s} (\tau^s_{hi})^{1-\epsilon^s} \left(\frac{\epsilon^s}{\epsilon^s-1}\right)^{-\epsilon^s} (P^s_h)^{\epsilon^s} Q^s_h$ captures the market access of country i as a production location for sector s.

Suppressing the superscript s, I derive in Appendix B the probability that a location i is the best choice for a producer from j

$$\mathbb{P}\left(v_{ij}(a_{ij}) = \max_{i'} v_{i'j}(a_{i'j})\right) = \frac{\tilde{v}^\theta_{ij} G^j_i(\tilde{v}^\theta_{1j}, \tilde{v}^\theta_{2j}, \ldots, \tilde{v}^\theta_{Nj})}{G^j(\tilde{v}^\theta_{1j}, \tilde{v}^\theta_{2j}, \ldots, \tilde{v}^\theta_{Nj})},$$

where $G^j_i \equiv \frac{\partial G^j(x_1, x_2, \ldots, x_N)}{\partial x_i}$, and $\tilde{v}_{ij} = v_{ij}(1)$ is the profits of a producer from j operating in i with a normalized productivity $a = 1$, which I refer to as the value of operation in i for producers from j. The numerator measures how good location i is as a production location, taking the correlation structure of productivity draws across locations into account. The denominator is the sum of this measure across all locations, i.e., $G^j(\tilde{v}^\theta_{1j}, \tilde{v}^\theta_{2j}, \ldots, \tilde{v}^\theta_{Nj}) = \sum_i \tilde{v}^\theta_{ij} G^j_i(\tilde{v}^\theta_{1j}, \tilde{v}^\theta_{2j}, \ldots, \tilde{v}^\theta_{Nj})$.

For example, when the correlation function is additive and thus productivity

draws are independent across locations as in Eaton and Kortum (2002), the location choice probability simplifies to $\mathbb{P}\left(v_{ij}\left(a_{ij}\right) = \max_{i'} v_{i'j}\left(a_{i'j}\right)\right) = \frac{\tilde{v}_{ij}^{\theta}}{\sum_{i'} \tilde{v}_{i'j}^{\theta}}$. Here, the choice probability depends solely on the relative value of $\tilde{v}_{ij}$ and the parameter θ.

The correlation function captures the correlation structure of productivity draws across locations. Given the value of operation for a location, if the productivity draw there is more correlated with locations with higher values of operation, it is intuitively less likely to be chosen. I will show later that not only the levels of location choice, but also the responsiveness depends on the correlation structure, which is important for the patterns of FDI diversion in response to trade policies like the trade war.

The conditional distribution of productivity of producers from j in i is

$$\tilde{\mathbb{F}}_{ij}(a) \equiv \mathbb{P}\left(a_{ij} < a | v_{ij}\left(a_{ij}\right) = \max_{i'} v_{i'j}\left(a_{i'j}\right)\right) = e^{-z_j \frac{G^j\left(\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \dots, \tilde{v}_{Nj}^{\theta}\right)}{\tilde{v}_{ij}^{\theta}} a^{-\theta}}.$$

Given these endogenous producer distributions, I can derive the aggregate variables, including sectoral price indices P_h^j, country price indices P_h, and bilateral sectoral profits values D_{ij}^s. See Appendix B for details.

Correspondingly, a key property of the model is that the producers' location choices will respond to changes in model parameters. For example, suppose that the US imposes a tariff increase on Chinese exports in sector s: $d \ln \tau_{US,CN}^s$. Holding the production location for each producer constant, producers will adjust their prices, leading to the standard trade diversion. Moreover, such shocks also bring about FDI diversion, as the production location choice depends on trade fundamentals. To see this more clearly, China's market access in sector s, A_{CN}^s, is directly affected by $d \ln \tau_{US,CN}^s$, which in turn affects the values of operation $\tilde{v}_{ij}^s$, and the equilibrium producer allocations $\tilde{\mathbb{F}}_{ij}^s(a)$.

3.5   FDI Diversion & Elasticity

I derive in the Appendix that the aggregate profits that producers from j in sector s get from operating in i equals

$$D_{ij}^s = \frac{\left(\tilde{v}_{ij}^s\right)^{\theta} G_i^j}{G^j} \left(G^j\right)^{\frac{1}{\theta}} \tilde{z}_j.$$

25

The first term is the probability that location i is chosen (remember $G^j = \sum_i \left(\tilde{v}_{ij}^\theta\right)^\theta G_i^j$). The second term $(G^j)^{\frac{1}{\theta}} \tilde{z}_j$ represents the aggregate profits that producers from j obtain across all locations, which depends on the correlation function G^j, values of operation $\left\{\tilde{v}_{ij}^s\right\}_{i=1}^N$, the normalized productivity $\tilde{z}_j \equiv \Gamma\left(1 - \frac{1}{\theta}\right) z_j^{\frac{1}{\theta}}$, and the parameter θ. Denoting the aggregate sectoral profits for producers from j as $D_j^s = (G^j)^{\frac{1}{\theta}} \tilde{z}_j$, the above bilateral profits can be expressed in a gravity equation form,

$$D_{ij}^s = \frac{\left(\tilde{v}_{ij}^s\right)^\theta G_i^j}{G^j} D_j^s.$$

I now examine the determinants of the magnitude and heterogeneity of the elasticity of the FDI diversion with respect to the values of operation $\tilde{v}_{ij}^s$ due to shocks such as tariffs, which hinges on the assumption of the correlation function G^j. I will start with two examples featuring standard assumptions that have been used in the literature (e.g., Ramondo and Rodriguez-Clare (2013)[16]). An important feature of these assumptions is that they could not generate heterogeneous FDI elasticities.

Example 1: No correlation

Consider a correlation function that implies independence of draws across locations, $G^j\left(x_1, x_2, \ldots, x_N\right) \equiv \sum_{i=1}^N x_i$. In this case, the joint distribution of $\mathbf{a}_j$ (suppressing superscript s) follows a standard Fréchet distribution that is i.i.d. across locations, i.e.

$$\mathbb{P}\left(a_{1j} \leq a_1, a_{2j} \leq a_2, \ldots, a_{Nj} \leq a_N\right) = e^{-z_j \sum_{i=1}^N a_i^{-\theta}}.$$

In this case, the FDI gravity simplifies to

$$D_{ij} = \frac{\left(\tilde{v}_{ij}\right)^\theta}{G^j} D_j,$$

where $G^j = \sum_{i'} \left(\tilde{v}_{i'j}\right)^\theta$. The first-order deviation of D_{ij} across two equilibria in re-

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[16] Arkolakis et al. (2018) uses a similar assumption that is based on a multivariate Pareto distribution.

sponse to any shocks, using $\tilde{v}_{ij} = A_i w_i^{1-\epsilon^s}/\kappa_{ij}^{\epsilon^s-1}$, and defining $\tilde{A}_i \equiv A_i w_i^{1-\epsilon^s}$,

$$\mathrm{d}\ln D_{ij} = \theta\left[\mathrm{d}\ln \tilde{A}_i - (\epsilon^s - 1)\,\mathrm{d}\ln \kappa_{ij}\right] + \mathrm{d}\ln \frac{D_j}{G^j}. \tag{5}$$

$\mathrm{d}\ln \tilde{A}_i$ captures the changes of attractiveness of i as an FDI receiver country (either due to changes in market access, or cost of production). There are two observations from this equation on the FDI diversion elasticity. First, the magnitude of the FDI diversion elasticity is governed by the dispersion parameter θ. When θ is larger, the dispersion of productivity draws is smaller, and thus the changes of the values of operation have larger impacts on the producers' location choices, and thus the FDI diversion.

Second, the FDI elasticity is homogeneous in the sense that conditional on the source and receiver country fixed effects, the only remaining bilateral variation comes from $\mathrm{d}\ln \kappa_{ij}$. In other words, without changes in $\mathrm{d}\ln \kappa_{ij}$, for whatever shocks that lead to $\mathrm{d}\ln \tilde{A}_i$ across i, the bilateral FDI growth from any source country j to two different receiver countries should be proportional to $\mathrm{d}\ln \tilde{A}_i$. In the absence of a predefined relationship between bilateral operation frictions and country characteristics, this model would fail to find country characteristics that could systematically explain the magnitude of bilateral FDI elasticities across country pairs, in contrast to the empirical evidence.

Example 2: Uniform correlation

As an intermediate step, suppose the correlation function is $G^j(x_1, x_2, \ldots, x_N) = \left(\sum_{i=1}^N x_i^{\frac{1}{1-\rho}}\right)^{1-\rho}$ with $0 < \rho < 1$, which introduces correlation to productivity draws across locations. A higher value of ρ means less dispersion of productivity draws across locations, as draws become more similar. Consequently, producers will be more responsive in substituting across locations when relative values of operation change. To see this more clearly, the first-order deviation of D_{ij} across two equilibria becomes

$$\mathrm{d}\ln D_{ij} = \frac{\theta}{1-\rho}\left[\mathrm{d}\ln \tilde{A}_i - (\epsilon^s - 1)\,\mathrm{d}\ln \kappa_{ij}\right] + \mathrm{d}\ln \frac{D_j}{(G^j)^{\frac{\rho}{1-\rho}}}.$$

The FDI elasticity is now characterized by $\theta/(1-\rho)$ – amplified by ρ. However, the

27

elasticity is still homogeneous across all country pairs.

Example 3: Bilateral correlations

Finally, I assume G^j is a cross-nested CES (CNCES) correlation function used in this paper, which basically combines the above two extreme cases together.

$$G^j \left(a_1^{-\theta}, a_2^{-\theta}, \ldots, a_N^{-\theta} \right) = \sum_{i=1}^{N} \left(1 - \eta_{ij} \right) a_i^{-\theta} + \left(\sum_{i=1}^{N} \left(\eta_{ij} a_i^{-\theta} \right)^{\frac{1}{1-\rho}} \right)^{1-\rho}.$$

One way to understand this correlation function is that there are two latent technology types available for producers to operate their firms. Within each technology type, the productivity draws across locations can be correlated. In the first type, productivity draws across locations are completely independent, with no correlation. In contrast, the second technology type allows for productivity draws to be correlated across locations, with a correlation coefficient of $0 < \rho < 1$. The resulting productivity draw is to apply the better of the two latent technology draws for each location.

The weight η_{ij} indicates the relative importance of each technology type for the country-pair $i - j$. This weight can be derived from the relative aggregate level of productivity for these two technology types between each country-pair $i - j$. For example, when η_{ij} is larger, it is as if that second technology type on average gives higher productivity for producers from j to operate in i. Thus, the second technology type will be used more often both unconditional and conditional on the location i being chosen by the producers. To see this more clearly, the profit share $\lambda_{ij} \equiv \frac{D_{ij}}{D_j}$ can be decomposed as

$$\lambda_{ij} = \lambda_j^{\mathrm{B}} \lambda_{ij}^{\mathrm{W}} + \lambda_j^{\mathrm{B}*} \lambda_{ij}^{\mathrm{W}*},$$

where $\lambda_j^{\mathrm{B}}, \lambda_j^{\mathrm{B}*}$ denote the between technology type profit shares for the source country j, and $\lambda_{ij}^{\mathrm{W}}, \lambda_{ij}^{\mathrm{W}*}$ denote the within productivity type profit shares from each receiver country i for source country j. Here, the superscript $*$ refers to the shares related to

the technology type with correlation ρ. More specifically,

$$\lambda_j^{\mathrm{B}*} = \frac{\left(\sum_{i'}\left(\eta_{i'j}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}{\sum_{i'}(1-\eta_{i'j})\tilde{v}_{i'j}^\theta + \left(\sum_{i'}\left(\eta_{i'j}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}, \quad \lambda_j^{\mathrm{B}} = 1 - \lambda_j^{\mathrm{B}*},$$

$$\lambda_{ij}^{\mathrm{W}*} = \frac{\left(\eta_{ij}\tilde{v}_{ij}^\theta\right)^{\frac{1}{1-\rho}}}{\sum_{i'}\left(\eta_{i'j}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}}, \quad \lambda_{ij}^{\mathrm{W}} = \frac{(1-\eta_{ij})\tilde{v}_{ij}^\theta}{\sum_{i'}(1-\eta_{i'j})\tilde{v}_{i'j}^\theta}.$$

Thus, $\lambda_j^{\mathrm{B}*}$ is the share of profits from all producers that use the technology type with correlation for the source country j, and $\lambda_{ij}^{\mathrm{W}*}$ is the share of profits from country i conditional on using this type of technology.

As examples 1 and 2 illustrate how the correlation ρ affects the magnitude of the FDI elasticity, it is intuitive that a source country with larger $\lambda_j^{\mathrm{B}*}$ is likely to have a larger FDI elasticity, and that a country pair with larger $\lambda_{ij}^{\mathrm{W}*}$ is likely to have a larger bilateral FDI elasticity. The weights η_{ij} and the correlation ρ are the key parameters that govern the heterogeneity across these elasticities.

The first-order deviation of D_{ij} across equilibria becomes

$$\mathrm{d}\ln D_{ij} = \theta\left(1 + \frac{\rho}{1-\rho}\frac{\eta_{ij}\left(\lambda_{ij}^{W*}\right)^\rho}{(1-\eta_{ij}) + \eta_{ij}\left(\lambda_{ij}^{W*}\right)^\rho}\right)\left[\mathrm{d}\ln\tilde{A}_i - (\epsilon^s - 1)\mathrm{d}\ln\kappa_{ij}\right]$$

$$- \frac{\rho}{1-\rho}\frac{\eta_{ij}\left(\lambda_{ij}^{W*}\right)^\rho}{(1-\eta_{ij}) + \eta_{ij}\left(\lambda_{ij}^{W*}\right)^\rho}\mathrm{d}\ln\lambda_j^{\mathrm{B}*} + \mathrm{d}\ln\frac{D_j}{G^j}. \tag{6}$$

The FDI elasticity now becomes heterogeneous in the sense that a change for the receiver country's $\tilde{A}_i$ leads to different response of FDI investments for different source countries j. This bilateral heterogeneity is crucial in aligning the model with the empirical findings presented in the empirical section.

3.6   Discussion of Simplifying Assumptions

Simplifying Assumption 1: Static Model

The model is formulated as a static framework. However, transition dynamics are interesting and potentially important, as the elasticities of producers' relocation

decisions might be different from a static framework and the welfare implications need to take the transition into account. Furthermore, when there is explicit modeling of capital in a world with FDI, the usual trade-off between investment and consumption becomes more intricate. For example, Vietnam does not need to sacrifice domestic consumption if all the increasing investment in Vietnam is made by foreign producers. Of course, the flipside is that the profits from this increased production capacity goes to foreign owners.

In the Appendix, I extend the static baseline model to a dynamic version with explicit capital investments. The representative household in each country makes a consumption and saving decision, and the saving equals lending to domestic producers for investments. The producers use both capital and labor for production, and the investment for capital is borrowed from the domestic household, subject to an endogenous interest rate.

The producers make similar production and location choice as in the static model. Moreover, they could also make relocation decisions if they find the expected value from operating in a new location – with new draws of productivities – is greater than the value of operation at the current location. The steady-state equilibrium of the dynamic model retains the properties in the static baseline model, with the exploration of dynamic transitions currently ongoing.

Simplifying Assumption 2: One-Location Firms

I assume that each producer is limited to operating in a single location, ruling out the possibility that one variety is produced in multiple locations to serve different markets. Alternatively, Arkolakis et al. (2018) makes the other extreme assumption by replacing operation fixed costs with marketing fixed costs for each export destination, thereby allowing each market to be independently served from different production locations. The key advantage of this simplifying assumption is that it rules out the joint decision across multiple locations for a firm, which results in a complicated combinatorial problem, as in Tintelnot (2017); Morales, Sheu and Zahler (2019); and Alfaro-Urena et al. (2023).

This assumption, however, has implications for the FDI diversion elasticity. When the US imposes tariff increases on Chinese exports, a producer may choose to only move its operation that serves the US market to other locations, while retain-

ing its operation that serves China and other markets within China. This implies a smaller capital movement out of China conditional on moving, but at the same time, a higher likelihood of movement for each producer.

As a result, I cannot speak to the different margins of FDI diversion for each individual producer. Although it is certainly interesting to explore how finite operation fixed costs would change the elasticity of FDI diversion in the model and its implications, I target the aggregate elasticity of FDI diversion at the country level in my calibration. Thus, the implications of my model at the aggregate level should be similar to a richer model with different margins of FDI diversion.

Simplifying Assumption 3: Homogeneous Trade Elasticity

Finally, I focus on the heterogeneity of the FDI diversion elasticity, while assuming a homogeneous trade diversion elasticity. Previous works, such as Lind and Ramondo (2023) have underscored the considerable heterogeneity in own- and cross-price elasticities of trade. For example, Chinese goods are estimated to be close substitutes for goods from Turkey for US consumers, but poor substitutes for goods from the US itself. Fajgelbaum et al. (2021) makes similar points specifically in the context of the China-US trade war, and highlights the importance of country-specific components in generating heterogeneous trade elasticities.

In the context of this model, the heterogeneity in trade elasticities are pertinent, as the incentives for FDI diversion are intertwined with trade fundamentals. When the US imposes tariff increases on China, Vietnam exports to the US increase substantially, presumably because the goods that Vietnam produces are close substitutes for Chinese goods, which means that the incentive for increasing production capacity in Vietnam is larger. However, conditional on Vietnam being a much better production location for FDI due to the heterogeneous trade elasticities, it does not necessarily mean that FDI from certain source countries would respond more, which is what this paper focuses on, namely the heterogeneity of FDI elasticities.

4 Calibration

I now take the model to data by calibrating it to the world economy in 2017 as the original equilibrium. In the next section, I will conduct counterfactuals to analyze

the effects of the Trump tariffs. The calibrated model has thirteen economies[17] and a combined rest of the world economy (labelled as WorldRest), and three sectors: 1) agriculture and mining, 2) manufacturing, and 3) service.

To calibrate the original equilibrium, I categorize the model's parameters into three groups. The first group of parameters are externally calibrated by direct measurement in the data, including $L_i, \phi_h^s, \tau_{hi}^s$. The second group includes fundamentals recovered by solving the model to match country-specific and bilateral observables, including $d_{hi}^s, \kappa_{ij}^s, z_j$. The last group of parameters are elasticities for both trade and FDI. Trade elasticities ϵ^s are calibrated using a standard gravity regression with fixed effects. The FDI elasticites are calibrated using indirect inference, including θ, ρ, and η_{ij} that govern the country-pair magnitude and heterogeneity of FDI elasticities.

4.1 External Calibration

I measure efficiency units of labor L_i by the product of employers (*emp*: Number of persons engaged, in millions) and human capital (*hc*: Human capital index, based on years of schooling and returns to education) from Penn World Table (PWT, version 10.01). I measure sectoral expenditure shares ϕ_h^s using the 2017 Inter-Country Input-Output (ICIO) Tables (OECD, 2021 edition). I also have PPP-adjusted total expenditures for each country from PWT. Together with nominal expenditures from ICIO, I can infer the price index P_i for each country. I use the ad-valorem equivalents of most-favored nation tariffs (AVEMFN) from WITS TRAINS for each HS 6-digit product. To get the sectoral level tariffs, I use the 2017 BACI bilateral trade data to get weighted tariffs between each country-pair and the three sectors.

4.2 Recover Original Steady State Fundamentals

With the externally calibrated parameters above, and conditional on the set of elasticities to be specified later, I find $\{z_j\}_{j=1}^N, \{d_{hi}^s\}_{h=1,i=1,h\neq s}^{N,N,S}, \left\{\kappa_{ij}^s\right\}_{i=1,j=1,j\neq i,s}^{N,N,S}$ to exactly match $\{X_j\}_{j=1}^N, \{\pi_{hi}^s\}_{h=1,i=1,h\neq s}^{N,N,S}, \left\{\lambda_{ij}^s\right\}_{i=1,j=1,j\neq i,s}^{N,N,S}$ for the 14 economies and

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[17]The calibrated economies include Australia, Canada, China, Germany and France (combined and labelled as DeFr), UK, India, Japan and Korea (combined and labelled as JpKr), Mexico, Malaysia, South America, Taiwan, US, Vietnam.

3 sectors for the year 2017.[18] The trade shares π_{hi}^s are from ICIO, by combining countries and sectors to my level of calibration. The bilateral capital stocks are from the official bilateral FDI data described in the empirical section for year 2017. I then get domestic capital stocks from the IMF Investment and Capital Stock Dataset (2021 version). With these two datasets, I calculate the capital shares across all receiver countries for each source country.

Since I don't have capital in the model, I target the corresponding aggregate profit shares. Specifically, I find $\left\{\kappa_{ij}^s\right\}_{i=1,j=1,j\neq i,s}^{N,N,S}$ such that λ_{ij}^s in my model equals $\frac{\text{FDK}_{ij}^s}{\sum_{i'}\text{FDK}_{i'j}^s}$ in the data, for all j and s.

Finally, productivity z_j intuitively affects total expenditure and income, conditional on other fundamentals including price indices and fundamentals like trade costs. Price indices, trade costs, and productivity cannot be separately identified if none of them can be measured directly (following the logic of Waugh (2010)). Since I only have country level measures of price indexes, I normalize the productivities to be the same across sectors for each country.

4.3 Trade Elasticities ϵ^s

The partial trade elasticities in the model are governed by the preference parameters ϵ^s alone, despite the presence of FDI. The ratio of imports from country i to the domestic import value (excluding tariff payments) for a sector can be represented as follows

$$\frac{X_{hi}^s}{X_{hh}^s} = \frac{\Phi_i^s \left(d_{hi}^s\right)^{1-\epsilon^s} \left(\tau_{hi}^s\right)^{-\epsilon^s}}{\Phi_h^s}.$$

Thus, I can use the standard regression method with fixed effects to estimate the trade elasticities using tariff changes as cost shifters.

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[18]The bilateral FDI stocks are only available at the country level. To get bilateral FDI stocks at the sector level, I use the fDi Markets to calculate the investment share of each sector for each country-pair in 2017. Specifically, using the cumulative number of projects invested from country j in country i in sector s in year 2017, denoted as N_{ij}^s, the sector bilateral FDI stocks from j in i in sector s is then $\frac{N_{ij}^s}{\sum_{s'} N_{ij}^{s'}}\text{FDK}_{ij}$.

More specifically, I run the following regression separately for sectors $s = 1, 2$,

$$\ln \text{EX}_{hit}^s = \text{FE}_{ht}^s + \text{FE}_{it}^s - \epsilon^s \ln \tau_{hit}^s + u_{hit}^s,$$

where the regression coefficient $\hat{\epsilon}^s$ is used for calibration. However, this standard method using tariff variations is not applicable to the service sector, as service trade (like tourism, legal service) generally do not incur tariffs at customs. To circumvent this issue, I use another cost shifter in the literature, namely the real exchange rate (RER). For sector 3, I substitute $\ln \tau_{hit}^s$ in the above regression with $\ln \text{RER}_{hit}$. Since the real exchange rate is defined such that $\text{RER}_{hit} = \text{RER}_{hjt} \text{RER}_{jit}$, the fixed effects FE_{ht}^s, FE_{it}^s would absorb all variations. Thus, I use FE_h^s, FE_i^s, FE_t^s as fixed effects instead:

$$\ln \text{EX}_{hit}^3 = \text{FE}_h^3 + \text{FE}_i^3 + \text{FE}_t - \epsilon_{\text{RER}}^3 \ln \text{RER}_{hit} + u_{hit}^3.$$

The bilateral trade values data from 2008 to 2021 are sourced from BACI. I constrain the sample to the largest 100 economies in terms of their total export values in 2017. I aggregate the HS 6-digit product-level export values to the model's three sectors, and calculate the tariffs for each sector weighted by the product-level export values, where the tariffs are the AVEMFN from WITS TRAINS. For the service sector, I get the total service trade values from ICIO for the available countries from 2008 to 2018 (the 2021 version ICIO is only available up to 2018). The real exchange rates are calculated using official exchange rates and PPP from WDI.

It is well-known that the trade elasticities inferred from RER shifters are often significantly lower than those inferred from tariff shifters.[19] To ensure that the elasticity for the service sector is comparable to those of the other two sectors, I assume that the underlying factors causing the discrepancy between RER and tariff pass-throughs affect all sectors similarly. Consequently, I adjust the service sector's estimated elasticity from RER shifters by multiplying it with the ratio of the manufacturing sector's estimated elasticities from both tariff and RER shifters. This approach yields the following calibrated parameter values: $\hat{\epsilon}^1 = 5.34, \hat{\epsilon}^2 = 3.29$, and

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[19]See a survey paper related to this by Burstein and Gopinath (2014).

$\hat{\epsilon}^3 = 2.84.$[20]

4.4 FDI Elasticities θ, ρ, η_{ij}

For the last set of parameters that govern FDI elasticities, there are no conventional methods of estimation in existing literature. One of the challenges is the lack of well-measured cost shifters for FDI (e.g. shifters for κ_{ij}^s), akin to tariffs for trade. Based on the empirical estimations in Section 2, I use the following indirect inference method for calibration.

Intuitively, both θ, ρ and η_{ij} play a crucial role in determining the average level of the FDI diversion elasticity. The first two dictate the FDI elasticities corresponding to the two latent nests, while η_{ij} defines the weights between the two nests. Moreover, ρ and η_{ij} are directly related to the heterogeneity of the FDI diversion elasticities. (2) and (4) are the empirical regressions that capture the magnitude and heterogeneity of the FDI diversion elasticities, and are thus used as targets for calibration.

To establish a direct connection between the parameters η_{ij} and the data, I parameterize η_{ij} using observable bilateral variables that have shown a significant correlation with the magnitude of the FDI responses in the empirical section. More specifically, I assume a functional form

$$\eta_{ij} = \frac{e^{\boldsymbol{Z}_{ij}\boldsymbol{\zeta}}}{1 + e^{\boldsymbol{Z}_{ij}\boldsymbol{\zeta}}}$$

$$\text{and } \boldsymbol{Z}_{ij}\boldsymbol{\zeta} = \zeta_0 + \zeta_1 \ln \text{dist}_{ij} + \zeta_2 \ln \text{GDPpc}_j + \zeta_3 \text{ComparaAdv}_{ij}. \tag{7}$$

As a result, the parameters to be calibrated are $\theta, \rho, \boldsymbol{\zeta}$. The targets for calibration come from the following regressions using actual data

$$\text{d}\ln K_i = \vartheta \text{DI}_i + u_i, \tag{8}$$

$$\text{d}\ln K_{ij} = \text{FE}_i + \text{FE}_j + \boldsymbol{Z}_{ij}\tilde{\boldsymbol{\psi}} + (\text{d}\ln K_i \cdot \boldsymbol{Z}_{ij})\boldsymbol{\psi} + u_{ij},. \tag{9}$$

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[20]Let $\hat{\epsilon}_{\text{tariff}}^2$ and $\hat{\epsilon}_{\text{RER}}^2$ be the coefficients estimated using tariff and RER shifters, respectively, for the manufacturing sector, and let $\hat{\epsilon}_{\text{RER}}^3$ be the coefficients estimated using RER shifters for the service sector. I infer the elasticity that would have been estimated if there were tariff shifters to the service sector to be $\hat{\epsilon}_{\text{RER}}^3 \times \frac{\hat{\epsilon}_{\text{tariff}}^2}{\hat{\epsilon}_{\text{RER}}^2}$. The regressions have $\hat{\epsilon}_{\text{RER}}^3 = 0.066, \hat{\epsilon}_{\text{RER}}^2 = 0.077$, and thus $\hat{\epsilon}_{\text{RER}}^3 \times \frac{\hat{\epsilon}_{\text{tariff}}^2}{\hat{\epsilon}_{\text{RER}}^2} = 2.84.$

The changes are calculated using data for 2017 and 2019. All regressions are run at the country level. For the corresponding regressions using model simulation data, I replace capitals with profits.

To generate model moments, I need to take a stand on the specific shock processes that account for changes between the two periods, as different shocks would affect the estimates of coefficients. This can be seen more clearly by examining the decomposition in equation (6), which suggests that the error terms are correlated with the regressors in equation (9).

To proceed, consider a set of shocks that are possible within the model, $L_j, \phi_h^s, d_{ij}^s, z_j, \tau_{ij}^s, \kappa_{ij}^s$, which hit the original equilibrium. For $L_j, \phi_h^s, \tau_{ij}^s$, I can directly measure the values in both 2017 and 2019. For $z_j, d_{ij}^s, \kappa_{ij}^s$, I first calibrate similarly the 2019 equilibrium to deduce the necessary values for these shocks, given the directly measurable shocks and parameters, including θ, ρ, η_{ij}. I then decompose the bilateral operation frictions into $\mathrm{d}\ln\kappa_{ij}^s = \mathrm{d}\ln\kappa_i^{s,\mathrm{inward}} + \mathrm{d}\ln\kappa_j^{s,\mathrm{outward}} + \mathrm{d}\ln\tilde{\kappa}_{ij}^s$, where $\mathrm{d}\ln\kappa_i^{s,\mathrm{inward}}$ and $\mathrm{d}\ln\kappa_j^{s,\mathrm{outward}}$ represent the deviations in the receiver's and the source country's unilateral inward- and outward-operation frictions, respectively. I assume that $\mathrm{d}\ln z_j$, $\mathrm{d}\ln d_{ij}^s$, $\mathrm{d}\ln\kappa_i^{s,\mathrm{inward}}$, $\mathrm{d}\ln\kappa_j^{s,\mathrm{outward}}$ are deterministic, while $\mathrm{d}\ln\tilde{\kappa}_{ij}^s$ follows an i.i.d. distribution. The actual data is then considered as the result of one realization of this stochastic process.

The calibration process is as follows. Given an initial guess of the parameters to be calibrated, $\theta, \rho, \boldsymbol{\zeta}$, I can get a non-parametric distribution of $\mathrm{d}\ln\tilde{\kappa}_{ij}^s$. I then simulate the realization of $\mathrm{d}\ln\tilde{\kappa}_{ij}^s$ for many times, and run regressions (8) and (9), calculate the median of estimates for $\zeta_1, \zeta_2, \zeta_3, \vartheta$ and standard error of estimates for ϑ. I adjust parameter guesses to minimize the discrepancy between the empirical and simulated estimates.

The parameters θ and ρ are intrinsically linked to the estimate of ϑ. The simulated shocks using the backed-out distribution of $\mathrm{d}\ln\tilde{\kappa}_{ij}^s$ give us a set of regression coefficients θ. It turns out that ρ exerts a considerable influence on the median of the ϑ estimates, while θ has large impacts on the standard error of the ϑ estimates in the model. Hence, I adjust θ, ρ to target for the point estimate and standard error of ϑ in regression (8) in the data.

The parameters $\boldsymbol{\zeta}$ in the model are directly linked to the corresponding estimates

in the data. Although $\boldsymbol{\zeta}$ encompasses four parameters, with an extra one on the constant ζ_0, the empirical estimates have only three moments $\hat{\zeta}_1, \hat{\zeta}_2, \hat{\zeta}_3$. However, the parameters $\boldsymbol{\zeta}$ only affect the η_{ij} in the model. Given a set of $\boldsymbol{\zeta}$, and a different value for ζ_0, I can always find another set of $\zeta_1, \zeta_2, \zeta_3$ that yield very similar η_{ij}.

Fitting of the Indirect Inference

Table 3 displays the calibration results for θ and ρ using regression (8), and Table 4 shows the calibration results for $\boldsymbol{\zeta}$ using regression (9).

	Outcome: $\mathrm{d}\ln K_i$		Calibration	
	Data	Model	Parameter	Value
DI_i	18.67 **	18.29	ρ	0.82
	(7.83)	(7.60)	θ	5.79
R^2	0.471			
# of Obs.	117			

Notes: The first column reports empirical regression coefficient for ϑ. I constrain the sample to include the largest FDI receivers, while excluding those typically considered tax heavens, which results in 117 receiver countries. The second column reports the median and standard error of regression coefficients from 10 model simulation runs. Finally, the last column reports the corresponding parameter values. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Calibration for FDI Elasticities: θ, ρ

	Outcome: $\mathrm{d}\ln K_{ij}$		Calibration	
	Data	Model	Parameter	Value
$\mathrm{d}\ln K_i \times \ln\left(\mathrm{Dist}_{ij}\right)$	-0.169*	-0.176	ζ_1	-7
	(0.090)			
$\mathrm{d}\ln K_i \times \ln\left(\mathrm{GDPpc}_j\right)$	0.117**	0.116	ζ_2	5
	(0.059)			
$\mathrm{d}\ln K_i \times \mathrm{ComparaAdv}_{ij}$	0.576***	0.521	ζ_3	19
	(0.219)			
			ζ_0	-9.5
R^2	0.111			
# of Obs.	2621			

Notes: The first column reports empirical regression estimates of the interaction coefficients ψ. I constrain the sample to include investors with sufficient large number of receivers, while excluding those typically considered tax heavens, which results in 36 investor and 193 receiver countries. The second column reports the median of regression coefficients from 10 model simulation runs. Finally, the last column reports the corresponding parameter values. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Calibration for FDI Elasticities: $\boldsymbol{\zeta}$

Figure 5 shows the resulting bilateral η_{ij} values, where each column represents a producer country, and each row represents a receiver country. Rich economies in general have high η_{ij} to most of the receiver economies. Country pairs that are close to each other also have high η_{ij}. The VNM row highlights the comparison between Taiwan and French FDI investment in it. The smaller geographic distance and larger comparative advantage similarity between Vietnam and Taiwan, compared to Vietnam and France, contribute to a much larger $\eta_{\text{VNM,TWN}}$ than $\eta_{\text{VNM,DeFr}}$.
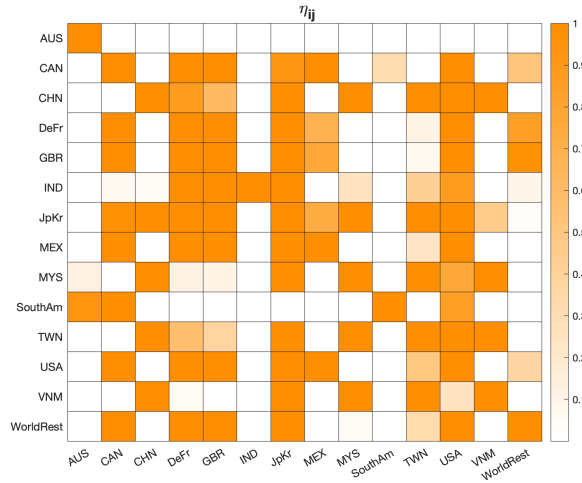
Figure 5: η_{ij}

5 Quantitative Implications of the Trump Tariffs

I now use the calibrated model to evaluate the quantitative implications of the Trump tariffs. I highlight the importance of FDI diversion and, furthermore, the role of heterogeneous FDI diversion elasticities in influencing the effects of the Trump tariffs on trade, FDI allocation, and country welfare.

I implement tariff increases at the sector level on Chinese exports to the US.[21] Aggregating over product level tariff changes weighted by 2017 export value from

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[21]The effects of the Trump tariffs shock may have extended beyond what is captured in the counterfactual analysis here. In fact, many believe that the China-US trade war marked the beginning of a broader shift in globalization, potentially leading to the implementation of related policies targeting various aspects such as investment and technology control, and anticipatory effects. Acknowledging the potentially more complicated nature of the Trump tariffs, the counterfactual I study here is limited to the direct and indirect effects of a tariff shock.

China to the US over HS 6-digit goods, the tariff increases at the sector level are 16.3% for the agriculture and mining sector, and 19.7% for the manufacturing sector.

I focus on three sets of results. I first show that FDI adjustments due to the Trump tariffs is an important margin of export value responses.

Next, I show the model's predictions about the unilateral and bilateral FDI stock responses. China experiences the largest decrease in inward FDI stock, accompanied by a noteworthy surge in outward FDI stock growth. The bilateral inward and outward FDI stock responses for China are particularly large for certain economies, including Vietnam. This underscores the importance of heterogeneity in FDI diversion elasticities in shaping the patterns of FDI diversion. To provide further clarity, I compare the predictions of the baseline model to those of a model with homogeneous FDI diversion elasticity, where I set $\rho = 0$, maintain $\theta, \epsilon^s, L_i, \phi_h^s, \tau_{hi}^s$ identical to the baseline model, and recalibrate $z_j, d_{hi}^s, \kappa_{ij}^s$ to match the 2017 equilibrium observables.

Finally, I discuss both the aggregate and distributional welfare implications of the Trump tariffs across countries.

5.1 Export Response Decomposition

I derive in the Appendix that the export value net of tariff payment from country i to country h in sector s can be expressed as:

$$\frac{X_{hi}^s}{\tau_{hi}^s} = \frac{X_h^s}{\tau_{hi}^s} \pi_{hi}^s = \frac{X_h^s}{\tau_{hi}^s} \frac{\sum_j \tilde{M}_{ij}^s \left(P_{hij}^s\right)^{1-\epsilon^s}}{\left(P_h^s\right)^{1-\epsilon^s}},$$

where $\tilde{M}_{ij}^s \equiv \left(\left(\tilde{v}_{ij}^s\right)^\theta G_i^j/G^j\right)^{\frac{\theta-1}{\theta}} \left(G_i^j\right)^{\frac{1}{\theta}}$, and $P_{hij}^s = \frac{\epsilon^s}{\epsilon^s-1} d_{hi}^s \tau_{hi}^s \kappa_{ij}^s w_i / \left(\left(\Gamma(1-\frac{1}{\theta})\right) z_j^{\frac{1}{\theta}}\right)^{\frac{1}{\epsilon^s-1}}$. $\tilde{M}_{ij}^s \left(P_{hij}^s\right)^{1-\epsilon^s}$ captures the aggregate price index for varieties that are imported to h by producers from j operating in i in sector s. $\tilde{M}_{ij}^s$ captures the mass of producers, adjusted for the productivity distribution of producers from j that are located in i, while P_{hij}^s takes into account the producer fundamentals z_j, production location cost w_i, and bilateral frictions $d_{hi}^s, \tau_{hi}^s, \kappa_{ij}^s$. The numerator captures contributions to exports from i to h by all producers from different source countries j, and the denominator captures the exports from different i, including from h. The first-order

deviation decomposes the change of export values $\frac{X_{hi}^s}{\tau_{hi}^s}$ into three parts:

$$\mathrm{d}\ln\frac{X_{hi}^s}{\tau_{hi}^s} = \mathrm{d}\ln\frac{X_h^s}{\tau_{hi}^s}\frac{1}{\left(P_h^s\right)^{1-\epsilon^s}} + \left(1-\omega_h^s\right)\mathrm{d}\ln\tilde{M}_{ii}^s\left(P_{hii}^s\right)^{1-\epsilon^s} + \omega_h^s\,\mathrm{d}\ln\sum_{j\neq i}\tilde{M}_{ij}^s\left(P_{hij}^s\right)^{1-\epsilon^s},$$

(10)

where $\omega_h^s \equiv \frac{\sum_{j\neq i}\tilde{M}_{ij}^s\left(P_{hij}^s\right)^{1-\epsilon^s}}{\sum_j\tilde{M}_{ij}^s\left(P_{hij}^s\right)^{1-\epsilon^s}}$ captures the share of foreign production capacity in country i for sector s. The first term on the right-hand-side captures the change of the importer's sectoral expenditure, which includes general equilibrium effects on its sectoral price index, and the effect of direct tariff change. The second and third terms capture the export value changes that are associated with adjustments in domestic and foreign production capacity.

Figure 6 shows the aggregate changes in export values to the US for all economies (other than China) at the country level (by aggregating over sectors), as well as the decomposition into the three terms described in equation (10).
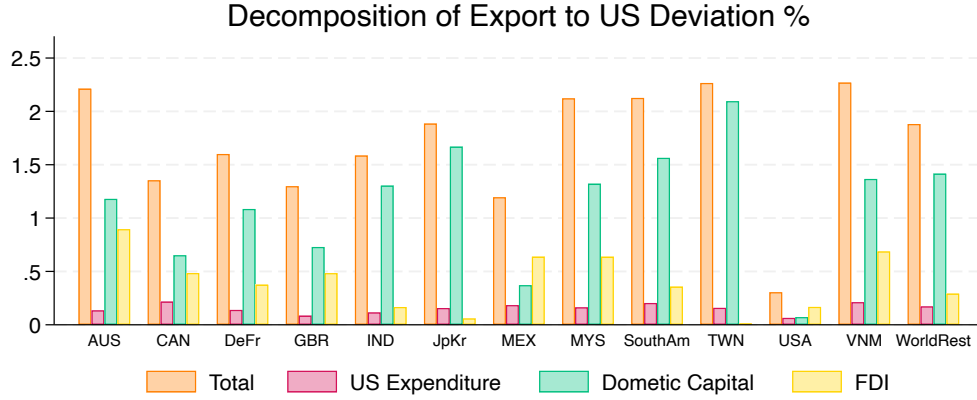
Figure 6: Export Deviation Decomposition

Comparing the total export deviation (shown in orange) across economies, economies like Canada and Mexico are actually not the ones with the largest growth of exports

to the US. This is because the decrease in wage rates for Canada and Mexico are small compared to the decreases in other economies. In contrast, economies like Vietnam, Taiwan, Malaysia increase their exports to the US the most, as they both export a lot to the US for the first two sectors, and face large wage rate decreases.

Comparing the contributions from FDI (shown in yellow) and domestic production capacity (shown in green), FDI is particularly important for Mexico, and also significant for economies like Vietnam, Australia, Canada, Britain, and Malaysia, while less so for economies like Japan, Korea, Germany, France, and Taiwan. The relative contribution of FDI and domestic production capacity depends on how important foreign producers are for the exporting country i in the first two sectors, and the FDI diversion. For example, FDI accounts for a large part of production capacity in the manufacturing sector for economies like Mexico, Australia, Canada, and Britain, while very little for Japan and Korea. For Mexico, it also receives large increase in inward FDI stocks (see next section). What's more, Mexico's domestic producers have relatively low productivity compared to the incoming foreign producers, making the contribution of FDI in export growth even more important.

5.2 FDI Diversion

I now show the model's predictions about FDI diversion. Figure 7 shows the bilateral FDI stock responses, where each column represents a source economy, and each row represents a receiver economy. The US tariffs on Chinese exports makes China a a less favorable place for serving the US market, and thus almost all economies decrease their FDI investments in China. The large relocation of FDI is also salient for two other economies that have large FDI stocks in China, namely Japan and Korea, and Taiwan.

On the other hand, China also increases its outward FDI investments a lot, as other economies become relatively better locations for production. Importantly, there is huge heterogeneity in the responsiveness of FDI diversion from China across receiver economies. The increases of FDI investment from China to Japan and Korea and Vietnam are around 20% while the increases are almost zero for most other locations. Unsurprisingly, the receivers economies with large increases are those with large η_{ij} in the calibration.

In Figure 20 in Appendix C, I provide a comparison between the FDI diversion predictions of the baseline model and those of the homogeneous FDI model. The key difference between the two models is that, in the homogeneous model, the source and receiver economy fixed effects could explain most of the bilateral FDI responses, as in equation (5), and FDI diversion pattern is rather uniform across receiver economies for each source economy, and across source economies for each receiver economy.
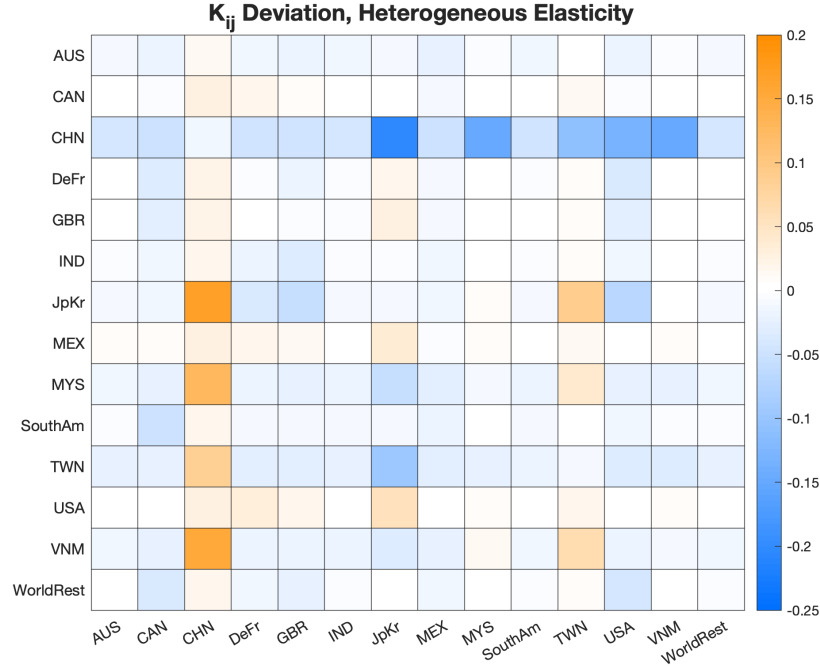

Figure 7: Bilateral FDK Diversion

Figure 8 shows the unilateral inward FDI stocks responses under the homogeneous and heterogeneous FDI elasticity model.
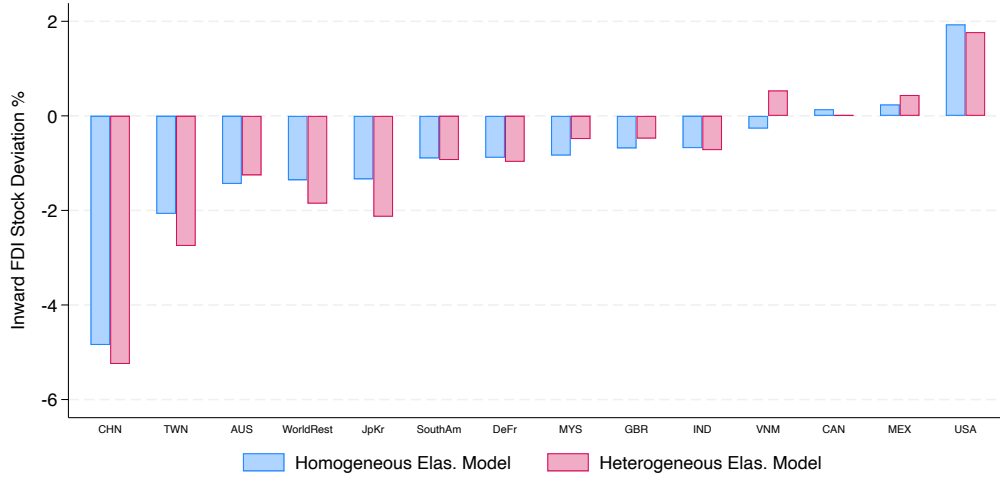
Figure 8: FDK Response: Homo. vs. Hetero. Elasticity Model

Focus on the baseline model's predictions first (the red bars). As the world, overall, becomes less efficient, the majority of economies experience a decrease in their FDI stocks. Economies that are closer to China tend to experience larger FDI decreases, while the opposite is true for those that are closer to the US.

The tariff shock leads to economies that were significant exporters to the United States becoming more attractive production locations for serving the US market. The US itself is the main source country to serve its domestic markets, and thus receives large increase in FDI. Although both Mexico and Canada are large exporters to the US, their domestic prices increases make them less attractive for FDI investments. The fact that they are close substitutes for FDI as production locations also makes them relatively less attractive locations for FDI diversion in this case.

Finally, the difference between the two models' predictions regarding inward FDI stock changes is particularly large for economies like Vietnam, Taiwan, Japan and Korea, and the Rest of the World. To the extent that FDI have other effects on the economy beyond the scope of this paper (e.g., technology diffusion), this comparison highlights the significance of the heterogeneity of the FDI diversion elasticity for understanding the impacts of the Trump's tariffs.

5.3 Impacts on Real Consumption

I now turn to the real consumption implications of the Trump tariffs, which is the measure of welfare in my model. Figure 9 shows the real consumption responses of China and the United States, as well as the decomposition of the aggregate welfare changes into different sources.
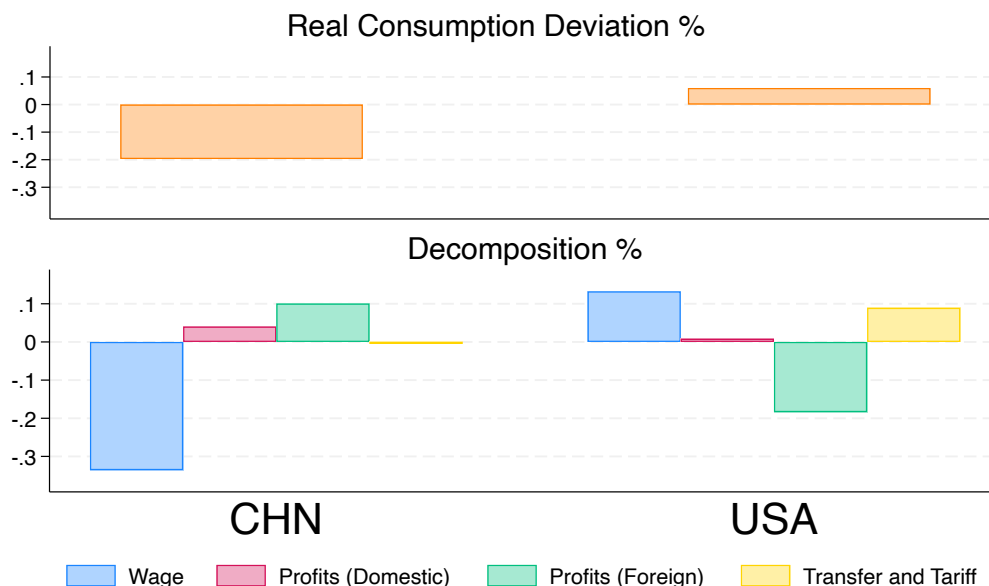

Figure 9: Real Consumption Implications for China and US

China experiences a real consumption loss of around 0.2% while the US sees a gain of around 0.05%. In comparison, Fajgelbaum et al. (2020) suggests that the US incurs losses due to higher prices, but gains because of tariff revenues and profits to domestic producers. In total, the US has a net loss of around 0.04%. The key reason that the welfare calculation for the US in my model reverses is because of FDI diversion. In a world with FDI, the US attracts more FDI because of the Trump tariffs, leading to an increase in the domestic wage rate. On the other hand, US producers reduce their investments in foreign economies, and some of them move back to the US, which results in a large decrease in US foreign profits, and slightly positive increase in domestic profits.

On the other hand, China's losses primarily come from a large decrease in its domestic wage rate, resulting from reduced US import demands and the outflows of

FDI previously invested in China. As producers from China relocate production to foreign economies, China has higher foreign profits. Interestingly, domestic profits increase for Chinese producers. This highlights the fact that producers are linked to productivities in the model, and when foreign producers with high productivities pull out of China, Chinese domestic producers face lower competition.

The large differences between wage, domestic, and foreign profit responses for China and the US underscore the substantial distributional implications of the Trump tariffs. These varying income changes are likely to benefit different segments of the population (Helpman, Melitz and Yeaple (2004)). One of the motivations behind the Trump tariffs, as argued by policymakers, is to encourage the return of manufacturing and benefit labor. However, as shown in Figure 7, the producers relocating to the US are more likely to originate from advanced economies, given their larger bilateral η_{ij}.

Figure 10 presents the corresponding aggregate and distributional welfare implications for the two other countries mostly affected by the Trump tariffs, Mexico and Vietnam.
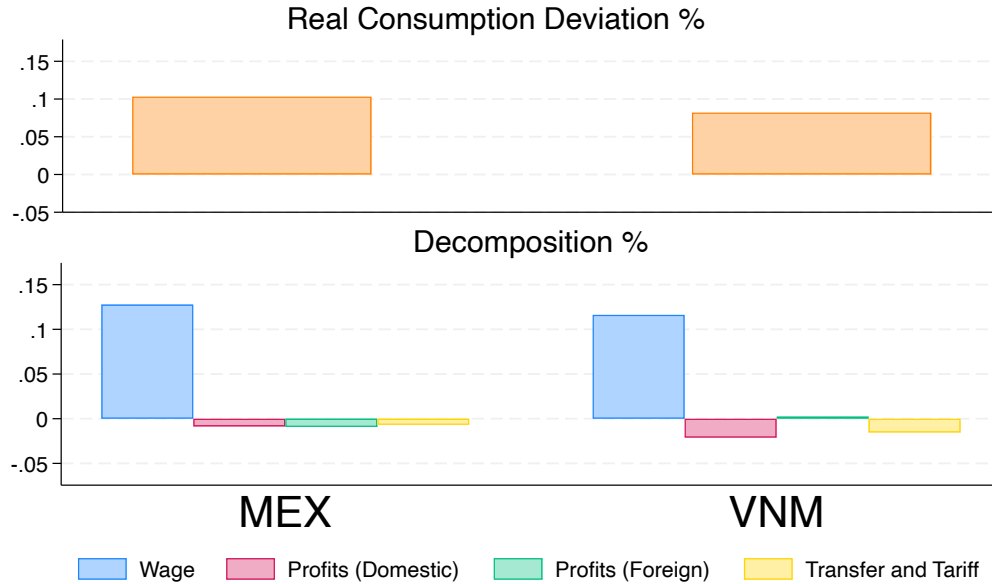
Figure 10: Real Consumption Implications for Mexico and Vietnam

Both countries experience gains in aggregate consumptions of around 0.1%, primarily driven by increases in domestic wages. However, domestic profits for both countries decrease slightly, which is again related to the fact that the influx of more

productive foreign producers raises the production cost in the domestic markets of Mexico and Vietnam.

Figure 11 presents the welfare implications for the remaining calibrated economies.
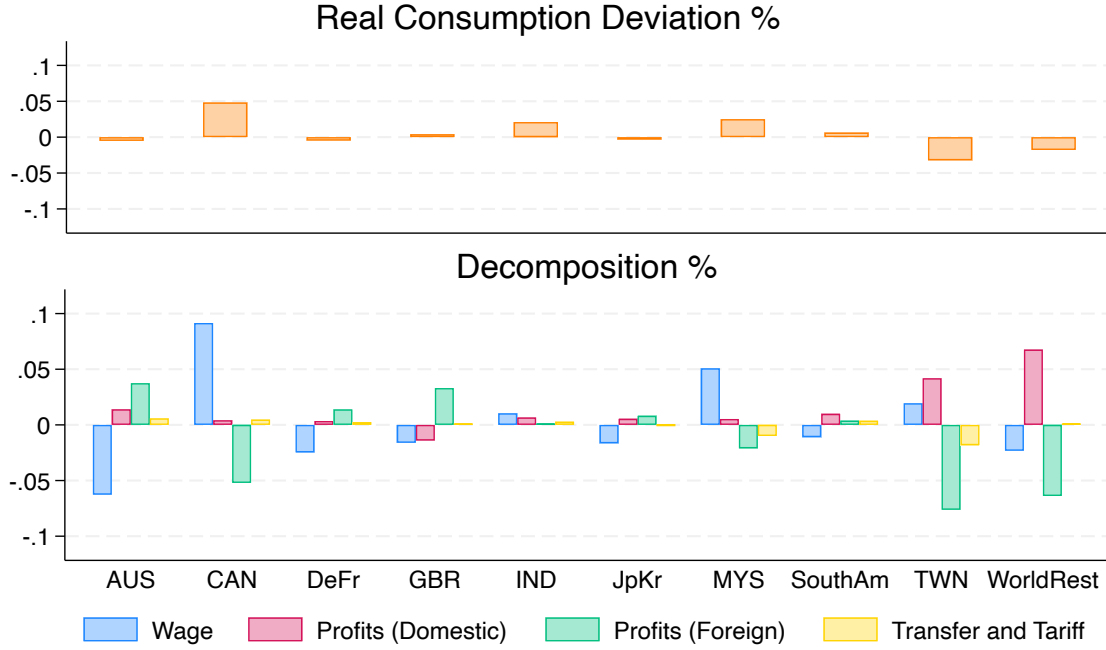

Figure 11: Real Consumption Implications for Other Economies

In terms of aggregate welfare, Canada, India, and Malaysia benefit from the Trump tariffs, while Taiwan experiences losses. The gains for Canada and Malaysia are primarily due to increases in wage rates, similar to the US and Vietnam. Taiwan's losses are mostly attributed to decreasing foreign profits, as Taiwan heavily invests in China. Some Taiwanese producers move back to Taiwan, leading to increases in labor and domestic profits.

Finally, in the Appendix, I compare the welfare implications from the baseline model to two other models, the trade-only model and the homogeneous FDI elasticity model.[22] In the trade-only model, most economies experience slight gains from higher wages and domestic profits due to diverted import demand from the US. However, the

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[22]In the trade-only model, the producers can only operate domestically. This model is calibrated using the same values for $\epsilon^s, L_i, \phi_h^s, \tau_{hi}^s$, while z_j, d_{hi}^s are recalibrated to match the 2017 equilibrium observables X_h and π_{hi}^s.

FDI diversion amplifies the losses for China, and brings gains for the US. The general equilibrium effects resulting from the FDI diversion also lead to negative effects on real consumptions for economies that export a lot to China (e.g., Vietnam) due to the lower income in China. The large increase in FDI in the US also reduces the benefits for other economies, compared to the trade-only model.

The differences in welfare implications between the homogeneous and heterogeneous FDI elasticity models are unsurprisingly larger for economies that have larger differences in FDI diversion predictions between the two models, e.g., Vietnam, Japan and Korea, the Rest of the World. These disparities highlight the potential for misinterpretations of the implications of the Trump tariffs when using standard models in the literature that do not consider FDI or models that do not account for the substantial heterogeneity in FDI diversion elasticity.

6   Conclusion

This paper underscores the significance of taking FDI diversion, along with the associated frictions and country-specific characteristics related to FDI, into account when examining the effects of trade policies on trade and welfare. The recent China-US trade war serves as a pertinent case study in the context of today's highly interconnected global economy.

Third-party countries are greatly affected by this bilateral trade policy, and their experiences vary widely. I demonstrate the critical role of considering heterogeneous FDI elasticity in understanding these effects. For many smaller and developing economies, how to explore the potential opportunities or shield from such shocks are of utmost importance. Can other countries attract FDI like Vietnam? Examining the mechanisms involved in greater detail is an area for future research and can inform policy designs.

The FDI diversion resulting from trade shocks also carries significant distributional implications. While China can mitigate some of the losses through outward FDI investments, addressing the well-being of domestic labor and producers remains a crucial concern. In the case of the US, the counterfactual scenarios suggest the potential to attract capital for reshoring, but they also emphasize that the scale and

composition of reshored investments could have important implications for welfare. Future research could delve into empirical evidence and examine potential policy measures aimed at addressing these dimensions of the issue.

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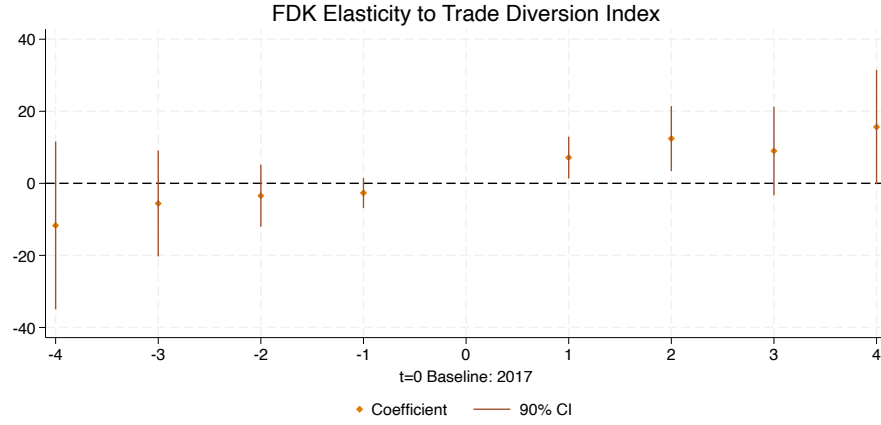
A   Extra Empirical Analysis

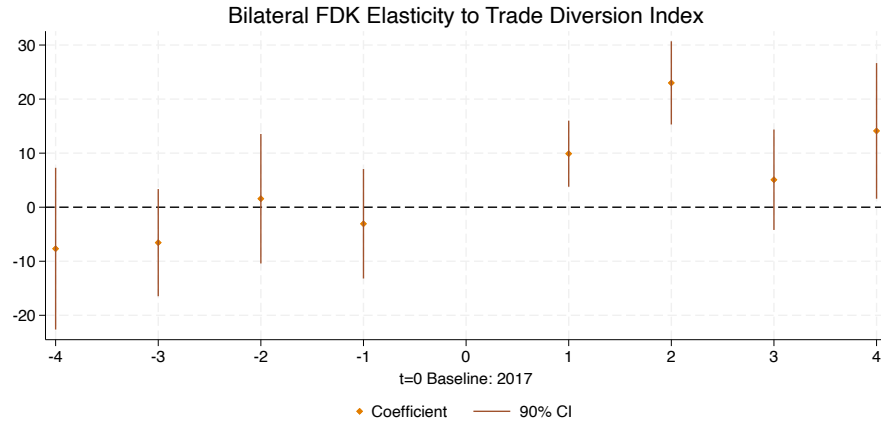## A.1   Robustness Check for Country-Level Result
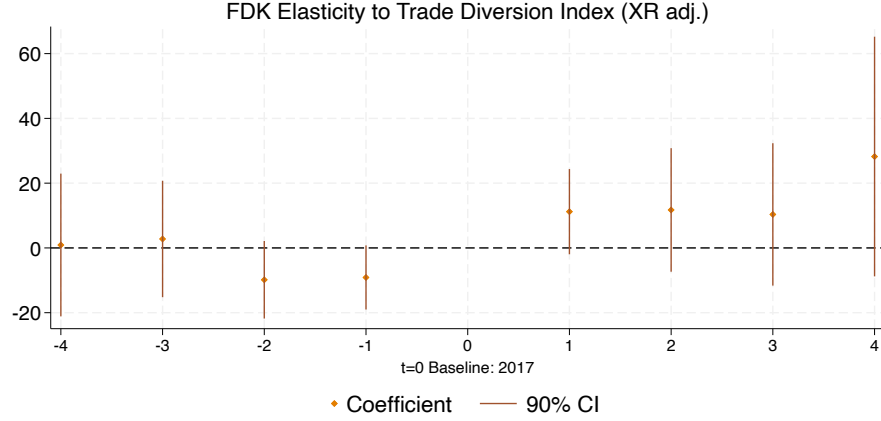
Notes: The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. I constrain the sample to include those countries with to be those with the largest inward FDI stocks in 2017, while excluding those typically considered tax heavens. This results in 91 countries. The FDI stocks are exchange rate adjusted, i.e., $\text{FDI}_i^{\text{XR}} = \text{FDI}_i \frac{\text{XR}_i^{\text{official}}}{\text{PPP}_i}$, where $\text{XR}_i^{\text{official}}$ is the official exchange rate of country i's currency to USD, and PPP_i is country i's purchasing power parity to the US, both from World Development Index by World Bank. The trade diversion index is constructed using equation (1), with ν at HS 6-digit level, trade value from BACI for year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 12: Robustness: Event Study at Country Level, Exchange Rate Adjusted FDI Stocks

FDK Elasticity to Trade Diversion Index

Notes: The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. I constrain the sample to include those countries with the largest inward FDI stocks in 2017, while excluding those typically considered tax heavens. This results in 97 countries. The trade diversion index is constructed using equation (1), with ν at ISIC 2-digit level, trade values from BACI for the year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 13: Robustness: Event Study at Country Level, ISIC 2-digit Level Tariffs

Bilateral FDK Elasticity to Trade Diversion Index

Notes: The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. I constrain the sample to include those countries with the largest inward FDI stocks in 2017, while excluding those typically considered tax heavens. I further constrain the sample to include receivers who have FDI investments from more than four source countries. This results in 74 source countries and receiver countries, and 1650 country pairs. The trade diversion index is constructed using equation (1), with ν at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 14: Robustness: Event Study at Country Level, Bilaterl FDI Stocks
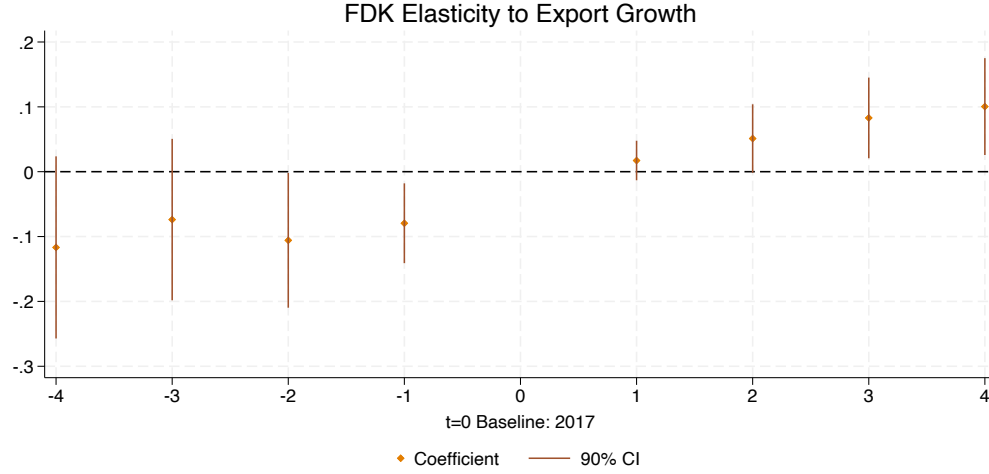
Notes: The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. I constrain the sample to include those countries with the largest inward FDI stocks in 2017, while excluding those typically considered tax heavens. This results in 145 countries. The export growth is constructed using BACI data collapsed to get each country's export value growth to the US from 2017 to 2021. Standard errors are clustered at the receiver country level.

Figure 15: Robustness: Observed Export Growth as Explanatory Variable

A.2 Robustness Check for Sector-Level Result
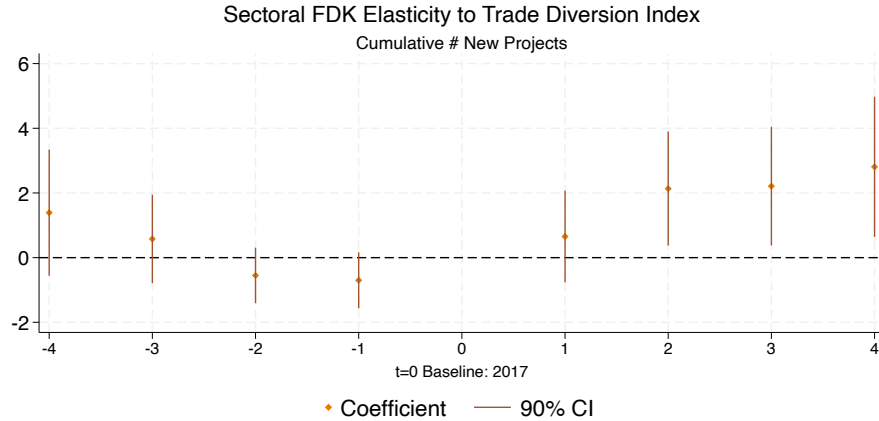
Notes: The FDI data used are the fDi Markets database measure of greenfield FDI investments. The dependent variable is the cumulative number of projects invested, aggregated at the source-receiver-sector level. The sectors are broadly categorized according to the NAICS 2012 3-digit level. I constrain the sample include those receiver-sector pairs with at least 10 projects before 2017, and service sectors are excluded. This results in a sample of 31 receiver countries and 24 sectors. The regression controls for the receiver-year, receiver-sector, and sector-year fixed effects. The trade diversion index is constructed similarly to equation (1) at the country-sector level, with ν at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 16: Robustness: Event Study at Sector Level, Number of Projects
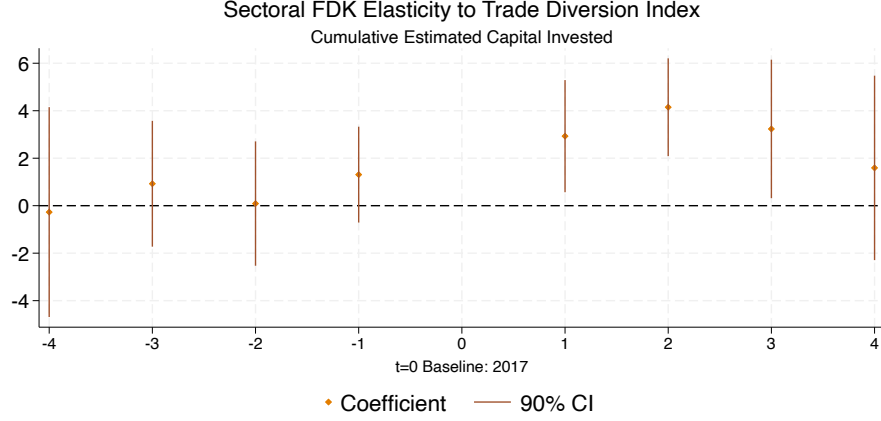
Sectoral FDK Elasticity to Trade Diversion Index

Cumulative Estimated Capital Invested

Notes: The FDI data used are the fDi Markets database measure of greenfield FDI investments. The dependent variable is the cumulative estimated amount of capital invested by these projects, aggregated at the source-receiver-sector level. The sectors are broadly categorized according to the NAICS 2012 3-digit level. I constrain the sample include those receiver-sector pairs with at least 10 projects before 2017, and service sectors are excluded. This results in a sample of 31 receiver countries and 24 sectors. The regression controls for the receiver-year, receiver-sector, and sector-year fixed effects. The trade diversion index is constructed similarly to equation (1) at the country-sector level, with ν at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 17: Robustness: Event Study at Sector Level, Estimated Capital Invested

A.3 Additional Empirical Analysis on Export and FDI

Export (ex. CHN) Elasticity to Trade Diversion Index
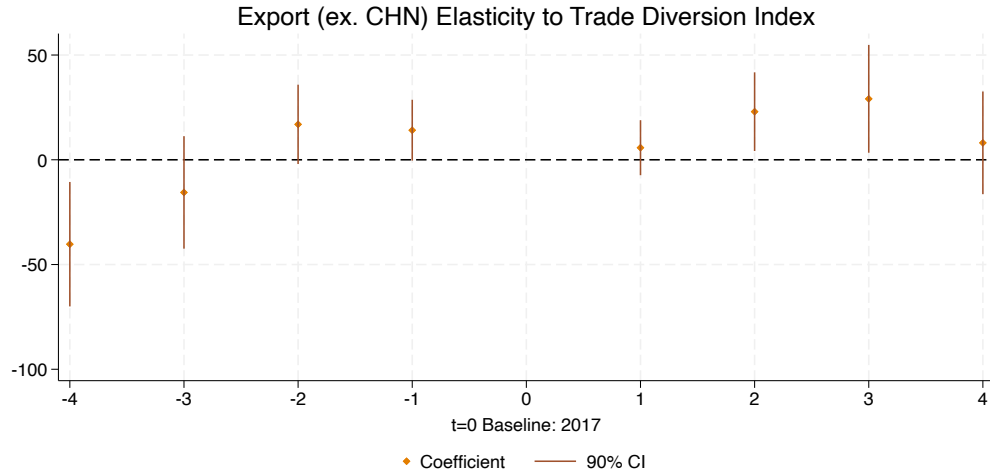
Notes: The dependent variable is the log of total export value (excluding China) for each country using data from BACI from 2013 to 2021. I constrain the sample to include those countries with the largest export values in 2017, while excluding those typically considered tax heavens, which results in a sample of 170 countries. The trade diversion index is constructed using equation (1), with ν at the HS 6-digit level, trade values from BACI for year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 18: Trade Diversion: Export (ex. CN) Elasticity to Trade Diversion Index
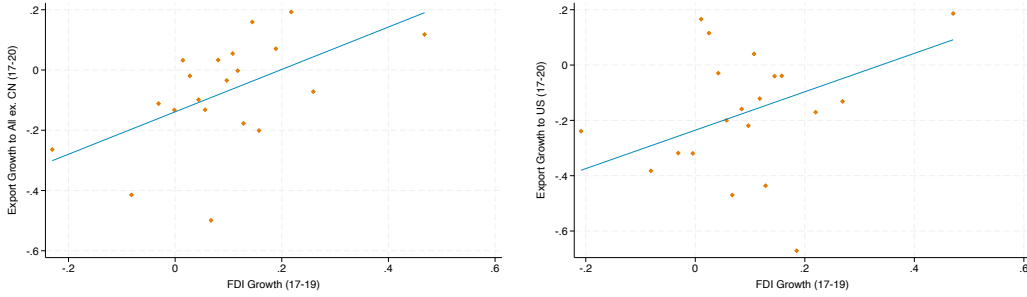
Figure 19: Binscatter for Export and FDI growth

	To All (ex. CN)		To US	
	(1)	(2)	(3)	(4)
Diversion Index	26.692	14.536	88.429**	74.273*
	(19.479)	(19.445)	(41.371)	(39.604)
FDK Growth		0.591***		0.791**
		(0.185)		(0.383)
Controls	✓	✓	✓	✓
R2 adj.	.02	.06	.07	.09
# of Obs.	140	140	141	141

Table 5: Export Growth on Trade Diversion Index and FDI Growth

B Model Derivation

I derive the model solution in an environment with capital. The production function is

$$q_{ij}^s(a) = \frac{a^{\frac{1}{\sigma^s-1}}}{\kappa_{ij}^s} \left(k_{ij}^s(a)\right)^{\alpha_i} \left(l_{ij}^s(a)\right)^{1-\alpha_i}.$$

The model without capital in the main text simply takes $\alpha_i = 0$.

B.1 Pricing

Let λ_{ij}^s be the Lagrange multiplier on the output constraint; The FOC wrt p_{hij}:

$$q_{hij}^s + p_{hij}^s \frac{\partial q_{hij}^s}{\partial p_{hij}^s} = d_{hi}^s \tau_{hi}^s \lambda_{ij}^s \frac{\partial q_{hij}^s}{\partial p_{hij}^s},$$

$$\Rightarrow \quad p_{hij}^s = \frac{\epsilon^s}{\epsilon^s - 1} d_{hi}^s \tau_{hi}^s \lambda_{ij}^s;$$

and FOC wrt $l_{ij}(s)$:

$$w_i = \lambda_{ij}^s \frac{a^{\frac{1}{\epsilon^s - 1}}}{\kappa_{ij,t}^s} k^{\alpha_i^s} (1 - \alpha_i^s) \left(l_{ij}^s\right)^{-\alpha_i^s}.$$

Using the resource constraint

$$l_{ij}^s = \left[A_i^s \left(\frac{w_i}{1 - \alpha_i^s}\right)^{-\epsilon} \frac{a}{\left(\kappa_{ij}^s\right)^{\epsilon^s - 1}} k^{(\epsilon^s - 1)\alpha_i^s} \right]^{\frac{1}{1 + (\epsilon - 1)\alpha_i^s}},$$

$$\text{where } A_i^s = \sum_h \left(\tau_{hi,t}^s\right)^{-\epsilon^s} \left(d_{hi,t}^s\right)^{1-\epsilon^s} \left(\frac{\epsilon^s}{\epsilon^s - 1}\right)^{-\epsilon^s} (P_h^s)^{\epsilon^s} Q_h^s.$$

Plug this into the price,

$$p_{hij}^s = d_{hi}^s \tau_{hi}^s \frac{\epsilon^s}{\epsilon^s - 1} \left[(A_i^s)^{\alpha_i^s} \left(\frac{w_i}{1 - \alpha_i^s}\right)^{1-\alpha_i^s} \left(\frac{a^{\frac{1}{\epsilon^s - 1}}}{\kappa_{ij}^s}\right)^{-1} k^{-\alpha_i^s} \right]^{\frac{1}{1 + (\epsilon^s - 1)\alpha_i^s}}.$$

B.2 Investment

The FOC wrt k' is

$$P_i R_j = \frac{\partial V_{ij}^s(k'; a)}{\partial k'}$$

while the Benveniste-Scheinkman envelop condition is

$$\frac{\partial V_{ij}^s(k; a)}{\partial k} = \frac{\partial v_{ij}^s(k; a)}{\partial k} + \Theta_j R_j P_i (1 - \delta).$$

In steady state, $\Theta_j = \beta$, $R_j = 1/\beta$, and thus the steady state capital and profit are

$$k_{ij}^s(a) = \Lambda_i^s P_i^{-\left(1+(\epsilon^s-1)\alpha_i^s\right)} \frac{a}{\left(\kappa_{ij}^s\right)^{\epsilon^s-1}} \left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s,$$

where $\Lambda_i^s \equiv \left(\left(\frac{\epsilon^s}{\epsilon^s-1} - (1-\alpha_i^s)\right) \frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s} \frac{1}{\frac{1}{\beta}-(1-\delta)}\right)^{1+(\epsilon^s-1)\alpha_i^s}$;

$$v_{ij}^s(a) = \left(\frac{\epsilon^s}{\epsilon^s-1} - (1-\alpha_i^s)\right) (\Lambda_i^s)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \frac{a}{\left(\kappa_{ij}^s\right)^{\epsilon^s-1}}.$$

Plug this back into the price,

$$p_{hij}^s = \frac{\epsilon^s}{\epsilon^s-1} d_{hi}^s \tau_{hi}^s (\Lambda_i^s)^{\frac{-\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{1-\alpha_i^s} \left(\frac{a^{\frac{1}{\epsilon^s-1}}}{\kappa_{ij}^s}\right)^{-1}.$$

B.3 Location Choice

The entrants' investment decisions conditional on i being the optimal location is

$$\max_{\iota} V_{ij}^s(\iota; a) - R_j P_i \iota,$$

which gives $\iota = k_{ij}^s(a)$. Thus, the entry value net of entry cost is $\frac{1}{1-\beta}$ times the following

$$\tilde{v}_{ij}^s(a) \equiv V_{ij}^s(a) + \left(1 - \delta - \frac{1}{\beta}\right) P_i k_{ij}^s(a)$$

$$= \tilde{\Lambda}_i^s \left(P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \frac{a}{\left(\kappa_{ij}^s\right)^{\epsilon^s-1}}\right),$$

where $\tilde{\Lambda}_i^s = \left(\frac{\epsilon^s}{\epsilon^s-1} - (1-\alpha_i^s)\right) (\Lambda_i^s)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} + \left(1 - \delta - \frac{1}{\beta}\right) \Lambda_i^s.$

Note that $\tilde{v}_{ij}^s(a)$ is a linear function in a. Denote $\tilde{v}_{ij}^s = \tilde{v}_{ij}^s(1)$ when suppressing the argument. I first derive the case under CES correlation function. Let the productivity

draw be a_{ij}^s, $i = 1, \ldots, N$, the probability of choosing location i is

$$\Pr_{ij}^s = \text{Prob}\left(\tilde{v}_{ij}^s(a_{ij}^s) > \tilde{v}_{i'j}^s(a_{i'j}^s), \forall i' \neq i\right) = \text{Prob}\left(\tilde{v}_{ij}^s a_{ij}^s > \tilde{v}_{i'j}^s a_{i'j}^s, \forall i' \neq i\right)$$

$$= \text{Prob}\left(a_{i'j}^s < \frac{\tilde{v}_{ij}^s}{\tilde{v}_{i'j}^s} a_{ij}^s, \forall i' \neq i\right) = \int_0^\infty \prod_{i' \neq i} e^{-z_j\left(\frac{\tilde{v}_{ij}^s}{\tilde{v}_{i'j}^s} a_{i'j}^s\right)^{-\theta}} \, \mathrm{d}e^{-z_j\left(a_{ij}^s\right)^{-\theta}}$$

$$= \frac{\left(\tilde{v}_{ij}^s\right)^\theta}{\sum_{i'}\left(\tilde{v}_{i'j}^s\right)^\theta}.$$

Thus, the productivity draw cdf conditional location i being chosen is

$$G_{ij}^s(a) \equiv \frac{1}{\Pr_{ij}^s} \int_0^a \prod_{i' \neq i} e^{-z_j\left(\frac{\tilde{v}_{ij}^s}{\tilde{v}_{i'j}^s} a\right)^{-\theta}} \, \mathrm{d}e^{-z_j a^{-\theta}} = e^{-z_j \frac{\sum_{i'}\left(\tilde{v}_{i'j}^s\right)^\theta}{\left(\tilde{v}_{ij}^s\right)^\theta} a^{-\theta}},$$

which is a Fréchet distribution with parameter $z_j^s \dfrac{\sum_{i'}\left(\tilde{v}_{i'j}^s\right)^\theta}{\left(\tilde{v}_{ij}^s\right)^\theta}$.

Now I derive the similar result using CNCES. I will suppress the superscript s. First, the probability of a_{ij} being the highest productivity draw across locations is

$$\mathbb{P}\left(a_{ij} = \max_{i'} a_{i'j}\right) = \frac{z_j G_i^j(z_j, z_j, \ldots, z_j)}{G^j(z_j, z_j, \ldots, z_j)},$$

$$\text{where } G_i^j = \frac{\partial G^j(x_1, x_2, \ldots, x_N)}{\partial x_i}\Big|_{x_1 = z_j, \ldots, x_N = z_j}.$$

Since $\tilde{v}_{ij}(a_{ij}) = \tilde{v}_{ij} \frac{a_{ij}}{z_j}$, the vector of value across locations $\{\tilde{v}_{ij}\}$ follows a max-stable multivariate Fréchet distribution with shape θ, correlation function G^j, and scale parameters $\left\{z_j^{1-\theta} \tilde{v}_{ij}\right\}$. Thus, the probability that a location is the best choice is

$$\mathbb{P}\left(\tilde{v}_{ij}(a_{ij}) = \max_{i'} \tilde{v}_{i'j}(a_{i'j})\right) = \frac{\tilde{v}_{ij}^\theta G_i^j(\tilde{v}_{1j}^\theta, \tilde{v}_{2j}^\theta, \ldots, \tilde{v}_{Nj}^\theta)}{G^j(\tilde{v}_{1j}^\theta, \tilde{v}_{2j}^\theta, \ldots, \tilde{v}_{Nj}^\theta)}$$

$$= \frac{(1 - \eta_{ij})\tilde{v}_{ij}^\theta + \eta_{ij}\left(\dfrac{\left(\eta_{ij}\tilde{v}_{ij}^\theta\right)^{\frac{1}{1-\rho}}}{\sum_{i'}\left(\eta_{i'j}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}}\right)^\rho \tilde{v}_{ij}^\theta}{\sum_{i'}(1 - \eta_{i'j})\tilde{v}_{i'j}^\theta + \left(\sum_{i'}\left(\eta_{i'j}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}.$$

The conditional distribution of value is

$$\mathbb{P}\left(\tilde{v}_{ij}\left(a_{ij}\right) < v | \tilde{v}_{ij}\left(a_{ij}\right) = \max_{i'} \tilde{v}_{i'j}\left(a_{i'j}\right)\right) = \mathbb{P}\left(\max_{i'} \tilde{v}_{i'j}\left(a_{i'j}\right) < v\right) = e^{-z_j^{1-\theta} G^j\left(\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \dots, \tilde{v}_{Nj}^{\theta}\right) v^{-\theta}},$$

which is a max-stable multivariate Frechet with θ and scale $z_j G^j\left(\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \dots, \tilde{v}_{Nj}^{\theta}\right)$. Correspondingly, the conditional distribution of productivity draw is

$$\mathbb{P}\left(a_{ij} < a | \tilde{v}_{ij}\left(a_{ij}\right) = \max_{i'} \tilde{v}_{i'j}\left(a_{i'j}\right)\right) = e^{-z_j \frac{G^j\left(\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \dots, \tilde{v}_{Nj}^{\theta}\right)}{\tilde{v}_{ij}^{\theta}} a^{-\theta}},$$

which is again a max-stable multivariate Frechet with θ and scale $z_j \frac{G^j\left(\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \dots, \tilde{v}_{Nj}^{\theta}\right)}{\tilde{v}_{ij}^{\theta}}$.

B.4   Aggregate Variables

I now calculate the aggregate variables in steady state. The source-importer-sector level price index is

$$P_h^s = \left(\sum_{j=1}^{N}\sum_{i=1}^{N}\int_{M_{ij}^s} p_{hij}^s(\omega)^{1-\epsilon^s}\, d\omega\right)^{\frac{1}{1-\epsilon^s}} = \left(\sum_j\sum_i \Pr_{ij}^s \int_0^{\infty} p_{hij}^s(a)^{1-\epsilon^s}\, dG_{ij}^s(a)\right)^{\frac{1}{1-\epsilon^s}}$$

$$= \left(\sum_j\sum_i \left(\frac{\left(\tilde{v}_{ij}^s\right)^{\theta}}{\sum_{i'}\left(\tilde{v}_{i'j}^s\right)^{\theta}}\right)^{\frac{\theta-1}{\theta}} \Gamma\left(1-\frac{1}{\theta}\right)(z_j)^{\frac{1}{\theta}}\left(\frac{\epsilon^s}{\epsilon^s-1} d_{hi}^s \tau_{hi}^s \kappa_{ij}^s \left(\Lambda_i^s\right)^{\frac{-\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{\alpha_i^s}\left(\frac{w_i}{1-\alpha_i^s}\right)^{1-\alpha_i^s}\right)^{1-\epsilon^s}\right)$$

Denote

$$\tilde{M}_{ij}^s \equiv \left(\frac{\left(\tilde{v}_{ij}^s\right)^{\theta}}{\sum_{i'}\left(\tilde{v}_{i'j}^s\right)^{\theta}}\right)^{\frac{\theta-1}{\theta}}, \quad z_j^s \equiv \left(\Gamma\left(1-\frac{1}{\theta}\right)(z_j)^{\frac{1}{\theta}}\right)^{\frac{1}{\epsilon^s-1}},$$

$$\text{and } P_{hij}^s \equiv \frac{\epsilon^s}{\epsilon^s-1} d_{hi}^s \tau_{hi}^s \kappa_{ij}^s \left(\Lambda_i^s\right)^{\frac{-\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{\alpha_i^s}\left(\frac{w_i}{1-\alpha_i^s}\right)^{1-\alpha_i^s}\left(z_j^s\right)^{-1},$$

so that I can ease notation

$$P_h^s = \left(\sum_{j=1}^{N}\sum_{i=1}^{N}\tilde{M}_{ij}^s\left(P_{hij}^s\right)^{1-\epsilon^s}\right)^{\frac{1}{1-\epsilon^s}}.$$

The source-production-sector level capital value is

$$K_{ij}^s = \int_{M_{ij}^s} P_i k_{ij}^s(\omega)\, \mathrm{d}\omega$$

$$= \tilde{M}_{ij}^s \left(\Lambda_i^s P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s} \right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \left(\frac{z_j^s}{\kappa_{ij}^s} \right)^{\epsilon^s-1} \right),$$

$$D_{ij}^s = \int_{M_{ij}^s} v_{ij}^s(\omega)\, \mathrm{d}\omega$$

$$= \tilde{M}_{ij}^s \left(\left(\frac{\epsilon^s}{\epsilon^s-1} - (1-\alpha_i^s) \right) (\Lambda_i^s)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s} \right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \left(\frac{z_j^s}{\kappa_{ij}^s} \right)^{\epsilon^s-1} \right).$$

The trade share is

$$\pi_{hi}^s = \frac{X_{hi}^s}{X_h^s} = \frac{\sum_j \int_{M_{ij}^s} p_{hij}^s(\omega) q_{hij}^s(\omega)\, \mathrm{d}\omega}{P_{h\cdot j}^s Q_{h\cdot j}^s}$$

$$= \frac{\sum_j \tilde{M}_{ij}^s \left(\frac{\epsilon^s}{\epsilon^s-1} d_{hi}^s \tau_{hi}^s \kappa_{ij}^s (\Lambda_i^s)^{\frac{-\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s} \right)^{1-\alpha_i^s} \left(z_j^s \right)^{-1} \right)^{1-\epsilon^s}}{(P_h^s)^{1-\epsilon^s}}$$

$$= \frac{\sum_j \tilde{M}_{ij}^s \left(P_{hij}^s \right)^{1-\epsilon^s}}{(P_h^s)^{1-\epsilon^s}}.$$

Finally, the following result helps for calibration

$$\left(\frac{\tilde{v}_{ij}^s}{\tilde{v}_{i'j}^s} \right)^\theta = \frac{K_{ij}^s}{K_{i'j}^s} \left(\frac{\tilde{\Lambda}_i^s}{\tilde{\Lambda}_{i'}^s} \Big/ \frac{\Lambda_i^s}{\Lambda_{i'}^s} \right).$$

Thus, I can calibrate variety masses from the observed capital stocks.

B.5   Gravity Equation

Using P_{hij}^s and $\tilde{v}_{ij}^s$,

$$\left(P_{hij}^s \right)^{1-\epsilon^s} = \left(\frac{\epsilon^s}{\epsilon^s-1} d_{hi}^s \tau_{hi}^s \right)^{1-\epsilon^s} \frac{(\Lambda_i^s)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}}}{\tilde{\Lambda}_i^s} \frac{1}{A_i^s} \tilde{v}_{ij}^s \left(\left(z_j^s \right)^{\epsilon^s-1} \right).$$

Thus, the import value from i relative to domestic import value is

$$\frac{X_{hi}^s}{X_{hh}^s} = \frac{(\Lambda_i^s A_i^s)^{\theta-1} \left(P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)(1-\alpha_i^s)}\right)^\theta \frac{(\Lambda_i^s)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}}}{\tilde{\Lambda}_i^s} \left(\sum_j \left(\frac{z_j^s}{\kappa_{ij}^s}\right)^{\epsilon^s-1}\right)^\theta (\tau_{hi}^s)^{-\epsilon^s} (d_{hi}^s)^{1-\epsilon^s}}{(\Lambda_h^s A_h^s)^{\theta-1} \left(P_h^{-(\epsilon^s-1)\alpha_h^s} \left(\frac{w_h}{1-\alpha_h^s}\right)^{-(\epsilon^s-1)(1-\alpha_h^s)}\right)^\theta \frac{(\Lambda_h^s)^{\frac{(\epsilon^s-1)\alpha_h^s}{1+(\epsilon^s-1)\alpha_h^s}}}{\tilde{\Lambda}_h^s} \left(\sum_j \left(\frac{z_j^s}{\kappa_{hj}^s}\right)^{\epsilon^s-1}\right)^\theta}.$$

All terms other than $(\tau_{hi}^s)^{-\epsilon^s} (d_{hi}^s)^{1-\epsilon^s}$ above only depend on the exporting country i and importing country h, and thus can be absorbed by fixed effects. The partial trade elasticity wrt both trade cost and tariff (for tariff-inclusive export value) is simply $1 - \epsilon^s$.

Similarly, the bilateral FDI stock value can also be written in terms of $\tilde{v}$

$$K_{ij}^s = \frac{\left(\tilde{v}_{ij}^s \left(\left(z_j^s\right)^{\epsilon^s-1}\right)\right)^\theta \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}}{\left(\sum_{i'} \left(\tilde{v}_{i'j}^s \left(\left(z_j^s\right)^{\epsilon^s-1}\right)\right)^\theta\right)^{\frac{\theta-1}{\theta}}}.$$

While the total capital stocks the source country j holds is

$$K_j^s \equiv \sum_i K_{ij}^s = \frac{\sum_i \left(\tilde{v}_{ij}^s \left(\left(z_j^s\right)^{\epsilon^s-1}\right)\right)^\theta \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}}{\left(\sum_{i'} \left(\tilde{v}_{i'j}^s \left(\left(z_j^s\right)^{\epsilon^s-1}\right)\right)^\theta\right)^{\frac{\theta-1}{\theta}}}.$$

Thus, the FDI gravity equation can be written as

$$K_{ij}^s = \frac{\left(\tilde{v}_{ij}^s\right)^\theta \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}}{\sum_{i'} \left(\tilde{v}_{i'j}^s\right)^\theta \frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}} K_j^s.$$

Note that since $v_{ij}^s(\cdot)$ is linear in its argument, and the above FDI equation is capturing the same source country j, the argument in the $v_{ij}^s(\cdot)$ function does not matter.

Further plug in the $v_{ij}^s(\cdot)$ function,

$$
K_{ij}^s = \frac{\left(\tilde{\Lambda}_i^s P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s} \right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \left(\kappa_{ij}^s \right)^{1-\epsilon^s} \right)^\theta \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}}{\sum_{i'} \left(\tilde{\Lambda}_{i'}^s P_{i'}^{-(\epsilon^s-1)\alpha_{i'}^s} \left(\frac{w_{i'}}{1-\alpha_{i'}^s} \right)^{-(\epsilon^s-1)\left(1-\alpha_{i'}^s\right)} A_{i'}^s \left(\kappa_{i'j}^s \right)^{1-\epsilon^s} \right)^\theta \frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}} K_j^s.
$$

It's easy to see that the partial FDI elasticity (FDI stock value wrt operation friction κ) is $\theta \left(1 - \epsilon^s \right)$.

B.6 Aggregate Variables & Gravity Equations with CNCES

Again, the above variables can be defined in similar ways.

$$
\tilde{M}_{ij}^s \equiv \left(\frac{\left(\tilde{v}_{ij}^s \right)^\theta G_i^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s \right)}{G^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s \right)} \right)^{\frac{\theta-1}{\theta}} G_i^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s \right)^{\frac{1}{\theta}},
$$

while z_j^s, P_{hij}^s are all defined the same as before. The trade shares also have the same form

$$
\pi_{hi}^s = \frac{\sum_j \tilde{M}_{ij}^s \left(P_{hij}^s \right)^{1-\epsilon^s}}{\left(P_h^s \right)^{1-\epsilon^s}}.
$$

However, I now cannot separate $\tilde{v}_{ij}^s$ to the source and production country part in the same way for all i because I have different η_{ij}. Thus, in general, the partial trade elasticity no longer just depend on the preference parameter ϵ^s. Intuitively, when importer h impose a tariff on exporter i, it causes producers from all source countries j to relocate in different ways, each have different productivity distributions, and thus have different impacts on the price indexes.

I next derive the FDI gravity. First, the bilateral capital value is of the same form with differently defined $\tilde{M}_{ij}^s$

$$
K_{ij}^s = \tilde{M}_{ij}^s \left(\Lambda_i^s P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s} \right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \left(\frac{z_j^s}{\kappa_{ij}^s} \right)^{\epsilon^s-1} \right).
$$

The FDI gravity becomes

$$K_{ij}^s = \frac{\left(\tilde{v}_{ij}^s\right)^\theta G_i^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right) \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}}{\sum_{i'} \left(\tilde{v}_{i'j}^s\right)^\theta G_{i'}^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right) \frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}} K_j,$$

which is basically the entry probability adjusted for capital intensity for each production location. Nothe that $\sum_{i'} \left(\tilde{v}_{i'j}^s\right)^\theta G_{i'}^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right) = G^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right)$, and $G^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right)^{\frac{1}{\theta}} \equiv \tilde{v}_j$ can be understood as an aggregate value index for j, analogous to the usual ideal aggregate price index. I can redefine the correlation function to adjust for the capital intensity

$$G^j (x_1, x_2, \ldots, x_N) = \sum_{i=1}^N (1 - \eta_{ij}) \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s} x_i + \left(\sum_{i=1}^N \left(\eta_{ij} \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s} x_i\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}.$$

The investment portfilio for produers from j can be denoted in a simplier way

$$\lambda_{ij}^s = \frac{\left(\tilde{v}_{ij}^s\right)^\theta \tilde{G}_i^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right)}{\sum_{i'} \left(\tilde{v}_{i'j}^s\right)^\theta \tilde{G}_{i'}^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right)}.$$

With our specific correlation function, this protfolio share can be decomposed as

$$
\lambda_{ij}^s = \frac{(1-\eta_{ij})\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\tilde{v}_{ij}^\theta + \eta_{ij}\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\left(\dfrac{\left(\eta_{ij}\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\tilde{v}_{ij}^\theta\right)^{\frac{1}{1-\rho}}}{\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}}\right)^{\rho}\tilde{v}_{ij}^\theta}{\sum_{i'}(1-\eta_{i'j})\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta + \left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}
$$

$$
= \underbrace{\frac{(1-\eta_{ij})\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\tilde{v}_{ij}^\theta}{\sum_{i'}(1-\eta_{i'j})\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta}}_{\equiv\lambda_{ij}^W}\underbrace{\frac{\sum_{i'}(1-\eta_{i'j})\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta}{\sum_{i'}(1-\eta_{i'j})\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta + \left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}}_{\equiv\lambda_j^B}
$$

$$
+\underbrace{\frac{\eta_{ij}\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\left(\dfrac{\left(\eta_{ij}\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\tilde{v}_{ij}^\theta\right)^{\frac{1}{1-\rho}}}{\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}}\right)^{\rho}\tilde{v}_{ij}^\theta}{\left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}}_{\equiv\lambda_{ij}^{W*}}\underbrace{\frac{\left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}{\sum_{i'}(1-\eta_{i'j})\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta + \left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}}_{\equiv\lambda_j^{B*}}.
$$

λ_{ij}^W and λ_{ij}^{W*} are the within-factor share for the technology type without correlation (no $*$) and with correlation ρ (with $*$), and λ_j^B and λ_j^{B*} are the between-factor share. $\lambda_{ij}^W\lambda_j^B$ measures the overall share of producer capitals from j that use the first technology type to operate in country i, while $\lambda_{ij}^{W*}\lambda_j^{B*}$ measures the share the other technology type.

The cross-elasticity can be shown to be

$$
\frac{\partial \ln \lambda_{ij}}{\partial \ln \frac{\tilde{v}_{i'j}}{\tilde{v}_j}} = \theta\frac{\tilde{v}_{i'j}^\theta \tilde{G}_{ii'}^j\left(\tilde{v}_{1j}^s,\tilde{v}_{2j}^s,\ldots,\tilde{v}_{Nj}^s\right)}{\tilde{G}_i^j\left(\tilde{v}_{1j}^s,\tilde{v}_{2j}^s,\ldots,\tilde{v}_{Nj}^s\right)}.
$$

Plug in again the specific form of the correlation function,

$$
\frac{\partial \ln \lambda_{ij}}{\partial \ln \frac{\tilde{v}_{i'j}}{\tilde{v}_j}} = -\theta\frac{\rho}{1-\rho}\lambda_{ij}^{W*}\lambda_{i'j}^{W*}\frac{\lambda_j^{B*}}{\lambda_{ij}}.
$$

When two production locations have similar within-factor shares for the producer,

they are strong head-to-head choices and this elasticity is high. Similarly, when two production locations have operation technology concentrated on the type with high correlation across countries (high ρ), they are more substitutable. Since the first technology type has zero correlation across i, it does not appear in the formula. As I will assume in later quantitative analysis $\eta_{jj} = 1, \forall j$, this cross-elasticity of portfolio share in i with respect to relative domestic value change can be further simplified to

$$
\frac{\partial \ln \lambda_{ij}}{\partial \ln \frac{\tilde{v}_{jj}}{\tilde{v}_j}} = -\theta \frac{\rho}{1-\rho} \lambda_{ij}^{W*} = -\theta \frac{\rho}{1-\rho} \frac{\left(\eta_{ij} \frac{\Lambda_i^s}{\Lambda_i^s} \tilde{v}_{ij}^\theta \right)^{\frac{1}{1-\rho}}}{\sum_{i'} \left(\eta_{i'j} \frac{\Lambda_{i'}^s}{\Lambda_{i'}^s} \tilde{v}_{i'j}^\theta \right)^{\frac{1}{1-\rho}}}.
$$

For example, when China is hit by tariff from the US and thus domestic production value $\tilde{v}_{jj}$ is relatively lower, countries i with relative higher η_{ij} will see larger increase of FDI investment from China.

B.7   Trade-only Model

I compare the baseline model to the one without the FDI possibility. In other words, the producers only produce domestically, with the same productivity draws, but no reallocation and entry decisions. There is only one layer of demand system (besides across sectors), which I still denote the elasticities to be ϵ^s. I specify the different parts from the baseline model.

The price index for goods that country h import from country i in sector s is

$$
\begin{aligned}
P_{hi}^s &\equiv \left(\int_0^\infty p_{hi}^s(a)^{1-\epsilon^s} \, \mathrm{d}G_i^s(a) \right)^{\frac{1}{\theta(1-\epsilon^s)}} \\
&= \frac{\epsilon^s}{\epsilon^s - 1} \gamma_{hi}^s \tau_{hi}^s \left(\Lambda_i^s \right)^{\frac{-\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s} \right)^{1-\alpha_i^s} \left(\Gamma \left(1 - \frac{1}{\theta} \right) (z_i^s)^{\frac{1}{\theta}} \right)^{\frac{1}{1-\epsilon^s}}.
\end{aligned}
$$

The aggregate capital stocks and profits for country i in sector s is

$$K_i^s = \int_0^\infty k_i^s(a)\,\mathrm{d}G_i^s(a)$$

$$= \Gamma\left(1 - \frac{1}{\theta}\right)(z_i^s)^{\frac{1}{\theta}}\left(\Lambda_i^s P_i^{-\left(1+(\epsilon^s-1)\alpha_i^s\right)}\left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s\right),$$

$$D_{ij}^s = \int_0^\infty d_i^s(a)\,\mathrm{d}G_i^s(a)$$

$$= \Gamma\left(1 - \frac{1}{\theta}\right)(z_i^s)^{\frac{1}{\theta}}\left(\left(\frac{\epsilon^s}{\epsilon^s-1} - (1-\alpha_i^s)\right)(\Lambda_i^s)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{-(\epsilon^s-1)\alpha_i^s}\left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s\right).$$

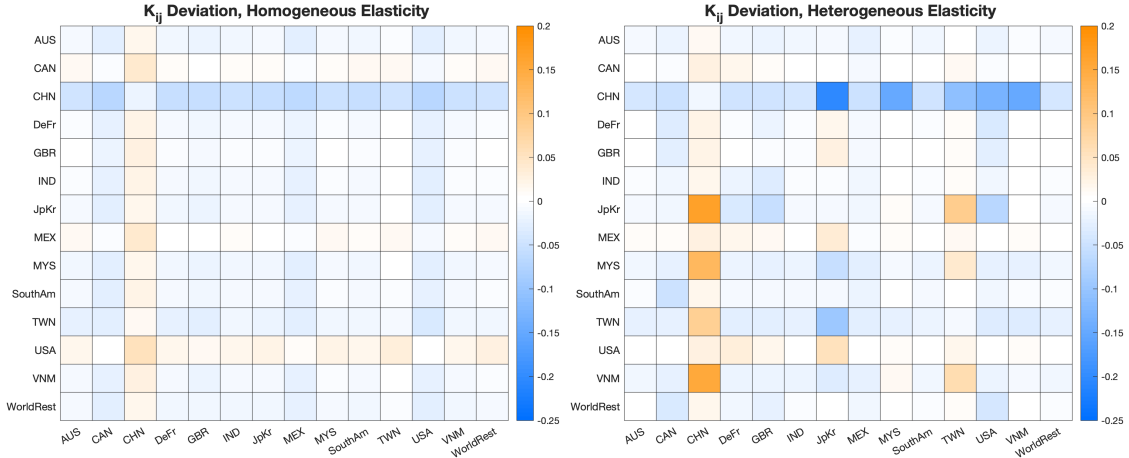# C   Counterfactuals: Extra Results

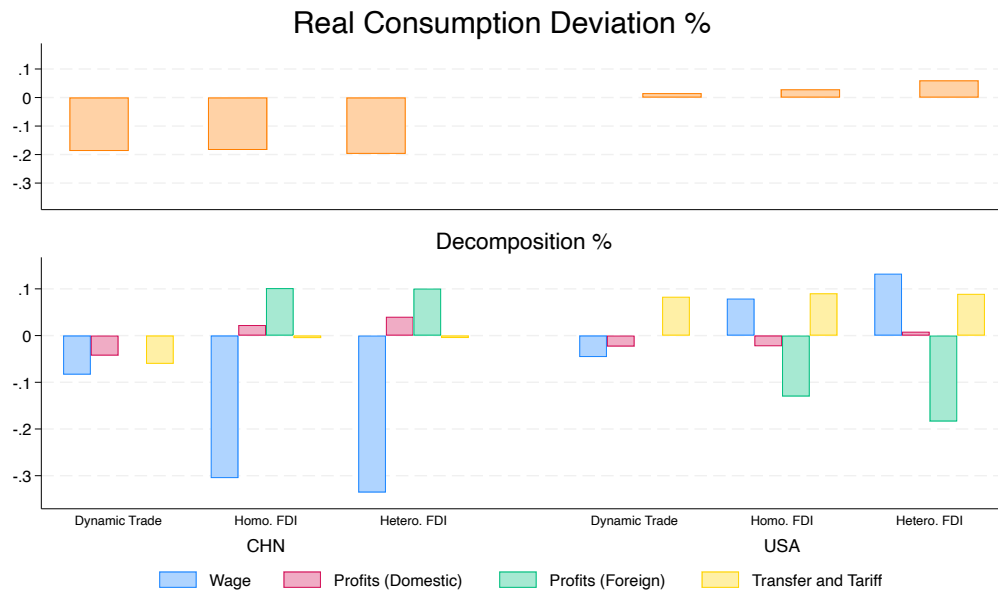Figure 20: Bilateral FDK Deviation: Homo. vs. Hetero. Elasticity Model

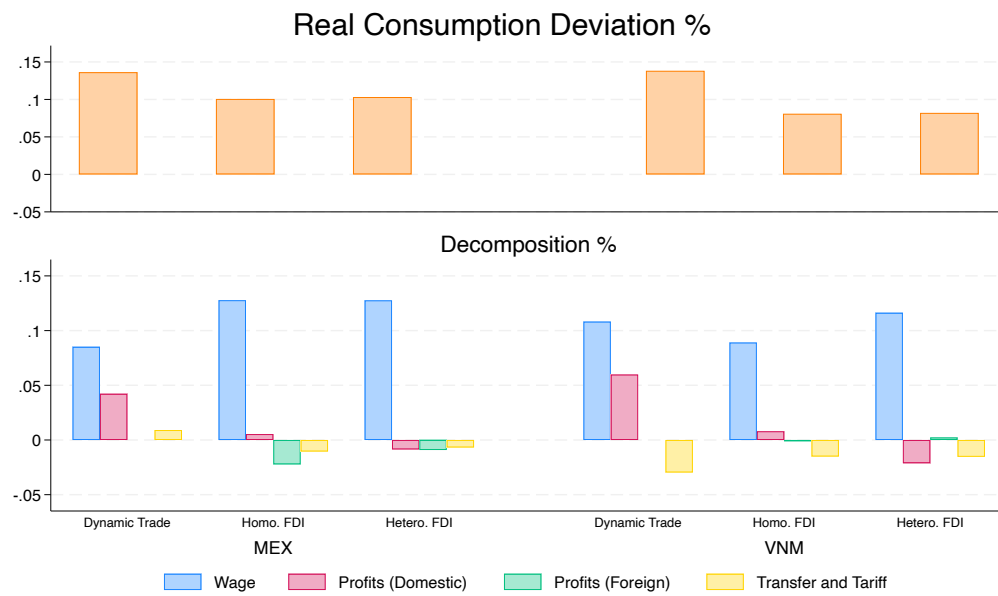Figure 21: Real Consumption Deviation for China and US
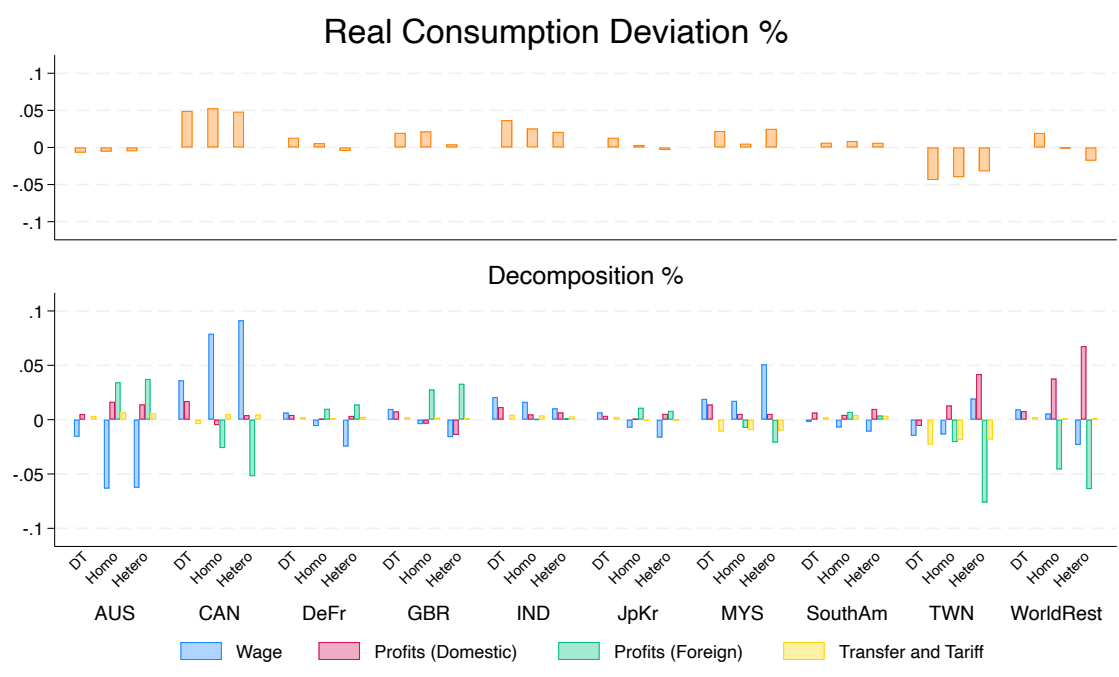

Figure 22: Real Consumption Deviation for Mexico and Vietnam

69

Figure 23: Real Consumption Deviation for Other Economies