Essays on Globalization and Labor Markets

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For Takuya, Momo, and my parents in Japan

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Preface

In recent decades, the phenomenon of globalization has exerted a profound influence on numerous aspects of our life and has obtained significant global attention. One topic that has garnered particular interest among scholars and the public is the impact of globalization on labor markets, given its potential to affect a wide range of workers.

This dissertation consists of three chapters that investigate the effect of globalization on labor markets from different perspectives. The first chapter examines the wage effects of immigration in Germany, which have been one of the public concerns in recent years. The second chapter analyzes the effect of trade liberalization on local labor markets from a theoretical perspective. The third chapter estimates the effects of the so-called 'China Shock' on labor markets in several countries. The following section provides a brief overview of each of these chapters.

Chapter 1: In the first chapter, I address the research questions: What are the effects of the EU enlargement on different types of workers? Does firm heterogeneity matter when estimating the wage effect of labor supply shocks? To address these questions, this chapter estimates the wage effects of immigration due to the EU enlargement with a multiple discrete choice model. Estimating model parameters shows that observable and unobservable firm-level characteristics are significantly associated with a firm's labor demand. The calculation of wage effects reveals that the EU enlargement had a sizable negative impact on the wages of low-skilled foreign workers while very small effects on the other types of workers, including low-skilled native workers. By comparing the wage effects with the case of eliminating firm heterogeneity, I find that ignoring firm heterogeneity can lead to overestimating the negative wage effects of immigration on foreign workers.

Chapter 2: The second chapter investigates the relationship between globalization and regional inequality, especially focusing on the effect of trade shocks on local labor markets. To do so, I construct a spatial equilibrium model with international trade and heterogeneous workers. As a main result of the comparative statics, I find that when trade cost declines in one location, there are within- and between-location reallocations of workers. Especially between locations, the most-skilled workers in another location move to the location with a trade cost decline and medium-skilled workers move in the opposite direction. As a result, the location with trade cost shock experiences labor market polarization since it has more most-skilled workers, fewer medium-skilled workers, and unchanged least-skilled workers compared to the equilibrium without trade cost shock. These results suggest that globalization, especially in terms of trade cost shock, can lead to the differentiated reallocation of workers across regions.

Chapter 3: The third chapter examines the impact of an increase in imports from China on employment in six advanced countries. We find that the import penetration of final goods from China has negative effects on manufacturing employment in these countries, whereas the import penetration of intermediate inputs from and exports to China could have positive effects. Moreover, such positive effects could offset or even outweigh the negative effects in some countries. These results together suggest that a careful interpretation is needed when evaluating the external validity of the China shock that is obtained in one country.

While the three chapters have very different applications, they all center around the topic of globalization and labor markets and complement one another. Therefore, these three chapters together with each other will provide a comprehensive perspective on the topic.

Chapter 1

What is the Impact of EU Enlargement?: Estimating the wage effect of labor supply shocks with a discrete choice model

1.1 Introduction

The effect of globalization on workers has been one of the important topics in international economics. The effects of labor supply shocks on labor market outcomes are getting greater attention given the recent labor market integrations, such as the EU enlargement. The literature points out that the effect can be diverse among different types of workers defined by worker-level characteristics.[1] Thus, there has been a strand of literature estimating the

[1] For example, see Dustmann, Schönberg, and Stuhler (2017).

differentiated effects of immigration on different types of workers.[2] However, although a strand of literature examines the effects of immigration due to the EU enlargement in the 2000s, the impact on the German labor market focusing on various worker groups is still limited. Especially the effects in the 2010s after fully opening the border to the newly-joined EU workers are unexamined.[3]

Therefore, the first research question of this paper is: What are the effects of the EU enlargement on different types of workers in Germany?

In addition, in this strand of the literature, the role of firm heterogeneity has yet to be explored. Firms can behave heterogeneously in labor markets. With the German employer-employee matched dataset, I find that larger firms demand not only a larger number of workers but also various types of workers. Moreover, I show that firms with similar sizes can demand workers heterogeneously: some firms have only one type of worker while others have multiple types of workers. [4] These firm heterogeneity can affect the effect of immigration since it affects the elasticity of substitutions among different types of workers.

Thus the second question is: Does firm heterogeneity matter when estimating the wage effect of labor supply shocks? If so, how does it matter?

To answer these questions, I estimate the wage effects of labor supply shock on heterogeneous workers considering firm-level heterogeneity. First, I show descriptive evidence of relationships between firm-level characteristics

[2] Card (2001), Borjas (2003), Ottaviano and Peri (2012), Dustmann, Schönberg, and Stuhler (2017) etc. See Dustmann, Schönberg, and Stuhler (2016) for a comprehensive review.

[3] Baas, Brücker, and Hauptmann (2009) and Kahanec, Zaiceva, and Zimmermann (2009) examine the effect of the EU enlargement in the former EU member countries including Germany. Elsner and Zimmermann (2013) and Brinatti and Morales (2021) investigate the effect on German labor markets. These studies look at the effects during the 2000s when the labor mobility from the new member country to Germany was still closed (I will explain this point in the next section). Kennan (2017) and Caliendo et al. (2021) estimate the effect of the EU enlargement including 2010s. Their focuses are more on the aggregate welfare impact in the former EU member countries.

[4] Worker types are defined by worker-level characteristics. I will explain more detail in the following section.

and firm-level labor demand behavior using the German employer-employee matched dataset. Based on this evidence, I adopt a multiple-discrete-choice model proposed by Hendel (1999) to the labor market context to provide a firm-level labor demand model. [5] In the model, heterogeneous firms choose multiple types and multiple numbers of workers to maximize their profits. Each firm has a different number of tasks, and the task-level profit function is defined in a specific functional form. Firm-level observable and unobservable characteristics are embedded in the profit function as parameters that affect the firm's labor demand behavior. I estimate the model parameters by using the simulated method of moment estimation. Using the estimated parameters, I then calculate the aggregate demand for each type of worker and the wage effects of labor supply shock on different types of workers, using the rapid labor supply increase in Germany due to the EU enlargement in 2004. Finally, I compare the calculated wage effects to those without several firm heterogeneity channels in the model in order to examine how firm heterogeneity plays a role in estimating the wage effects of immigration.

This paper has several findings. First, by estimating the model parameters, I find that both observable and unobservable firm-level characteristics affect a firm's labor demand. This finding suggests the importance of incorporating firm heterogeneity when considering the wage effects of immigration. Second, the calculated wage effects of the EU enlargement are heterogeneous across workers: the low-skilled foreign worker group experienced the most negative effects, while the native groups experienced much smaller negative or positive effects. This result suggests that the substitutability between low-skilled native and low-skilled foreign workers is very small. Lastly, comparing

[5] Hendel (1999) provides a framework of multiple discrete choice model. Different from canonical discrete choice models as in Berry (1994), his model incorporates choosing multiple types of product and multiple numbers of a product, which is plausible when we think about a firm's labor demand behavior. Hendel (1999)'s model is also applied to the other literature. For instance, Dubé (2004) estimates his model to analyze consumers' demand for carbonated soft drinks.

the wage effects of immigration due to the EU enlargement in 2004 with the model eliminating several firm heterogeneity channels implies that the negative wage effects on foreign workers can be overestimated without firm heterogeneity: calculated aggregate negative wage effect on foreign groups can be 13.5% larger than the wage effects with firm heterogeneity. These results suggest that considering firm heterogeneity can play an important role in estimating the wage effects of immigration and the wage effects can be different when ignoring firm heterogeneity.

This paper contributes to the existing literature in several ways. First, this paper provides a flexible estimation of the elasticities of substitutions between different types of workers. A main challenge of the literature is to estimate the elasticity of substitutions between many worker groups while estimating the parameters as little as possible. Thus the estimations in the literature are typically based on the model with a specific aggregate demand structure, i.e., the CES aggregate production function (e.g., Card, 2001; Borjas, 2003). However, this type of model imposes restrictive assumptions on the elasticity, such as an identical elasticity for all worker groups. So the early-stage literature mainly estimates the own-elasticity and thus considers the effects of immigration on the competing skill/education groups of workers.

Recent literature uses the nested-CES model to mitigate this restriction while avoiding estimating a large number of parameters. Ottaviano and Peri (2012), D'Amuri, Ottaviano, and Peri (2010), and Manacorda, Manning, and Wadsworth (2012) estimate multiple groups of workers' own- and cross-elasticities of substitutions by assuming a nested-CES aggregate demand structure. This nested structure enables us to estimate the identical elasticity of substitution within a nested group but different elasticities between nested groups. While this setting provides more flexibility than the canonical aggregate CES structure, several assumptions on elasticities remain since the identical elasticity has to be assumed within a nested group.

The model in this paper has the advantage of not requiring the CES demand structure, which means that the model in this paper gives more flexible estimates of the demand elasticity of substitutions between worker groups.

Another contribution is that this model incorporates firm heterogeneity. As stated above, a few studies consider firm heterogeneity in estimating the effects of immigration. A notable exception is Brinatti and Morales (2021). They provide a general equilibrium model to incorporate firm heterogeneity in estimating the effect of immigration. In their framework, each firm produces a variety by combining native and domestic workers, and they are imperfectly substituted. Firms are heterogeneous in terms of innate productivity and fixed cost for hiring immigrants. Their study suggests the importance of considering firm heterogeneity: they show that the aggregate welfare gains from immigration are underestimated when ignoring firm heterogeneity.

As another contribution, the estimation in this paper provides evidence of the effects of labor supply shocks on different types of workers in Germany. Although several papers studied the impacts of immigration on German labor markets (see Bonin (2005), D'Amuri, Ottaviano, and Peri (2010), Dustmann, Schönberg, and Stuhler (2017)), the results differ in studies, and the evidence of the effects after the full border opening to the new EU member countries is limited. Therefore, this project also contributes to the literature by providing additional evidence of the effect of immigration in Germany.

The paper is organized as follows: In Section 1.2, I show descriptive evidence regarding firm heterogeneity in labor markets in Germany. Section 1.3 briefly introduces the EU enlargement in 2004, which is treated as a labor supply shock to German labor markets in this paper. In Section 1.4, I explain the model. Section 1.5 will further show how to proceed with the estimation and the dataset, as well as the functional-form assumptions I use in the estimation. In Section 1.6, I show the estimates of the model parameters and the estimated wage effects of the EU enlargement for different types of workers in Germany. Section 1.7, I examine how firm heterogeneity affects the wage effects of immigration. Lastly, Section 2.5 concludes the paper.

1.2 Firm Heterogeneity in German Labor Market

In this section, I show evidence of firms' heterogeneous behavior in labor markets in Germany. The labor demand of firms can be heterogeneous for various reasons. When a firm is large, the firm tends to have more departments, divisions, and tasks, which require different types of workers. For example, a firm wants more skilled workers for the R&D department but less skilled workers for the production department. Besides, even among firms with similar characteristics, some would be more productive with a particular type of labor; a firm may want a worker with a particular qualification, a unique skill, or knowledge about a foreign customer's cultural background. They are not observable in the data, but they would affect a firm's labor demand.

Table 1.1 presents the relationship between establishment size and the number of types of workers in an establishment. The types are defined by three education levels and domestic and foreign workers: six types of workers in total. Each row shows the number of types of workers in a size group. Each column represents the number of establishments with a certain number of worker types. This table shows that, as expected, some firms hire only one type of worker while others have multiple types of workers. There are two implications from this table. First, it suggests the firms' heterogeneous behavior in labor markets based on their observable characteristics: larger establishments tend to have a larger number of types of workers. Second, there will be heterogeneity among firms with similar characteristics, such as firm

Table 1.1: Establishment size and the number of establishments with each number of types of workers

Est. Size	1	2	3	4	5	6	Total
1-4	2,14*	1,01*	41*	8*	2*	/	3,693
5-10	391	401	383	115	/	/	1,314
11-20	240	427	531	213	8*	/	1,504
21-50	96	298	799	532	238	77	2,040
51-100	/	7*	339	414	261	135	1,227
101-500	0	/	20*	470	506	623	1,808
501-1000	0	0	/	2*	56	175	261
1001-	0	0	0	/	/	181	193
Total	2,875	2,218	2,673	1,859	1,189	1,226	12,040

Notes: The table is created by the author using the German employer-employee matched data set (LIAB) in 2011. I use stratified samples of all establishments without weights. The cell with '/' means that the entry is a small number but cannot be reported due to the confidentiality rule. '*' indicates a one-digit number that cannot be shown for the same reason. The type of workers is defined using three schooling qualification levels and domestic/foreign workers. Schooling classifications are a lower-secondary school certificate/no certificate, an upper-secondary school certificate, and a university-level certificate. Domestic workers are those with German nationality, and foreign workers are the others.

size, which leads to the motivation for incorporating firm-level heterogeneity in the model that is unobservable to economists.

Then, does firm heterogeneity have a statistically significant role when considering a firm's labor demand behavior? To examine this question, I run a simple regression to estimate the firm-level wage elasticity of labor demand. I include the establishment size dummy as a proxy of firm-level characteristics and interact with the wage elasticity. If the size dummy is significantly associated with wage elasticity, it suggests that (observable) firm-level characteristics affect the firm's labor demand behavior. I run the following reduced-form regression:

$$\Delta \ln l_{ft} = \alpha + \beta_1 \Delta \ln w_{ft} + \beta_2 Size + \beta_3 Size \cdot \Delta \ln w_{ft} + \gamma_t + \eta_s + \epsilon_{ft}. \quad (1.1)$$

l_{ft} is the number of full-time employees in establishment f at year t. It includes all types of workers. w_{ft} is the average daily wage of full-time employees in f at year t. $Size$ is a dummy variable for establishment size: it takes 1 if the number of total employees is larger than 100. For l_{ft} and w_{ft}, I take logs and one-year differences. γ_t and η_s represent year and industry fixed effects, respectively.[6] The data source is the German employer-employee-matched data (LIAB) provided by the Institute for Employment Research (IAB). This is a stratified dataset that provides information for establishments and their employees. The data used in this paper covers from 1999 to 2014. I will explain the dataset in detail in Section 1.5.2. [7]

With this specification, the labor demand elasticity for large and small firms can differ. Column (1) shows the coefficients without size dummy and fixed effects, and Column (2) shows the coefficients with industry and year fixed effects. Column (3) corresponds to the specification in equation (1.1) that includes the size dummy and the intersection with log employment change. The first column shows the estimates of β_1 that we can interpret as the percentage change in establishment-level employment associated with a 1% increase in the average wage at the establishment level. The second and third columns show the coefficients of the size dummy and its interaction with the wage variable. As we see in Column (3), for small establishments, 1% increase in the average wage is associated with approximately 0.1% decline in the labor demand. On the other hand, it is associated with 0.36% decline in the labor demand for large establishments, which is three times larger than the value for small establishments.[8] This implies that larger establishments would demand labor more elastically in response to wage changes compared

[6]Industry is defined by the two-digit WZ 93 classification.

[7]Since the dataset I use is cross-sectional, in this section, I only include the establishments that I can calculate at least a one-year difference in wage and employment. The number of employees and average wages is calculated only for full-time employees in the establishment.

[8]The sign of the coefficients stays unchanged when including firm fixed effects instead of industry fixed effects. The result table is available upon request.

Table 1.2: Estimated labor demand elasticity at establishment level

	(1)	(2)	(3)
$\Delta \ln w$	-0.110***	-0.110***	-0.109***
	(0.0272)	(0.0270)	(0.0268)
$Size$			0.0484***
			(0.00565)
$Size * \Delta \ln w$			-0.265**
			(0.129)
Constant	-0.0242***	-0.0293***	-0.0322***
	(0.00772)	(0.00702)	(0.00694)
Industry fixed effect	No	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Observations	152124	152124	152124

Standard errors are clustered by 3-digit industries.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

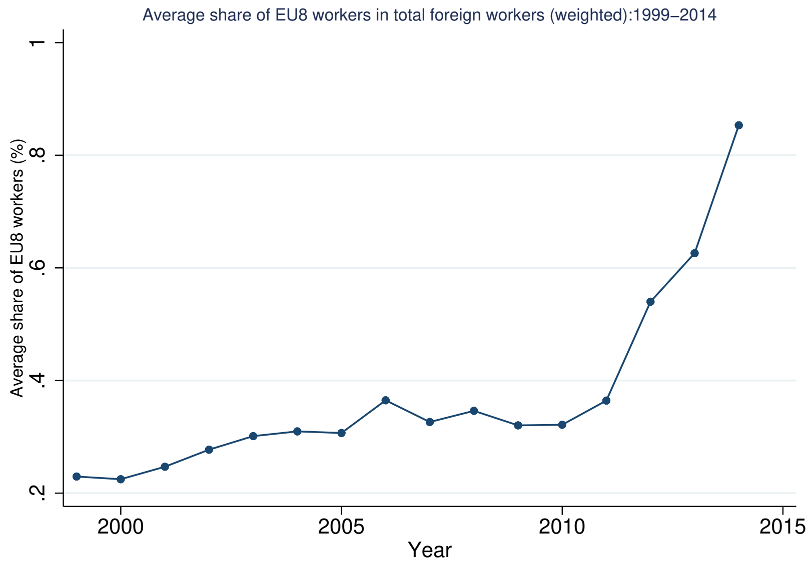
to smaller ones. Although the size is an example of firm-level characteristics, this result suggests that labor demand behavior is heterogeneous among firms.

1.3 EU Enlargement in 2004

In 2004, ten countries newly joined the European Union (EU). There was a concern about a rapid inflow of workers from the new member countries to the countries that were already EU members. Because of this concern, some countries, including Germany, have had restrictions on the free movement of people from newly joined EU members, except for Cyprus and Malta (Brenke, Yuksel, and Zimmermann, 2009). The free movement of workers in the new member countries was applied in May 2011 in Germany. As a result, the share of workers from new member countries has rapidly increased in Germany since 2011.

Figure 1.1 shows the share of workers from the newly joined EU countries

Figure 1.1: Share of workers from the new EU members in total workers, weighted: 1999-2014



Notes: The figure is drawn by the author using the German employer-employee matched dataset (LIAB), 1999-2014.

in total workers in Germany. Since the dataset is stratified data of all establishments in Germany, the share shown in this figure means the establishment-level average share of workers whose nationality is the newly joined eight countries out of workers whose nationality is other than Germany.

We see a rapid increase in the share after 2011 in contrast to a moderate increase from 1999 to 2011. This figure suggests a quick rise of workers from the newly joined EU member countries after removing the free-movement restriction. I regard this rapid increase in worker inflows as a supply shock to German labor markets and estimate how this shock affected labor market outcomes.

1.4 Model

1.4.1 Model setting

The model is based on Hendel (1999), which is an extension of the discrete choice model with random utility (e.g., Berry, 1994), allowing for multiple-unit purchases. He models establishment-level choices of differentiated products. As in Hendel (1999), I apply the characteristics approach that regards each worker group as a bundle of N attributes. [9]

Apart from Hendel (1999), establishments in this model choose workers in different characteristic groups. As in the previous literature, I define a worker group\ as a bundle of worker attributes. The attributes could contain, for example, schooling, work experience, nationality, and gender. I use these worker-level attributes to define choice sets.

Assume that each worker group has one component that is not observable to economists while establishments observe it. This unobservable component can be interpreted as an average of the attributes of workers in the group that are not perceived in the data. If this unobservable component affects the establishment's decision of worker types, it leads to endogeneity bias.

Establishments' demand for labor is modeled according to a random coefficient framework. By employing this framework, one can model their heterogeneous preferences towards the observable characteristics of worker groups. [10] Assume that the establishment's profit function is deterministic and known to the establishment, but it has unobservable components to the econometrician and is treated as random. Denote these random components of establishment

[9] In Hendel (1999)'s setting, he defines that each computer can be described as a bundle of M attributes and that N attributes among M are built-in ones on which he mainly focuses in the model. He defines $M - N$ are added attributes that can be modified after purchasing and are not essential to the model. So he disregards the added attributes in the model. Therefore, in this paper, I regard each type of worker as a bundle of N attributes that cannot be modified after a firm's choice.

[10] Or one can also think that an establishment's productivity with different types of workers will be different across establishments.

f as

$$A_f = [a_{f1}, ..., a_{fI}] \qquad \text{for } f = 1, 2, ..., F. \tag{1.2}$$

A_f represents the establishment's subjective quality (ability) perceptions about I different types of workers. For instance, establishment A would think type 1 workers have higher ability than type 2 workers because A would regard type 1 workers more productive for A's business. The I ability perceptions tell us how establishments on average rank the available types of workers. In other words, A_f is f's random coefficients on each worker-type dummy. Assume the establishment has more than one potential task. Then the random components can be written as

$$A_f = \begin{bmatrix} A_{f1} \\ A_{f2} \\ \vdots \\ A_{fJ_f} \end{bmatrix} = \begin{pmatrix} a_{1,f1} & \cdots & a_{I,f1} \\ a_{1,f2} & \ddots & \vdots \\ \vdots & & \\ a_{1,fJ_f} & \cdots & a_{I,fJ_f} \end{pmatrix} \tag{1.3}$$

where A_{fj} is the random coefficients in task j.

Using this setting, we can estimate the mean willingness to pay of establishments for the different types of workers, conditional on their characteristics. These characteristics include industry, size, age, technology adoption, and capital equipment.

Let D_f represent the observable characteristics of establishment f. The pair (D_f, A_f) completely describe f and determine its labor acquisition behavior in the labor market.

Assume that each establishment f assigns workers to perform J_f different potential tasks.[11] Given the number of potential tasks J_f, establishment f chooses the vector of worker's types and worker's amount in task j, $X_j(\text{for} j = 1, ..., J_f)$, to maximize its profit.

[11] The concept of tasks in Hendel (1999)'s model is rather general. For example, it can be interpreted as tasks, divisions, or departments in a firm.

As in Hendel (1999), we have two distinct tasks in this model: potential tasks and actual tasks. The actual tasks are a part of potential tasks done by workers and are determined by the profit maximization of each establishment given J_f, its characteristics, the random coefficients, and factor price (wage). The actual tasks represent the establishment's optimal behavior given its preferences and choice set. When the factor price increases, the number of potential tasks is unchanged, while the number of actual tasks can change.

Assume that the task-level profit function is

$$\pi_j^f(D_f, A_{fj}, X_j) = \left(\sum_{i=1}^{I} \omega_{ijf} X_{ijf}\right)^{\alpha} \cdot S(D_f) - \sum_{i=1}^{I} W_i X_{ijf} \tag{1.4}$$

where X_{ijf} is the number of workers of type i used by establishment f in task j, $S(D_f)$ is a demand shifter that incorporates the effect of establishment-level characteristics on the returns from recruiting workers, W_i represents the wage of type i worker, which is given for establishments. ω_{ijf} is f's valuation or weight for type i worker in task j, which incorporates establishments' subjective productivity to different worker types. The parameter α is assumed to be $0 < \alpha < 1$, which means that different types of workers are perfect substitutes at the task level. This is a key assumption to make the model tractable. As in Hendel (1999), the functional form of this weight is assumed to be:

$$\omega_{ijf} = \left(\max\left(0, A_{fj} \cdot I_i\right)\right)^{m(D_f)}, \tag{1.5}$$

where I_i is the I vector, which consists of zeros except 1 in i's position. $m(D_f) > 0$ captures f's evaluation for an unobserved component of each type. $A_{fj} \cdot I_i$ represents (the sum of f's evaluations for the type i worker's attributes plus) establishment's taste for the ability of type i workers. The random coefficients only enter the model through ω_{ijf}. The outside option is hiring no worker, which is chosen by establishments with negative $A_{fj} \cdot I_i$ for all i. The establishment-level profit function is an aggregate of the task-level profit function. As equation (1.4) shows, this model specifies the establishment's profit as a function of multiple types and multiple numbers of workers. This setting is also reasonable for labor markets because it is natural for firms to hire multiple types of multiple workers in a year, for example. [12]

1.4.2 Profit maximization problem

Since we assume that the overall profit function is an aggregate of π_j^f, establishment f's profit maximization equals maximizing each π_j^f over X_j. That is, establishments choose which type and how many workers to hire to perform task j, which does not depend on the other tasks of the establishment.

Worker types are perfect substitutes at the task level (see the first part of equation (1.4)), which means one type of worker per task is actually used at most. This assumption simplifies the problem because establishments just compare maximum profits for I different types of workers to employ for each task.

Therefore, a vector of task j's latent profits is:

$$\pi_j^* = \left(\pi_{j1}^*, ..., \pi_{jI}^*\right) \tag{1.6}$$

where

$$\pi_{ji}^* = \max_X \pi_j(D_f, A_{fj}, X_{fj}) \quad s.t.\ X_{fj} \text{ is of type } i. \tag{1.7}$$

f chooses type i' workers for task j if

$$\pi_{ji'}^* = \max(\pi_{j1}^*, ..., \pi_{jI}^*). \tag{1.8}$$

Now suppose that non-integer purchase is allowed. Then one can take the derivative of the profit function and set it to 0. Then the task level optimal

[12]This aspect cannot be captured by models with only one type of labor, including a standard discrete choice model where agents choose only a single product.

purchase is expressed as

$$X^*_{ijf} = \left(\frac{\alpha \omega^{\alpha}_{ijf} S_f}{W_i} \right)^{\frac{1}{1-\alpha}}. \tag{1.9}$$

Equation (1.9) implies that f's purchase of i type of worker for a given task is larger when the wage of type i is smaller, the weight on type i, ω_{ijf}, is larger, and the demand shifter S_f is larger.

In this model, $S(D_f)$ and $m(D_f)$ play different but essential roles in determining an establishment's behavior. $S(D_f)$ affects the number of workers the establishment demands but does not affect the worker's type choice. The choice of the types of workers is determined by $m(D_f)$, which inversely has no influence on the scale of the establishment's labor demand.

1.5 Estimation

1.5.1 Estimation process

This model predicts worker acquisition in every establishment as a function of observed characteristics, random tastes, and the vector of parameters to be estimated:

$$X^*_{fj}(D_f, A_{fj}, \theta) = \Big(X^*_{1fj}(D_f, A_{fj}, \theta), ..., X^*_{Ifj}(D_f, A_{fj}, \theta) \Big) \qquad \text{for } f = 1, ..., F \text{ and } j = 1, ..., J_f. \tag{1.10}$$

$X^*_{fj}(D_f, A_{fj}, \theta)$ is $1 \times I$ vector of the number of workers of each type adopted by establishment f for task j. Its entries are zero except for one that can take any non-negative integer value because an establishment utilizes only one type of worker in a given task j.

Establishment f's predicted purchase of labor conditioned on D_f are expressed as the sum (over tasks) of expected purchases conditional on the number of (potential) tasks J_f:

$$X_f^e(D_f, \theta) = \sum_0^{J_f} \left\{ \int_{-\infty}^{+\infty} X_{fj}^*(D_f, A_{fj}, \theta) \mu \left(dA | D_f, \theta \right) \right\} \tag{1.11}$$

where $\mu(\cdot|D)$ is the distribution of the random coefficients, conditional on the information D.[13]

Define the prediction error as

$$\epsilon_f(D_f, \theta) = X_f^e(D_f, \theta) - X_f \tag{1.12}$$

where X_f is the vector of actual labor acquisition of f. If the model explains actual establishment behavior, the error at the true value of parameter,s θ_0, becomes

$$E(\epsilon_f | D_f, \theta_0) = 0 \qquad \text{for } f = 1, ..., F \tag{1.13}$$

Consequently, any function of observed establishment-level characteristics, D_f, independent of the unobservables, must be uncorrelated with ϵ at $\theta = \theta_0$, which is used to construct a method of moment estimator for θ. Let

$$G(\theta) = E(T(D) \otimes \epsilon(D, \theta)) \tag{1.14}$$

where $T(\cdot)$ is any function. From (1.13), $G(\theta_0) = 0$. The sample analogue is thus

$$G_F(\theta) = \frac{1}{F} \sum_{f=1}^{F} T(D_f) \otimes (X_f^e(D_f, \theta) - X_f). \tag{1.15}$$

Under some assumptions, this will uniformly converge to $G(\theta)$ in θ, which

[13] In Hendel (1999), J_f is a stochastic function of a firm's characteristics: in the estimation, it is simulated with the Poisson process. However, since the number of occupations in each establishment is available in the dataset, I use this number as a proxy of a potential number of tasks in this paper.

assures the consistency of the GMM estimator

$$\theta_{GMM} = Argmin||G_F(\theta)||. \tag{1.16}$$

That is, I minimize the quadratic form of these moment conditions:

$$Q_F(\theta) = G'_F(\theta)\boldsymbol{W}G_F(\theta) \tag{1.17}$$

where $\boldsymbol{W}$ is $r \times r$ weighting matrix, r is the number of moment conditions.[14] As in Cameron and Trivedi (2005), optimal weighting matrix is defined as $\boldsymbol{W_F} = \hat{\boldsymbol{S^{-1}}}$ with

$$\hat{\boldsymbol{S}} = \frac{1}{F}\sum_{f=1}^{F}(T(D_f) \otimes \hat{\epsilon_f})(T(D_f) \otimes \hat{\epsilon_f})' \tag{1.18}$$

where $\hat{\epsilon_f} = \epsilon(D_f, \hat{\theta_1})$, $\hat{\theta_1}$ is the set of GMM parameters estimated using the identity matrix as a weighting matrix.

The asymptotic variance of the estimates can be written as

$$\hat{V}(\hat{\theta}_{GMM}) = F\left(\left(\frac{\partial G_F}{\partial \theta'} |_{\hat{\theta}_{GMM}}\right)' \boldsymbol{W_F}\left(\frac{\partial G_F}{\partial \theta'} |_{\hat{\theta}_{GMM}}\right)\right)^{-1}. \tag{1.19}$$

I employ the simulated method of moment estimation according to Hendel (1999). The detailed estimation procedure is provided in Appendix.

1.5.2 Data

I use the German employer-employee-matched data (LIAB) for the estimation. The LIAB dataset is stratified data of all establishments in Germany. The data I use in this paper is cross-sectional, offering detailed establishment-level data and its employees' rich data. This feature of LIAB is essential to the

[14] In this model, $r$corresponds to (the number of establishment characteristics used as instruments for the model parameters)$\times$(the number of worker types in the market).

estimation because it requires information on both the establishment (firm) and its employees. I regard the EU enlargement in the 2000s as an exogenous labor supply shock in Germany.

On the worker side, I use nationality and schooling qualifications to define worker groups.[15] The wage of worker types is defined as the average daily wages of each type of worker. As pointed out in the other literature, this wage data in the LIAB is right-censored. Thus the censored wages are replaced by imputed wages that are obtained by following the method provided by Gartner (2005). On the establishment side, industry, total investment value, technology investment indicator, and the number of trainees are used to estimate the model parameters that depend on establishment-level characteristics. The number of occupations in each establishment is used as a proxy for the number of tasks.

I use the dataset in 2011 to estimate the elasticity of substitution between different types of workers. Then the effect of labor supply shock will be estimated in 2011-2014 using the estimated elasticities. In the estimation, I will focus on several industries.[16]

1.5.3 Equational assumption

The parameters to be estimated include coefficients of the establishment-level characteristics that consist of the key model parameters S and m. Since the estimation of these parameters requires equational assumptions, as in Hendel

[15] I use the worker's nationality as a proxy for being an immigrant since I do not observe if the worker is an immigrant or not.

[16] The industries are 61, 62, 63, 64, and 73 in the two-digit WZ 93 classification. They include transportation industries (except for land transport) and research and development industry. These industries are selected because they experienced worker inflows in each type group from the newly joined EU countries and have enough number of establishments in the data.

(1999), I assume they have the following linear structures:

$$m(D_f) = m_0 + m_1 \cdot Tech\,Investment\,Dummy_f + m_2 \cdot Num\,Trainees_f \tag{1.20}$$

$$S(D_f) = s_0 + s_1 \cdot Industry\,Dummy_f + s_2 \cdot Total\,Investment_f \tag{1.21}$$

I assume that these variables affect the labor demand of the establishment through the parameters m and S. $Tech\,Investment\,Dummy_f$ takes one if establishment f made any investment in communication technology/data processing in the last three years. $Num\,Trainees_f$ is the mean number of trainees f has in the last three years. These two variables can affect the choice of worker type. If an establishment has invested in technology, then it would demand more skilled workers who complement high-tech machines or services. If an establishment has more trainees, it might not hire low-skilled workers since trainees are substitutes for those workers. $Industry\,Dummy_f$ takes one if the industry is 73 (Research and Development) in the two-digit industry classification (WZ93). This is because the labor demand structure in industry 73 might differ from the other industries used in the estimation. $Total\,Investment_f$ is a log of the mean of total investment value in the last three years in establishment f. If an establishment spends more on investment, it may reduce the labor demand.[17]

1.5.4 Summary statistics

Table 1.3 displays the summary statistics of variables used in estimating the model parameters. The first four variables consist of D_f and observable firm-level characteristics used for estimating S and m. The number of occupations is a proxy for the number of tasks in each establishment. The last six rows

[17]It can also increase the labor demand if the establishment's productivity increases due to the investment.

Table 1.3: Descriptive Statistics

	Mean	S.D.	Min	Max
Industry dummy	0,27	0,44	0	1
Log total investment value	8,85	5,55	0	20
Communication & data investment dummy	0,66	0,47	0	1
Number of trainees	7,54	31,65	0	417,7
Number of occupation	8,36	11,41	1	92
Type 1: Low-skilled, Domestic	73,25	337,95	0	5791
Type 2: Low-skilled, Foreign	8,21	69,57	0	1375
Type 3: Med-skilled, Domestic	23,72	204,53	0	4000
Type 4: Med-skilled, Foreign	1,76	18,62	0	362
Type 5: High-skilled, Domestic	28,83	126,23	0	1332
Type 6: High-skilled, Foreign	4,56	25,35	0	292
Observations		426		

Note: I constructed all the variables from the LIAB dataset. I replace the log total investment value with zero when the total investment value is zero.

show the basic stats of employment of each worker type at the establishment level.

1.5.5 Estimates of model parameters

Table 1.4 shows the estimates of model parameters. $s0$, $s1$, and $s2$ are the coefficients in the equation (1.21). Similarly, $m0$, $m1$, and $m2$ are the coefficients in the equation (1.20). We see that the coefficients in S are positive and statistically significant, which suggests that the establishment's industry and investment value affect the establishment-level magnitude of labor demand. We also see that the coefficients in m are significant, which implies that the establishment's technological investment and trainee variable are associated with the choice of the types of workers. α is estimated as 0.11, which confirms that the profit function is concave. Finally, the variance

Table 1.4: The estimated model parameters

	Coefficient	Std. Errors
$s0$	3.770	0.710
$s1$	7.642	1.063
$s2$	4.898	1.717
$m0$	0.159	0.040
$m1$	0.271	0.081
$m2$	0.036	0.002
α	0.114	0.078
$var(A_i)$	6.511	1.334
N obs = 426		

of random coefficients, $var(A_i)$, is statistically significant. This result implies that establishment-level unobservable heterogeneity exists in the labor markets.

1.6 Calculating the wage effects of the EU enlargement

In this section, I calculate the impact of the EU enlargement on the wages of different worker groups in Germany.

First, using the estimated parameters in Section 1.5, calculate the aggregate demand for each type of worker. I insert the estimated model parameters into the objective function and rewrite it as a function of a wage vector. [18] The aggregate demand function can be expressed as

$$\mathbf{X} = f(\mathbf{W}|\theta^E) \tag{1.22}$$

[18] I fix the random coefficients to the average of the last evaluation of the objective function, i.e., the random coefficients that are used when the coefficients are converged.

where $\boldsymbol{X}$ is a $I \times 1$ vector of aggregate demand for each type of worker, $\mathbf{W}$ is a $I \times 1$ wage vector of each type. θ^E is the estimated model parameters. [19]

With this aggregate demand function, I calculate the Jacobian and then own- and cross-demand elasticities:[20]

$$\epsilon_d = \begin{pmatrix} \frac{\partial x_1}{\partial w_1}\frac{w_1}{x_1} & \cdots & \frac{\partial x_1}{\partial w_I}\frac{w_I}{x_1} \\ \frac{\partial x_2}{\partial w_1}\frac{w_1}{x_2} & \ddots & \vdots \\ \vdots & & \\ \frac{\partial x_I}{\partial w_1}\frac{w_1}{x_I} & \cdots & \frac{\partial x_I}{\partial w_I}\frac{w_I}{x_I} \end{pmatrix}. \tag{1.23}$$

With the inverse function theorem, the inverse of the Jacobian of an invertible function is the Jacobian of the inverse function. Therefore, using the inverted Jacobian, I calculate the matrix of wage elasticities of labor supply.[21]

The estimated wage changes of each type of worker due to the EU enlargement are calculated using the elasticities. First, I calculate the change ratios of EU8 workers using the data in 2011 and 2014.[22] Let the type i's wage elasticity of labor supply i' be $\epsilon_{ii'}$. Then the wage change ratio of type i due to the EU enlargement is

$$\hat{W}_i = \sum_{i' \in \{2,4,6\}} \epsilon_{ii'} \hat{L}_{i'}^{EU}, \tag{1.24}$$

where $\hat{L}_{i'}^{EU}$ is the change ratio of EU8 workers of type i'.[23]

The calculated wage ratio changes for each type are shown in Table 1.5. As

[19] I aggregate establishment-level demands with weights since the data is stratified.

[20] Since the demand function is not analytically differentiable, I use an approximation to take derivatives when calculating the elasticities. I employ the five-point method with step size $h = 1e - 12$.

[21] I assume that the market labor supply is perfectly inelastic so that the wages are completely determined by the demand side, which is a common assumption in the literature. I also assume that the aggregate labor demand function is invertible.

[22] Establishment-level data is weighted, and the aggregated data is weighted with the share of EU8 workers out of foreign workers within each type.

[23] The wage effects are weighted using wage shares of type i' in 2011. The derivation of this equation is in Appendix.

we see, the worker group with the most negative impact is Type 2, low-skilled foreign workers. This is because the share of low-skilled workers is the largest among all skill levels in the immigrants from the newly joined EU countries, and their own elasticity is much larger compared to the cross elasticities. On the other hand, Type 1, the low-skilled native wage was negatively affected, but the magnitude is very small. [24] Medium-skilled foreign workers also had an adverse effect, while the medium-skilled native group experienced a slight increase in their wages. High-skilled foreign workers' wages also increased, but this would be because the number of this type of worker slightly decreased in the target industries in 2011-2014. These results suggest strong imperfect substitutability between natives and immigrants, even within the same skill group.

The aggregate wage effects are calculated as -0.007% for domestic and -2.59% for foreign workers, respectively. This aggregate result also suggests that, on average, native workers' wages had almost no impact of increased workers' inflow while foreign workers were negatively affected.

In sum, low-skilled foreign workers have the most negative impacts from the increased inflow of immigration due to the EU enlargement. However, the native workers experienced a very small decline or an increase in wages, which is consistent with the literature (e.g., D'Amuri, Ottaviano, and Peri (2010), Ottaviano and Peri (2012), Brinatti and Morales (2021)). Besides, except for low-skilled and medium-skilled foreign workers, the magnitudes of the wage effects are limited and smaller compared to the wage effects suggested in the literature without firm heterogeneity. Although the results are not directly comparable with the literature since the previous study does not examine the

[24]The cross-wage elasticities of Type 1 to worker types are very small but positive, which would also drive the positive wage effects on Type 1 workers. A possible reason for this result is that the model does not have assumptions on the aggregate elasticities among worker groups, which is a distinction from the literature. However, I need to investigate this further.

Table 1.5: Estimated wage changes by immigration in 2011-2014

Type	Wage change ratio in %
Low-skilled, Native	-0.05%
Low-skilled, Foreign	-6.58%
Med-skilled, Native	0.02%
Med-skilled, Foreign	-6.16%
High-skilled, Native	0.06%
High-skilled, Foreign	2.58%

effect of EU enlargement in the 2000s, this result suggests that considering firm-level heterogeneity might cause smaller wage effects of immigration.

1.7 Role of firm heterogeneity: how it affects the wage effects?

In Section 1.6, I calculated the wage effect of immigration due to the EU enlargement in 2004. Then, what happens if there is no firm heterogeneity in the model? To examine how each heterogeneity channel influences the wage effects of worker types and hence the aggregate wage effects.

The evaluation proceeds as follows. To examine the wage effects without firm heterogeneity, I first derive the labor demand elasticities by closing several heterogeneity channels. Specifically, I insert zeros instead of a part of parameters estimated in Section 1.5.5. Then I use the elasticities to calculate the wage effects.

Table 1.6 shows the re-calculated wage effects on each six types of workers. Column (1) again shows the benchmark wage effects with full firm heterogeneity. In Column (2) to (4), the wage effects are represented for closing specified heterogeneity channels. More specifically, in Column (2), I assume that the

Table 1.6: Estimated wage changes due to the EU enlargement in 2011-2014

Type	(1) Benchmark	(2) Constant S*	(3) Constant m	(4) Constant m, S*
Low-skilled, Native	-0.05%	0.00%	0.09%	0.03%
Low-skilled, Foreign	-6.58%	-6.94%	-7.16%	-7.22%
Med-skilled, Native	0.02%	-0.07%	0.07%	0.05%
Med-skilled, Foreign	-6.16%	-6.85%	-6.05%	-6.71%
High-skilled, Native	0.06%	0.05%	-0.03%	-0.06%
High-skilled, Foreign	2.58%	2.57%	2.40%	2.57%

*Constant S means $s_2 = 0$ due to technical reasons.

model parameter S is common for all firms. [25] Which means that firms are indifferent in their labor demand scale and thus industry and investment values do not affect firm's labor demand behavior. Similarly, in Column (3), I assume that m has a constant value, which is equivalent to assuming $m_1 = 0$ and $m_2 = 0$. This assumption implies that technology investment and number of trainees do not influences firm's choice of labor types. Lastly, Column (4) shows the results when both of S and m are constant.

We see that the wage effects on each type of worker are more or less affected by closing heterogeneity channels, especially on foreign groups. When we see Column (2) – (4), we find that eliminating firm heterogeneity mostly increases the negative wage effects of the EU enlargement on foreign worker groups. Although the effect on high-skilled workers do not change much, the effect on low-skilled foreign workers becomes -7.22% when assuming both m and S constant, which is 9.7% larger compared to the benchmark effect. Medium-skilled foreign workers also experienced intensified negative effects: 8.9% more adverse effects when excluding heterogeneity in m and S. The wage effects on native workers still have very small values when eliminating heterogeneity channels while the signs of the changes tend to differ in several cases.

[25] At this moment, I assume that $s_2 = 0$ for technical reasons. I will fix this issue later.

Table 1.7: Aggregate wage changes due to the EU enlargement in 2011-2014

Type	(1) Benchmark	(2) Constant S*	(3) Constant m	(4) Constant m, S*
Total, Native	-0.007%	0.009%	0.05%	0.002%
Total, Foreign	-2.59%	-2.82%	-2.93%	-2.94%

*Constant S means $s_2 = 0$ due to technical reasons.

Aggregate wage effects also change according to the changes in wage effects on different types of workers. The calculated wage effects with closing several heterogeneity channels are represented in Table 1.7. The specification in each column is in line with Table 1.6. The total wage effect on foreign employees in Germany has 13.5% more negative value compared to the case with the benchmark with firm heterogeneity. The total wage effect on natives, on the other hand, becomes positive without firm heterogeneity but the magnitude stays quite limited.

Overall, with the counterfactual exercises, we see that the wage effects of immigration due to the EU enlargement in 2004 can be overestimated. Especially the aggregate negative impact on foreign workers' wages can be more than 13% larger when closing firm-level heterogeneity channels through parameters m and S. These results suggest that incorporating firm heterogeneity plays an important role when estimating the wage effects of immigration since it can overestimate its negative impacts without firm heterogeneity.

1.8 Conclusion

In this paper, I first show some descriptive evidence that suggests firms' labor demand behavior can be heterogeneous according to their characteristics. Then I adopt a firm-level multiple discrete choice model to the labor market context and estimate the own- and cross-wage elasticity of labor demand for different types of workers. I then estimate the wage effects of EU enlargement in the 2000s on German labor markets. Finally, I perform counterfactual exercises by eliminating several firm-heterogeneity channels to compare the wage effects with the presence of full firm heterogeneity. The estimation of the model parameters suggests that both observable and unobservable firm characteristics matter in deciding the firm's labor demand. By calculating the wage effects of increased labor supply due to the EU enlargement in 2004 in Germany, I also find a sizable negative wage effect on low- and medium-skilled foreign workers while only small impacts on the native worker group's wages, even within the same skill group. These findings suggest that there is strong imperfect substitutability between native and foreign and that the impact of immigration due to the EU enlargement on native workers is limited in Germany. The results in calculating the wage effects without firm heterogeneity imply that ignoring firm heterogeneity in estimating the effects of immigrants would overestimate the negative wage effect of immigration.

Chapter 2

Globalization and Local Labor Markets: The effect of trade shocks on worker reallocation

2.1 Introduction

Over the past decades, regional inequality has increased in several advanced countries including the U.S. (Moretti, 2012) and Germany (Dauth et al., 2022), and this trend has been accelerating. That is, some cities keep growing over time while some do not. Moretti (2012) calls this trend 'Great Divergence' taking the U.S. as a leading example.

Another important phenomenon attracting economists' attention is labor market polarization. After being introduced by Autor and Dorn (2013), the literature shows that, over the last decades, employment and wages of least- and most-skilled workers have grown while those of medium-skilled workers have declined in many countries.

In addition, the growing literature on international trade point out that the effects of trade shocks are heterogeneous across regions, which suggests expanding regional inequality. Then, what is the relationship between these phenomena above and globalization?

This paper addresses this question by examining the relationship between globalization and regional inequality, especially focusing on the effect of trade shocks on local labor markets. To do so, I construct a spatial equilibrium model with heterogeneous workers. Specifically, I incorporate a trade model with firms that can engage in exporting into a local labor market model. In the model, I assume that there are two locations in a country. Each location has a tradable sector and a non-tradable sector. Workers and firms are assumed to be mobile between sectors and locations. In the spirit of Yeaple (2005), workers are heterogeneous in terms of their innate skills. Firms are ex-ante homogeneous, and firm heterogeneity arises when firms endogenously choose heterogeneous workers and sectors. Firms use local labor for production, and they sell their products in both locations without additional cost. Firms can engage in international trade with an identical country by incurring variable and fixed costs.

As a main result of the comparative statics, I find that when trade cost declines in one location, there are within- and between-location reallocations. In the location that experienced trade cost reduction, the shares of workers working for firms with high technology and workers working in the non-tradable sector increase while the share of workers working for firms with low technology declines. Besides, workers reallocate between locations: the most-skilled workers in another location move to the location with a trade cost decline and medium-skilled workers move in the opposite direction. As a result, the location with trade cost shock experiences labor market polarization since it has more most-skilled workers, fewer medium-skilled workers, and unchanged least-skilled workers compared to the equilibrium without trade cost shock. These results suggest that globalization, especially in terms of trade cost shock, can lead to the reallocation of workers and affect regional inequality.

In which situation do we observe local-level trade cost shocks? There are multiple ways of considering the shock. One can think of recent technological progress such as digitization. For example, consider the emergence of digital platforms.[1] This can reduce the trade cost, variable or fixed cost, of exporters. This effect is larger in some industries: firms in software industries can export more easily with this new technology while the traditional manufacturing machine industry benefits less. One can think of this type of digitalization as a sector-biased technological progress as in Fort (2017). Since the industry structure differs for different locations, one can treat this kind of technological progress as trade cost shocks that can affect each location differently.

This paper is related to several strands of related literature. They include the literature on the great divergence (Moretti, 2012; Rubinton, 2020; Davis, Mengus, and Michalski, 2020), on labor market polarization (Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014; Dauth, 2014), and on international trade and regional disparities (Autor, Dorn, and Hanson, 2013; Dauth, Findeisen, and Suedekum, 2014; Dix-Carneiro and Kovak, 2017; Taniguchi, 2019; Helm, 2020; Bakker et al., 2021).

The remaining parts of this paper consist as follows: Section 2.2 presents the theoretical framework in the case of a closed economy. Section 2.3 expands the model to the open economy setting. In Section 2.4, I perform comparative statistics to examine the effects of a trade cost shock on local labor markets. Section 2.5 concludes.

[1]Good examples are Amazon in the e-commerce industry and Steam in the video-game industry.

2.2 Closed economy

First, consider the case of a closed economy without international trade. I combine a trade model in Yeaple (2005) and a local labor market model in, e.g., Moretti (2011) and Suárez Serrato and Zidar (2016). Suppose the economy consists of two sectors, non-tradable Y and tradable X, and two locations a, b in a country. Each location is treated as a small open economy. Each location has both sectors Y and X: location a has Y_a and X_a, and b has Y_b and X_b. Goods produced in sector X_c $(c = a, b)$ are freely tradable across locations but costly tradable internationally. Firms in sector X_c are ex-ante homogeneous and can freely enter and exit. Y_c sector represents a local service sector in each region: homogeneous goods produced in Y_c sector have to be consumed in location c and non-tradable internationally. Housing is also included in the local service. Workers consume non-traded homogeneous goods, differentiated goods, and supplying one unit of labor inelastically. Local labor supply is determined only by workers' location decisions.

2.2.1 Worker problem

Worker setting There is a continuum of workers in each location, with a mass of M_a and M_b. $M_a + M_b = M$ is the fixed total population of the country. Workers are heterogeneous in their skill, indexed by z in an increasing manner: a larger z indicates a worker with higher skills. The distribution of skills follows $G(z)$ with density $g(z)$, $z \in [0, \infty)$.

Utility maximization Assume that in each location c with amenity A_c, workers with skill level z maximize the utility over non-tradable good Y_c and tradable goods X_a and X_b, composites of differentiated goods $q_c(\omega)$:

$$\max_{X_a,X_b} \ln A_c + \alpha \ln Y_c + \beta_1 \ln X_a + \beta_2 \ln X_b$$
$$s.t.\ p_{Yc} Y_c + \sum_{c=a,b} \left[\int_{\omega\in\Omega_c} p_c(\omega) q_c(\omega) d\omega \right] = I_c$$

where

$$X_c = \left(\int_{\omega\in\Omega_c} q_c(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}},\ \sigma > 1, c = a, b.$$

p_{Yc} is a price of goods (local service) Y_c. I set the local service price in a, p_{Ya}, equals 1 as a numeraire. I_c is total wage in location c. r_c is rent in c, which is common for all workers. For simplicity, the elasticity of substitution between varieties is ρ $(0 < \rho < 1)$ and $\sigma = \frac{1}{1-\rho} > 1$ is assumed to be the same across industries and locations. $0 < \alpha, \beta_l < 1 (l = 1, 2)$ are Cobb-Douglas parameters which represent the share of expenditure on each good and the sum equals one. These parameters are common in any location. The CES price index for tradable sector X_c is defined as $P_{Xc} \equiv \left(\int_{\omega\in\Omega_c} p_{Xc}(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}$.

Since the utility function has the Cobb-Douglas structure, the utility maximization problem of a worker in location c is broken down into the following problem:

$$\max_{q_c} \left(\int_{\omega\in\Omega_c} q_c(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}$$
$$s.t.\ \int_{\omega\in\Omega_c} p_c(\omega) q_c(\omega) d\omega = \beta_l I_c.$$

We can assume $l = 1$ for $c = a$ and $l = 2$ for $c = b$ without loss of generality.[2] Define the aggregate quantity index in sector X_c as $Q_c \equiv \left(\int_{\omega\in\Omega_c} q_c(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}$.

By solving the maximization problem, we have the equation for optimal expenditure of individuals with skill z for industries in location c on each

[2]Note that there is only one tradable sector in each location.

variety ω:

$$p_c(\omega)q_c(\omega) = \left[\frac{p_c(\omega)}{P_{Xc}}\right]^{1-\sigma} \beta_l \left(I_a + I_b\right). \tag{2.1}$$

Worker location choice Workers maximize their indirect utility by choosing locations. The indirect utility of worker i with skill z in location c is given by

$$V_{ic}(z) = a_0 + w_c(z) - \alpha p_{Yc} + A_{ic},$$

where a_0 is a constant term and A_{ic} represents individual-location specific amenity.

Assume $\ln A_{ic} = \bar{A}_c + \xi_{ic}$: that is, the individual-location specific amenity consists of a location-specific term $\bar{A}_c$ and worker-specific idiosyncratic preferences for location, ξ_{ic}. Then the indirect utility can be written as

$$V_{ic}(z) = u_c(z) + \xi_{ic}$$

where $u_c(z) \equiv a_0 + w_c(z) - \alpha p_{Yc} + \bar{A}_c$. Workers choose location c if V_{ic} is higher than in the other location c':

$$\max_c u_c(z) + \xi_{ic}.$$

As in Moretti (2011), I assume that a worker's relative preference between location a and b follows the continuous uniform distribution with the bound parameters $-s$ and $s(s > 0)$:

$$\xi_{ia} - \xi_{ib} \sim \mathrm{U}[-s, s].$$

s indicates the importance of idiosyncratic preferences. If s is large, the preference is important for location choice for workers, i.e., they may choose location c even if the real wage is higher in location c' or location c' has a better amenity. A worker with skill z chooses location a if and only if $V_{ia}(z) > V_{ib}(z)$, that is,

$$\xi_{ia} - \xi_{ib} \;\; > \;\; (w_b(z) - \alpha p_{Yb}) - (w_a(z) - \alpha) + (\bar{A}_b - \bar{A}_a).$$

Assume that $m_c(z)$ represents a share of workers with skill z who will choose location c: $m_a(z) + m_b(z) = m(z)\ \forall z$. Then, the share of workers with skill z who choose location a can be written as:

$$\frac{m_a(z)}{m(z)} \;\; = \;\; \frac{1}{2s}\left[(w_a(z) - \alpha) - (w_b(z) - \alpha p_{Yb}) + (\bar{A}_a - \bar{A}_b) + s\right]. \quad (2.2)$$

The analogous equation holds for $m_b(z)$:

$$\frac{m_b(z)}{m(z)} \;\; = \;\; \frac{1}{2s}\left[(w_b(z) - \alpha p_{Yb}) - (w_a(z) - \alpha) + (\bar{A}_b - \bar{A}_a) + s\right]. \quad (2.3)$$

Rearranging them yields

$$w_b(z) = w_a(z) + \alpha(p_{Yb} - 1) + (\bar{A}_a - \bar{A}_b) + s\frac{m_b(z) - m_a(z)}{m(z)} \quad (2.4)$$

Since z is assumed to follow $G(.)$, the population in location c will be:

$$M_c \;\; = \;\; \int_0^\infty m_c(z)dz \quad (2.5)$$

for $c = a, b$.

Equation (2.4) indicates local labor supply curves for workers with each skill level z. One of the key aspects of these supply curves is that local labor supply depends on the parameter s. If s is larger, the slope of the supply curve is steeper, which implies labor supply does not respond much to wage changes. This is because the idiosyncratic preference for location is more important for workers.

2.2.2 Firm's problem

Assume that labor is the only production factor. As in Yeaple (2005), there is a single technology in sector Y, but there are two technologies in sector X: a new or high-tech technology H and an old or low-tech technology L. Technology H is characterized by a lower marginal cost of production and a higher fixed cost compared to technology L.

Suppose the amount of a good that worker with skill z using technology k produces is $\varphi_k(z)$, $k \in \{Y, L, H\}$.

Following Yeaple (2005), I further assume that

$$\frac{\partial \ln \varphi_H(z)}{\partial z} > \frac{\partial \ln \varphi_L(z)}{\partial z} > \frac{\partial \ln \varphi_Y(z)}{\partial z} > 0, \tag{2.6}$$

which means comparative advantage based on skills among workers. That is, more skilled workers have a comparative advantage in production with technology H relative to middle- and low-skilled workers.

Firms are free to enter both sectors, Y and X, but there is a fixed set-up cost to enter the tradable sector X: f_H for high-technology and f_L for low-technology firms. Assume that $f_H > f_L$. Firms in location c demand labor in the same location. I also assume that the production technology and cost structure are the same across locations.

2.2.3 Equilibrium conditions in closed economy

Now I characterize the optimal allocation of workers to technologies to derive two equilibrium conditions regarding the firm's problem. As in Yeaple (2005), I assume that some firms use technology L and some use H technology in the equilibrium. So we have all Y, L, and H firms. In this monopolistic competition setting, all firms in sector X set a price equal to a constant markup over unit cost. Firms in Y sector set a price equal to the unit cost.

As in Yeaple (2005), define the two skill-level thresholds: the most skilled worker's skill level in firms with Y technology as z_1 and the least skilled worker's in firms with H technology as z_2. These thresholds can differ in location. They are determined such that firms

- using technology Y hire least skilled workers ($z \leq z_{1c}$),
- using technology L hire medium-skilled workers ($z_{1c} \leq z \leq z_{2c}$),
- using technology H hire most-skilled workers ($z_{2c} \leq z$).

The wage schedule in location c will be

$$w_c(z) = \begin{cases} C_{Yc}\varphi_Y(z) & 0 \leq z \leq z_{1c} \\ C_{Lc}\varphi_L(z) & z_{1c} \leq z \leq z_{2c} \\ C_{Hc}\varphi_H(z) & z_{2c} \leq z \end{cases} \tag{2.7}$$

where C_{kc} is a unit cost for production for $k \in Y, L, H$ in location c.

Assume the price for non-tradable as $p_{Yc} \geq 1$. The unit cost for each technology will be

$$\begin{aligned} C_{Yc} &= p_{Yc} \\ C_{Lc}\varphi_L(z_{1c}) &= C_{Yc}\varphi_Y(z_{1c}) \\ \Leftrightarrow C_{Lc} &= p_{Yc}\frac{\varphi_Y(z_{1c})}{\varphi_L(z_{1c})} < p_{Yc} \\ C_{Hc}\varphi_H(z_{2c}) &= C_{Lc}\varphi_L(z_{2c}) \\ \Leftrightarrow C_{Hc} &= C_{Lc}\frac{\varphi_L(z_{2c})}{\varphi_H(z_{2c})} = p_{Yc}\frac{\varphi_Y(z_{1c})}{\varphi_L(z_{1c})}\frac{\varphi_L(z_{2c})}{\varphi_H(z_{2c})} < C_{Lc}. \end{aligned} \tag{2.8}$$

The zero profit condition for firms in sector X_c determines z_{2c}. Since all firms make no profit, revenue must be equal to the total cost. If both H-technology firms and L-technology firms make zero profits, then the following zero profit condition can be derived:

$$\frac{C_{Hc}}{C_{Lc}} = \frac{\varphi_L(z_{2c})}{\varphi_H(z_{2c})} = \left(\frac{f_H}{f_L}\right)^{-\frac{1}{\sigma}}. \tag{2.9}$$

Note that z_{2c} is pinned down by this zero-profit condition only.

The second equilibrium condition is the market clearing condition for sector Y_c. Since total expenditure on good Y_c should equal to the constant share of the total income of workers living in location c, we have

$$p_{Yc}Y_c = \alpha I_c$$

where I_c is the total income in c, $I_c = C_{Yc}\int_0^{z_{1c}} m_c(z)\varphi_Y(z)dG(z) + C_{Lc}\int_{z_{1c}}^{z_{2c}} m_c(z)\varphi_L(z)dG(z) + C_{Hc}\int_{z_{2c}}^{\infty} m_c(z)\varphi_H(z)dG(z)$.

Since the total expenditure on Y_c should be the same as the total income paid to workers in sector Y_c, $C_{Yc}\int_0^{z_{1c}} m_c(z)\varphi_Y(z)dG(z)$, we have the following market-clearing condition:

$$\begin{aligned} &C_{Yc}\int_0^{z_{1c}} m_c(z)\varphi_Y(z)dG(z) = \\ &\alpha\left(C_{Yc}\int_0^{z_{1c}} m_c(z)\varphi_Y(z)dG(z) + C_{Lc}\int_{z_{1c}}^{z_{2c}} m_c(z)\varphi_L(z)dG(z) + C_{Hc}\int_{z_{2c}}^{\infty} m_c(z)\varphi_H(z)dG(z)\right). \end{aligned} \tag{2.10}$$

2.3 Open Economy

In this section, I consider the open economy model with international trade. Assume that there are two identical countries. To serve differentiated goods to another country, firms must incur fixed export cost f_{ex} and iceberg trade cost $\tau_c > 1$, $c = a, b$, which can differ for each location.

2.3.1 Firm's problem in open economy

Now consider the case $f_L < \tau^{\sigma-1} f_{ex} < f_H$. Then, H heterogeneity firms export, and L technology firms only sell to domestic markets.

The skill thresholds z_{1c} and z_{2c} are determined by free entry condition and market clearing condition for non-tradable Y as in the closed economy:

$$H(z_{2c}) = \left(\frac{f_L \left(1 + \tau^{1-\sigma}\right)}{f_H + f_{ex}} \right)^{\frac{1}{\sigma}} \tag{2.11}$$

$$\begin{aligned} &\frac{1-\alpha}{\alpha} \frac{1}{S(z_{1c})} \int_0^{z_{1c}} m_c(z)\varphi_Y(z)dG(z) \\ &\quad = \int_{z_{1c}}^{z_{2c}} m_c(z)\varphi_L(z)dG(z) + H(z_{2c}) \int_{z_{2c}}^{\infty} m_c(z)\varphi_H(z)dG(z) \end{aligned} \tag{2.12}$$

where $H(z_{2c}) \equiv \frac{\varphi_L(z_{2c})}{\varphi_H(z_{2c})} = \frac{C_{Hc}}{C_{Lc}}$ and $S(z_{1c}) = \frac{\varphi_Y(z_{1c})}{\varphi_L(z_{1c})} = \frac{C_{Lc}}{C_{Yc}}$.[3]

The number of firms using L and H in location c can be written as a function of z_{1c} and z_{2c}:

$$\begin{aligned} N_{Lc} &= \frac{1}{\sigma f_L} \int_{z_{1c}}^{z_{2c}} m_c(z)\varphi_L(z)dG(z) \\ N_{Hc} &= \frac{1}{\sigma(f_H + f_{ex})} \int_{z_{2c}}^{\infty} m_c(z)\varphi_H(z)dG(z) \end{aligned} \tag{2.13}$$

The price index of tradable sector X in location c can be calculated as:

$$P_{Xc} = \frac{\sigma}{\sigma - 1} \left(\frac{1-\alpha}{\alpha} \frac{1}{\sigma f_L} \right)^{\frac{1}{1-\sigma}} \left(\int_0^{z_{1c}} m_c(z)\varphi_Y(z)dG(z) \right)^{\frac{1}{1-\sigma}} \tag{2.14}$$

2.3.2 General equilibrium conditions

The general equilibrium of the model of a closed economy is defined by the mass of workers in location a and b, M_a and M_b, two skill-level thresholds in each location, z_{1a}, z_{2a}, z_{1b}, and z_{2b}, the number of firms using technology

[3]Note that$H(.)$ and $S(.)$ are strictly decreasing.

H and L in each location, N_{La}, N_{Ha}, N_{Lb}, and N_{Hb}, wage schedules in each location, $w_a(z)$ and $w_b(z)$, local service price in each location, p_{Ya} and p_{Yb}, and price indices in sector X in each location, P_{Xa} and P_{Xb}, such that the equilibrium conditions (2.4), (2.5), (2.7), (2.8), (2.11), (2.12), (2.13), and (2.14) hold.

2.4 Comparative statics

In this section, I analyze the case when τdeclines in location a but not in location b. What are the effects on workers in both locations?

By (2.11), the threshold z_{2a} must decrease when τdecreases. By totally differentiating (2.12), we see that z_{2a} and z_{1a} need to move the opposite directions: that is, z_{1a} increases when z_{2a} decreases.

Then, the following proposition arises:

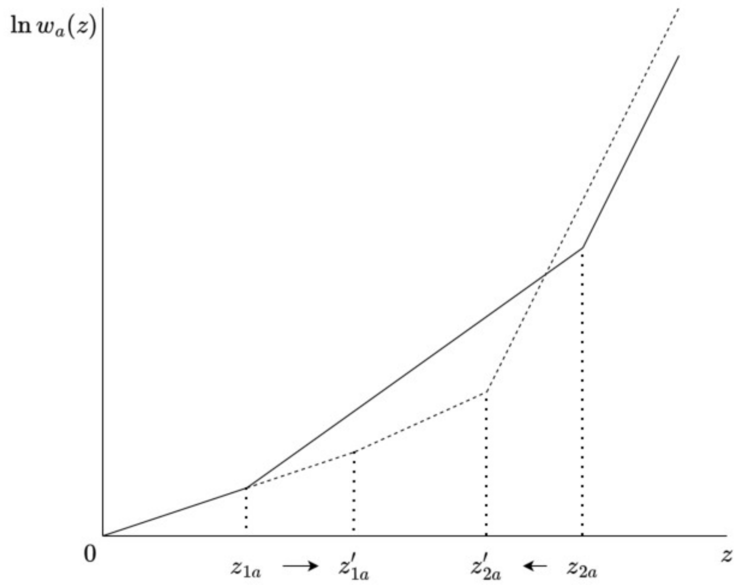
Proposition 2.1. *When variable trade cost decreases only in location a, the share of workers working in the firms with technology H and Y increases while the share of workers working in sector X_a decreases in location a. The skill thresholds in b are not affected.*

From equation (2.13), we can see that the number of firms using technology L falls and those using technology H rises in $a$as τ_a declines. This also implies that the number of exporters increases. As pointed out in Yeaple (2005), falling variable trade cost only in location a works like a technological advancement for firms employing technology H in a.

With equation 2.8, it is shown that a reduction in τ_a leads to a decline in the unit cost of production for technology L, C_{La} and a rise in that for technology H, C_{Ha}. These changes in unit costs lead to a change in the wage schedule in a through 2.7, which is illustrated in Figure 2.1.

Next, we will examine what happens to workers in location b and worker reallocations between a and b. When the trade cost τ_a decreases, the price

Figure 2.1: Changes in the wage schedule in a when τ_a decreases



index in sector X_a decreases.[4] Thus P_{X_a} decreases in both a and b. As a result, real wage (in terms of good X) increases for least-skilled and most-skilled workers in location a while the real wage for medium-skilled workers in a is ambiguous since their nominal wage decreases as we see in Figure 2.1. Because of the price decline in sector X_a, real wage in location b rises for all skill-level workers since they also consume goods produced in X_a. As a result, the following proposition holds:[5]

Proposition 2.2. *When τ_a decreases, the most skilled workers move to location a from b, medium-skilled workers move to b from a, and least-skilled workers do not move.*

This proposition has an implication on the labor market polarization: in the location that experienced trade cost reduction, we can see the labor market polarization occurs; that is, the share of most-skilled workers increases while the share of middle-skilled workers declines. On the other hand, polar-

[4]This can be seen in the equation 2.14.

[5]The proof is available upon request.

ization does not occur in location b: it increases the share of least-skilled and middle-skilled workers.

What happens to the total population in each location? Although it is an interesting question especially when we think about the Great Divergence, the answer depends on how many workers move between locations in total, which also depends on the skill distribution $G(.)$ and how much the skill thresholds change when trade cost τ_a changes, etc. So we need further assumptions/specifications in the model. Therefore, I will remain this question open in my future research.

2.5 Conclusion

In this paper, I investigate the effect of trade liberalization on local labor markets. To construct the general equilibrium model with international trade and heterogeneous worker reallocation, I combine a trade model in Yeaple (2005) and a local labor market model as in Moretti (2011) and Kline (2010). To understand the mechanism clearly, I consider the simplest case with two locations with a tradable sector and a non-tradable local service sector. In comparative statics, I find that there are within- and between-location labor reallocations when reducing the variable trade cost in one location. We see that in the location that experienced trade cost reduction, the share of most-skilled workers increases compared to before the trade cost falls while medium-skilled worker's share increases in another location. These results suggest that the trade cost shock can cause labor market polarization and that it can be heterogeneous across locations.

The model presented in this paper leads to future work on the topic of trade shocks and local labor markets, especially focusing on the reallocation of heterogeneous workers. For future research, one can expand this model to a multi-sector and multi-industry setting, which is a more realistic setting.

One can also investigate the impact on local population growth, the role of agglomeration, and labor market imperfection, which are also important factors when we think about the effect of trade shocks on regional economies.

Chapter 3

The China Syndrome: A cross-country evidence*

3.1 Introduction

For many advanced countries, import competition from low-wage countries is always one of the major concerns for policymakers and the general public because it is considered to be one of the most important adjustment processes in globalization.[1] In particular, the impact on employment of increasing import competition from China, which is also called "the China Syndrome" or "the China shock," has been a major topic of debate in the United States for the last two decades due to the rapid growth of the Chinese economy. Accordingly, several studies have examined the effects of imports from China on the US employment (e.g. Autor, Dorn, and Hanson, 2013, 2015; Acemoglu, Akcigit, and Kerr, 2016; Acemoglu et al., 2016; Pierce and Schott, 2016; and Wang et al., 2018).

*This chapter is the joint work with Kozo Kiyota and Sawako Maruyama, published in The World Economy 44.9 in 2021.

[1] For the earlier studies on this issue, see Revenga (1992) for the case of the United States and Tachibanaki, Morikawa, and Nishimura (1998) and Tomiura (2003) for the case of Japan.

Among these studies on the China shock, one of the most influential studies is Acemoglu et al. (2016). They examined the effects of imports from China on US employment between 1999 and 2011. Using detailed input–output data, they found that job losses from rising Chinese import competition for the above period amount to 2.0–2.4 million. Due to the huge negative impact on US employment, this number was featured in stories by news publications such as the *Washington Post* (12/15/2014) and the *New York Times Magazine* (9/5/2016).

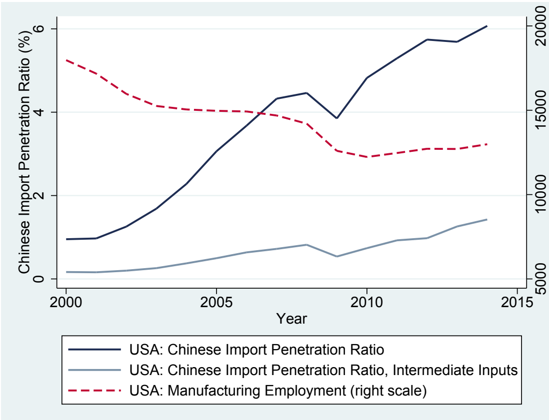
Concern about the China shock is not only limited to the United States but is also shared with other advanced countries. Figure 3.1 compares the Chinese import penetration and manufacturing employment for six advanced countries: France, Germany, Japan, South Korea, the United Kingdom, and the United States for the period between 2000 and 2014.[2] These are top six destination countries to which China exports intermediate inputs. On the one hand, import penetration from China increased throughout the period in all six countries. On the other hand, manufacturing employment declined over the period for all countries except South Korea. Indeed, the studies on the China shock thus have expanded from the United States to various other countries. For example, Dauth, Findeisen, and Suedekum (2014) have investigated the effects of imports from China and Eastern Europe on German employment. Taniguchi (2019) and Choi and Xu (2020) have studied the effects of imports from China on Japanese and Korean employment, respectively.

However, to our knowledge, the previous studies have paid little attention to the cross-country differences about the China shock. It is possible that the

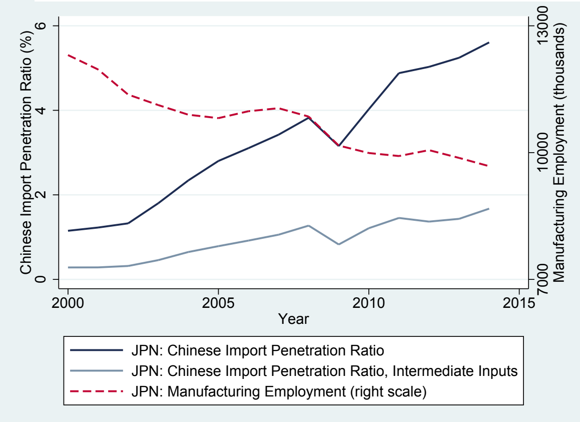
[2]The data come from the World Input–Output Database. Next section explains about the data used in this paper in more detail.

Figure 3.1: Import Penetration Ratio from China (*left scale*) and Share of Manufacturing Employment (*right scale*)

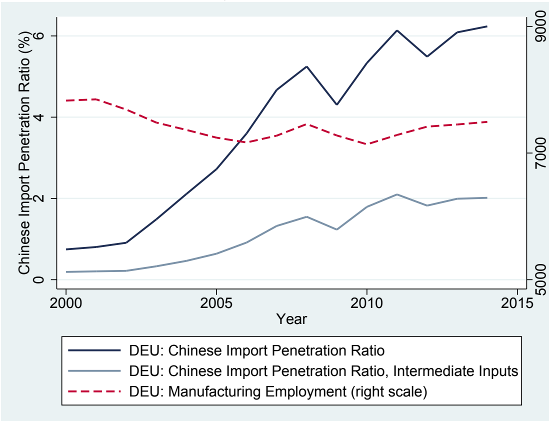
Panel A: United States



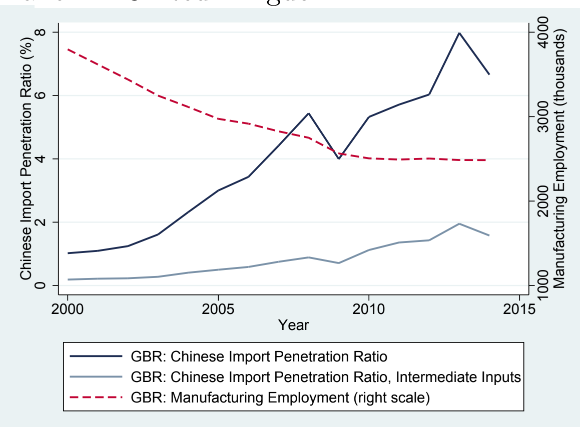
Panel B: Japan



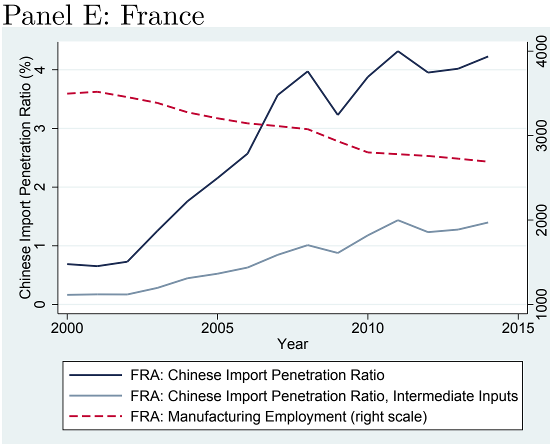
Panel C: Germany



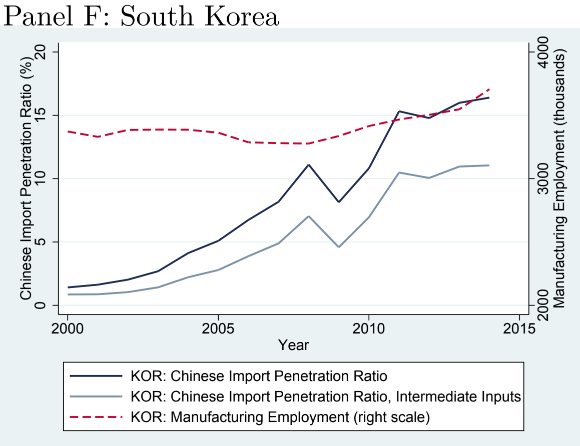
Panel D: United Kingdom



Panel E: France



Panel F: South Korea



Notes: The order of the country is based on the size of the GDP. Imports are limited to manufacturing sector.
Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

China shock could be different across countries, depending upon the volume and the composition of the products. Although the studies on the China shock have expanded from the United States to other countries such as Germany (Dauth, Findeisen, and Suedekum, 2014) and Japan (Taniguchi, 2019), these studies are conducted independently. Thus, their results are difficult to compare with each other due to differences in the period and industry coverage as well as differences in industry classification. More comprehensive analysis is needed for cross-country comparisons.

In this paper, we examine the effects of imports from China on employment in six advanced countries: France, Germany, Japan, South Korea, the United Kingdom, and the United States. Our empirical approach is similar to Acemoglu et al. (2016), but we extend their analysis in the following three aspects. First, we extend their analysis to cross-country comparisons during the same period under the same industry classification that enables us to compare the results across countries.[3] To do so, this paper utilizes the data from the World Input–Output Database (WIOD) between 2000 and 2014. This extension enables us to identify similarities and differences in the China shock across countries, based on the same analytical framework during the same period under the same industry classification.

Second, unlike Acemoglu et al. (2016), this paper distinguishes between imports of final goods and those of intermediate inputs. The imports of final goods could yield negative effects on domestic producers of final goods from import competition. In contrast, the imports of intermediate inputs can have two opposite effects. On the one hand, it could compete with domestic production of intermediate inputs. On the other hand, it could contribute to domestic production of final goods, and thereby could have positive effects on employment of final goods producers. Without considering such positive

[3]Our main focus is on the cross-country comparisons of the China shock on overall employment. Due to the limited availability of the local labor market data across countries, local labor market issue is not pursued here.

effects explicitly, the negative effects could be overemphasized. Indeed, Figure 3.1 also indicates that the imports of intermediate inputs increased in the six advanced countries, where imports of intermediate inputs are defined as imports that are not used for final demands. Nonetheless, there are still only a few studies that distinguish between the imports of final goods and those of intermediate inputs. Taniguchi (2019) examined the effects of increased imports from China on Japanese local labor markets. She found that increases in the imports of intermediate inputs from China had positive effects on employment. Wang et al. (2018) and Caliendo, Dvorkin, and Parro (2019) also found similar positive effects of imported intermediate inputs from China on US employment, where both studies utilize the WIOD to capture the imports of intermediate inputs. Building upon these studies and using the WIOD, this paper distinguishes the difference in the effects of the imports of final goods and those of intermediate inputs.

Finally, we take into account the effects of exports as well as imports. As Dauth, Findeisen, and Suedekum (2014) pointed out, while the growth of China increased import competition, it simultaneously leads to a substantial rise in market opportunities for companies in advanced countries. Without considering the effects of exports explicitly, one could overestimate the negative effects of foreign exposure on employment. Indeed, Dauth, Findeisen, and Suedekum (2014) found significantly positive effects of trade exposure on employment in Germany. In spite of the importance of exports, however, only a few studies such as Dauth, Findeisen, and Suedekum (2014), Feenstra and Sasahara (2018), Feenstra, Ma, and Xu (2019), and Choi and Xu (2020) explicitly took into account the effects of exports as well as imports in recent studies on the China shock.[4] Based on this background, this paper explicitly focuses on the effects of exports as well as those of imports.

To clarify the similarity in and the difference between the previous studies and our study, we summarize the related studies in Table 3.1. This table indicates that the use of the WIOD allows one to distinguish the imports of intermediate inputs and final goods while restricting the number of industries.

The major findings of our paper are twofold. First, the import penetration of final goods from China has a negative effect on manufacturing employment in most of the six countries, whereas the import penetration of intermediate inputs from and the exports to China show positive coefficients while they are statistically insignificant in most countries. Second, in the counterfactual analysis, we show that such positive effects could offset or even outweigh the negative effects in some countries. For the United Kingdom and the United States, the negative effects of the imports of final goods outweigh the positive effects of the imports of intermediate inputs and exports. In contrast, for France and Japan, the negative effects of the imports of final goods offset the positive effects of the imports of intermediate inputs and exports. For South Korea and Germany, the positive effects outweigh the negative effects. These results together suggest that a careful interpretation is needed when evaluating the external validity of the China shock that is obtained in one country.

These results have an important caveat. Our analysis is based on small sample. This could cause the small sample problem, which results in the less precise estimates. Noting that the small sample is caused by the aggregation of industries, this could also magnify the problem of within-industry

[4] In this connection, several studies have found the positive relationship between exports and employment. See, for example, Kiyota (2012) for the case of Japan. Kiyota (2016) extended the analysis of Kiyota (2012) to China, Indonesia, and South Korea as well as Japan.

Table 3.1: Summary of the Trade Data of the Related Studies

	Source	Country	Period	Industry (# of industries)	Imports: Separation of Final demands and Intermediate inputs	Exports
Autor et al. (2013)	UN Comtrade	US	1990-2007	Manufacturing (397)	No	No
Acemoglu et al. (2016)	UN Comtrade	US	1991-2007	Manufacturing (392)	No	No
Dauth et al. (2014)	UN Comtrade	Germany	1988-2008	Manufacturing (97)	No	Yes (to China)
Choi and Xu (2020)	UN Comtrade	South Korea	1993-2013	Manufacturing (180)	No	Yes (to China)
Acemoglu et al. (2015)	UN Comtrade	US	1991-2009	Manufacturing (392)	No	No
Wang et al. (2018)	Inter-Country Input-Output tables (OECD)	US	2000-2014	All (34) Manufacturing (16)	Yes (only in down-stream channel)	Yes (to China)
Feenstra et al. (2019)	UN Comtrade	US	1991-2011	Manufacturing (392)	No	Yes (to the world)
Fabinger et al. (2017)	JIP Database	Japan	1996-2009	Manufacturing (50)	No	No
Taniguchi (2018)	JIP Database; Japan-China Input-Output Table	Japan	1995-2007	Manufacturing (52)	Yes	No
Feenstra and Sasahara (2019)	World Input-Output Database	US	1995-2011	All (35) Manufacturing (13)	Yes (expressed in inverse matrix)	Yes (to the world)
Caliendo et al. (2019)	World Input-Output Database	US	2000-2007	All (22) Manufacturing (12)	Yes	Yes
Our study	World Input-Output Database	US, Japan, UK, Germany, France, South Korea	2000-2014	Manufacturing (19)	Yes	Yes (to China)

Notes: "Yes (to China)" in the last column indicates that only exports to China are included, whereas "Yes (to the world)" indicates that exports to the world are included.

heterogeneity. Therefore, our estimation results should be interpreted with caution.

The rest of this paper is organized as follows. The next section explains the methodology and data used in this paper. Section 3.3 presents the estimation results. Section 4 addresses issues to be discussed further on our approach and the estimation results. A summary of our findings and their implications are presented in the final section.

3.2 Methodology and Data

3.2.1 Methodology

Preliminary analysis

We first examine the effect of total imports on employment as a preliminary analysis. Following Acemoglu et al. (2016), the specification in our preliminary analysis has the following form:[5]

$$\Delta L_{j,\tau} = \alpha_\tau + \beta \Delta IP_{j,\tau} + \varepsilon_{j,\tau}, \tag{3.1}$$

where $\Delta L_{j,\tau}$ is 100 times the log change in employment in industry j in country c over the period τ; α_τ is a country- and period-specific constant; $\Delta IP_{j,\tau}$ is 100 times the change in import penetration from China in industry j in country c over the time period τ; and $\varepsilon_{j,\tau}$ is an error term. For ease of presentation, we omit country notation c, unless otherwise noted.

[5] One may argue that we employ alternative estimation strategy such as difference-in-differences (DID) design. However, the DID is based on a common trends assumption, which should be tested before the China shock (the early 2000s). As we will explain below, the data we use covers from 2000. The period of our data thus is not long enough to test this assumption, which makes it difficult to employ the DID design.

The change in import penetration from China is defined as follows:

$$\Delta IP_{j,\tau} = \frac{\Delta M^{CHN}_{j,\tau}}{Y_{j,0} - E_{j,0} + M_{j,0}}, \tag{3.2}$$

where $\Delta M^{CHN}_{j,\tau}$ is the change in imports during the period τ; $Y_{j,0} - E_{j,0} + M_{j,0}$ is the initial absorption (measured as industry outputs, $Y_{j,0}$, plus industry imports, $M_{j,0}$, minus industry exports, $E_{j,0}$). Equation (3.1) is estimated using two-stage least squares (2SLS) as well as ordinary least squares (OLS) specifications.

An instrumental variable (IV) for 2SLS is:

$$\Delta IPO_{j,\tau} = \frac{\Delta M^{CHN,O}_{j,\tau}}{Y^O_{j,0} - E^O_{j,0} + M^O_{j,0}}, \tag{3.3}$$

where $\Delta M^{CHN,O}_{j,\tau}$ is the change in imports from China during the period τ in other high-income countries; $Y^O_{j,0} - E^O_{j,0} + M^O_{j,0}$ is the initial absorption of other high-income countries. For the initial absorption, we choose the absorption value in 2000. We would note that using the absorption value in 2000 might lead to bias if the included economic variables are affected by an anticipated increase in imports and/or exports with China. If we use the earlier version of the WIOD, we may be able to choose the previous (or earlier) year for the absorption. However, because the industry classification in the earlier version of the WIOD is more aggregated, the sample size becomes further small. As a compromise, we choose the initial year of our sample for the absorption. Noting that the major export and import destination countries vary between final goods and intermediate inputs and across countries, we choose other high-income countries in which the correlation between IV and $\Delta M^{CHN}_{j,\tau}$ is relatively high and the first-stage F-value is also high.[6]

[6]The choice of other high-income countries thus varies between imports and exports and between final goods and intermediate inputs.

Benchmark specification

We extend the specification in the preliminary analysis in two ways. First, similar to Taniguchi (2019) and Wang et al. (2018), we distinguish between imports of intermediate inputs and those of final goods. As mentioned above, without considering the positive effects of the imported intermediate inputs explicitly, the negative effects of imports could be overemphasized.

Second, we control for the effects of exports as well as imports. As was pointed out by Dauth, Findeisen, and Suedekum (2014) and Choi and Xu (2020), employment could be affected not only by imports but also by exports. We thus include exports to the regression equation in an analogous measure.[7]

Our main regression is specified as follows:

$$\Delta L_{j,\tau} = \alpha_\tau + \beta_1 \Delta IP^{IM}_{j,\tau} + \beta_2 \Delta IP^{FN}_{j,\tau} + \gamma \Delta EP_{j,\tau} + \varepsilon_{j,\tau}, \tag{3.4}$$

where

$$\Delta IP^{IM}_{j,\tau} = \frac{\Delta x^{CHN}_{j,\tau}}{Y_{j,0} - E_{j,0} + M_{j,0}}, \tag{3.5}$$

where superscript IM denotes intermediate inputs and $\Delta x^{CHN}_{j,\tau}$ denotes the changes in the imports of intermediate inputs from China to industry j in the importing country over the period τ;

$$\Delta IP^{FN}_{j,\tau} = \frac{\Delta f^{CHN}_{j,\tau}}{Y_{j,0} - E_{j,0} + M_{j,0}}, \tag{3.6}$$

where superscript FN denotes final goods and $\Delta f^{CHN}_{j,\tau}$ denotes the changes in the imports of final goods from China to industry j in the importing country over the period τ. Their instruments are:

$$\Delta IPO^{IM}_{j,\tau} = \frac{\Delta x^{CHN,O}_{j,\tau}}{Y^O_{j,0} - E^O_{j,0} + M^O_{j,0}} \quad \text{and} \quad \Delta IPO^{FN}_{j,\tau} = \frac{\Delta f^{CHN,O}_{j,\tau}}{Y^O_{j,0} - E^O_{j,0} + M^O_{j,0}}, \tag{3.7}$$

[7] Choi and Xu (2020) employed similar indexes to export–output ratio that indicates the changes in Korean exports as well as those in Japanese exports as an instrument.

where $\Delta IPO_{j,\tau}^{IM}$ and $\Delta IPO_{j,\tau}^{FN}$ are the change in the imports of intermediate inputs and final goods, respectively, from China to industry j in other high-income countries during the period τ.

Similarly, $\Delta EP_{j,\tau}$ is 100 times the change in exports to China relative to output in industry j in country c over the time period τ:

$$\Delta EP_{j,\tau} = \frac{\Delta E_{j,\tau}^{CHN}}{Y_{j,0}}, \tag{3.8}$$

where $\Delta E_{j,\tau}^{CHN}$ is the change in exports from country c to China. Its instrument is:

$$\Delta EPO_{j,\tau} = \frac{\Delta E_{j,\tau}^{CHN,O}}{Y_{j,0}^{O}}, \tag{3.9}$$

where $\Delta E_{j,\tau}^{CHN,O}$ is the change in exports from other high-income countries to China during the period τ. Equation (3.4) is estimated using 2SLS as well as OLS specifications with IVs of $\Delta IPO_{j,\tau}^{IM}$, $\Delta IPO_{j,\tau}^{FN}$, and $\Delta EPO_{j,\tau}$.

Note that Acemoglu et al. (2016) featured the general equilibrium effect of an increase in imports from China including indirect effects through sectoral linkages. However, since the WIOD has limited number of industries, the inclusion of indirect effects causes severe multicollinearity and loss of a degree of freedom. Thus, while we follow the empirical specification with focusing on direct effect in Acemoglu et al. (2016), we extend the analysis on the direct effect, which explicitly distinguishes the imports of final goods, those of intermediate inputs, and exports.

Instrumental variables

Our instrumental strategy is similar to that of the previous studies such as Autor, Dorn, and Hanson (2013) and Acemoglu et al. (2016). That is, to instrument the imports from China by a target country c, we use the imports from China by other OECD countries which experienced a similar surge in the imports from China during the sample period. As in the previous literature, we choose a set of countries as the IV candidate that have characteristics similar to a target country regarding trade with China. We then take the mean of these countries' Chinese import penetration ratios and export-output ratios to form the instruments.

We choose countries to construct IV for each explanatory variable as follows. First, following the literature, we select nine high-income OECD countries that are available in the WIOD and experienced a large increase in trade with China. We consider these nine countries as a baseline set of countries, which consists of Australia, Canada, France, Germany, Japan, South Korea, Taiwan, the United Kingdom, and the United States. Then, in the case where the baseline set of countries does not satisfy the conditions that are required to be valid instruments, we modify a set of countries by adding or excluding some of these countries to satisfy these conditions.[8] We select the countries that have high correlations with a target country in terms of the imports of intermediate inputs or of final goods from China. We also adjust the set of countries in order to include at least three countries and not to choose the target countries and other IV countries from only one region. This would avoid the IV correlating to unobserved labor demand shocks that would also affect the employment change in the target country. The countries we use to construct the IV for each explanatory variable in six target countries are listed in Table B2.

We form the IVs for the export–output ratios in a similar way with those for the import penetration ratios of final good and intermediate inputs. To reduce the correlations between the IVs for each explanatory variable, we further adjust the sets of IV countries such that we do not have too low Shea's

[8]We consider a set of IV valid if the IV satisfies the following conditions at the first stage: 1) the IV is well correlated with the explanatory variable, 2) F-value in the first-stage regression is high enough, and 3) the IV is not strongly correlated with the other IVs (for example, the IV for import penetration ratio of final goods does not have a high correlation with the IV for import penetration ratio of intermediate inputs and the IV for export–output ratio), which means Shea's adjusted partial R^2 is high (see Shea, 1997). These first-stage statistics are provided in the Tables B4–B6.

adjusted partial R^2, which is an indicator for a valid IV in a multivariate model (see Shea, 1997).

3.2.2 Data

Source

This paper uses data from the WIOD for the period from 2000 to 2014.[9] The WIOD is built on national accounts data and was developed within the 7th Framework Programme of the European Commission. The WIOD provides time-series of global IO tables for 28 EU countries, 15 other major countries and the rest-of-the-world (ROW). The 15 countries include non-EU OECD member countries such as Japan and the United States as well as emerging economies such as China and Mexico. These tables are constructed on the basis of officially published IO tables in conjunction with national accounts and international trade statistics.

One advantage of using the WIOD is that it provides Socio Economic Accounts which include annual data such as employment at the industry level. This enables us to examine the effects of trade on employment more precisely. Moreover, throughout the data collection effort, harmonization procedures are applied to ensure the international comparability of the data. This enables us to conduct comparative analysis across countries for the same period under the same industry classification. If the period or the industry classification is different, one cannot figure out whether the difference of the effects of the China shock can be attributable to the differences in country, period, or industry classification.

Another advantage of using the WIOD is that it includes information

[9]The WIOD and all satellite accounts are available at http://www.wiod.org. The satellite accounts include National IO Tables, Socio Economic Accounts (i.e. data on employment, capital stocks, etc.) and Environmental Accounts. In this paper, we utilize World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018. For a detailed description of the database construction, see Timmer et al. (2015).

on the use of imported goods, whether for intermediate inputs or for final demand. It provides data for domestic and imported intermediate inputs as well as domestic and imported final demands separately and by country. In our analysis, imports in the intermediate demand sector are regarded as imports of intermediate inputs, whereas imports in the final demand sector are regarded as imports of final goods. In addition, information on both source and destination industries is also available. Note that the use of and the destination industry of imported goods are not reported in standard trade data. Similarly, the national input–output table reports the imports as a total and does not distinguish between intermediate inputs and final goods. These features in turn mean that the WIOD enables us to capture the imports of manufacturing goods for intermediate inputs as well as for final demand. Thus, the WIOD is useful for cross-country comparisons of international trade flows between a particular pair of countries with a separation of intermediate and final goods.

In contrast, a disadvantage of the WIOD is that the industry classification is less disaggregated than the classification in the previous studies. This makes it difficult to analyze the inter-industry linkages precisely, even though the recent studies such as Acemoglu et al. (2016) emphasized the importance of the general equilibrium effects. Therefore, this study does not pursue the issue of inter-industry linkages. In addition, many Eastern European and South East Asian countries are not included in the WIOD. This paper focuses on the imports from China rather than those from low-wage countries.

Note that the China shock became evident from the early 2000s. For example, Autor, Dorn, and Hanson (2013) confirmed that the share of imports from China in the United States increased from 2001 when China joined the World Trade Organization (WTO).[10] Similarly, Taniguchi (2019) pointed out

[10] In contrast, Pierce and Schott (2016) argued that the increased imports from China are attributable to the changes in US trade policy rather than the China's entry to the WTO.

that, in Japan, imports from China in 2002 exceeded imports from the United States that was the largest importing partner for a long time. Because the WIOD covers the period from 2000, it is desirable to examine the effects of the China shock.[11]

Definition of key variables

There are two key variables in our analysis: employment and trade (imports and exports). In Socio Economic Accounts in the WIOD, employment is defined as the number of persons engaged (EMP in the WIOD).[12] Note that there is neither distinction between temporary and permanent workers nor distinction between part-time and full-time workers in the WIOD. Therefore, employment in our analysis includes temporary as well as permanent workers.

Trade is measured as the transactions between countries. Imports of final goods are defined as the imports that are used for final demand. The rest of the imports are defined as the imports used for intermediate inputs. To ensure the comparability of our findings with previous studies, we focus on the effects of manufacturing trade; therefore, industries are limited to industries with the WIOD industrial codes from 5 to 23.[13] In this study, we define manufacturing by the supply side sector.[14] This, in turn, means that the imports of intermediate inputs in manufacturing do not include the imports from non-manufacturing industries such as natural resources because they do not directly cause competition in manufacturing industries.[15] When we measure procurement from China to industry j in a target country, the imports

[11] The Release 2013 version of the WIOD covers the period between 1995 and 2011. However, the number of sectors is much smaller (34 sectors) than the current version (the Release 2016). This makes a small sample problem much severe in our analysis. This paper thus uses the Release 2016 rather than the Release 2013.

[12] Although the WIOD provides us with the number of persons engaged (EMP) and that of employees (EMPE), we use the former because the latter excludes self-employed workers.

[13] For the list of industries, see Table B1 in Appendix B2.

[14] Appendix B1 explains the structure of the WIOD in more detail.

[15] For example, according to Japan Foreign Trade Council, the 1st and the 2nd major products of the Japanese imports in 2018 are oil (10.8 percent) and liquefied natural gas

of intermediate inputs are based on the user side sector. x_j^{CHN} in equation (3.5) indicates the imports of intermediate inputs from industries 5 to 23 in China to industry j in a target country. Note that an exporting industry can be different from an importing industry in the WIOD. E_j^{CHN} in equation (3.8) indicates the exports from industry j in the target country to industries 5 to 23 in China.

To compute the growth rate with enough observations, we split the sample into two sub-periods: 2000–2007 and 2007–2014. The growth rate is computed for 2000–2007 and for 2007–2014. The initial year for the first sub-period (2000–2007) is the year 2000. The year 2007 is the initial year for the second sub-period (2007–2014). One may propose the use of overlapping data (e.g., 2000–2007, 2001–2008, etc.) rather than non-overlapping data (i.e., 2000–2007 and 2007–2014). As Clark and Coggin (2011) point out, the use of overlapping data sometimes allows us to obtain greater statistical efficiency. However, overlapping data creates a moving average error term and thus OLS parameter estimates would be inefficient.[16] Besides, the previous studies on the China shock (e.g., Autor, Dorn, and Hanson, 2013) used non-overlapping data. In conformity with the existing literature, we use non-overlapping data.

Descriptive statistics

Table 3.2 presents the descriptive statistics for the main variables in the regression analysis (i.e., equations (3.1) and (3.4)). We highlight three main findings. First, manufacturing employment declined for all countries except for South Korea. Second, the growth of the imports of final goods from China is greater than that of intermediate inputs except for South Korea. Finally, total imports from China grew faster than total exports to China

(5.7 percent), respectively. It is difficult to imagine that these products bring competition in manufacturing industries.

[16]For more detail about the overlapping data problems, see Harria and Brorsen (2009).

from the United States, Japan, the United Kingdom, and France while total exports grew faster than total imports for Germany and South Korea. These results suggest that the effects of imports from and exports to China could be different across these six countries.

3.3 Estimation Results

3.3.1 Preliminary analysis

Table 3.3 presents the OLS and 2SLS regression results of equation (3.1). We use small option in Stata software to make degrees-of-freedom adjustments and report small-sample statistics to take into account the small sample problem. To avoid the potential endogeneity problem, the focus is on 2SLS results while the OLS results are presented as references. We highlight two results. First, the first-stage partial R^2 is relatively high in all countries.[17] This result supports the validity of our instruments.

Second, the imports from China have significantly negative effects on employment in most countries. Table 3.3 indicates that the significantly negative coefficients of Chinese import penetration (ΔIP) are confirmed in the United States, Japan, the United Kingdom, and France. This result implies that import competition from China negatively affected for employment in these countries.

As discussed in Section 3.2, however, the effects of import penetration may be different if the difference between intermediate inputs and final goods or the effects of exports are taken into account. Section 3.3.2 addresses these issues in more detail.

[17] Table B3 indicates the first-stage results. For each country, the coefficients in the first-stage estimations, F-value, and partial R^2 are listed for each explanatory variable. The results indicate that the correlations between explanatory variable and its instrument, F-values, and partial R^2 are high enough in each target country, which suggests that our instrumental variables are not weak and thus valid.

Table 3.2: Descriptive Statistics

	United States		Japan		Germany	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Δ Employment (ΔL)	-16.492	15.149	-10.282	17.367	-4.342	11.482
Δ Imports (ΔIP)	2.333	2.907	1.962	2.541	2.730	4.492
Δ Imports of final goods (ΔIP^{FN})	1.693	2.908	1.337	2.356	1.874	3.972
Δ Imports of intermediate inputs (ΔIP^{IM})	0.640	0.542	0.625	0.563	0.856	0.796
Δ Exports (ΔEP)	0.646	0.828	1.36	1.687	2.953	3.173
	United Kingdom		France		South Korea	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Δ Employment (ΔL)	-20.812	16.759	-16.672	14.968	5.171	22.672
Δ Imports (ΔIP)	2.938	3.831	2.143	3.558	6.415	5.130
Δ Imports of final goods (ΔIP^{FN})	2.227	3.753	1.37	3.313	2.012	3.318
Δ Imports of intermediate inputs (ΔIP^{IM})	0.711	0.545	0.774	0.880	4.403	3.668
Δ Exports (ΔEP)	1.27	2.818	1.373	2.346	7.861	8.664

Note: For the definition of variables, see main text.
Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

Table 3.3: Estimation Results: Preliminary Analysis

	United States		Japan		Germany	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration	-2.636***	-3.139***	-1.788	-2.353*	-0.378	-0.519
(ΔIP)	(0.863)	(0.826)	(1.285)	(1.357)	(0.503)	(0.608)
N	38	38	36	36	38	38
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2		0.9070		0.7928		0.8601
	United Kingdom		France		South Korea	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration	-2.650***	-2.553***	-1.811*	-2.483**	-0.695	-0.063
(ΔIP)	(0.551)	(0.573)	(0.918)	(1.015)	(0.596)	(1.049)
N	38	38	38	38	36	36
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2		0.8826		0.8885		0.7387

Notes: This table presents the estimation results of regression equation (3.1) with instruments (i.e., equations (3.2) and (3.3)) for 2SLS. ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses indicate heteroskedasticity robust standard errors. Observations are weighted by the 2000 employment level in the data set. The sample period consists of two sub-periods: 2000–2007 and 2007–2014. The number of industries thus is $N/2$. Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

3.3.2 Benchmark results

Table 3.4 indicates the OLS and 2SLS regression results of equation (3.4). As in the preliminary analysis, we focus on 2SLS results to avoid the potential endogeneity problem.[18] We highlight three results. First, the effects of imports of final goods from China on employment are generally negative and significant. Significantly negative coefficients of the imports of final goods are confirmed in all target countries except South Korea. The results imply that the increasing imports of final goods from China could pose a threat to employment in many advanced countries.

Second, however, the imports of intermediate inputs have different effects from those of final goods. The positive coefficients are confirmed in all target countries except the United States. Moreover, the coefficient is statistically significant at the 5 percent level for Germany. The results indicate that the increasing imports of intermediate inputs are not threats in all countries but it could affect employment positively in many of these countries.

Finally, the effects of exports are generally positive although insignificant. Insignificantly positive coefficients of export–output ratio are confirmed in all countries but Germany. The results weakly suggest that the increasing exports to China also affect employment positively in these countries.

These results together imply that the import penetration of final goods from China could have significantly negative effects on manufacturing employment in six target countries. In contrast, the import penetration of intermediate inputs from and the exports to China could have weak but positive effects in most of these countries. These results seem to suggest that these six advanced countries face similar reactions to the China shock. However,

[18] Table B6 indicates the first-stage results. Like the preliminary analysis, results indicate that the correlations between explanatory variable and its instrument, F-values, and partial R^2 are high enough in each target country, which suggests that our instrumental variables are not weak and thus valid.

Table 3.4: Estimation Results: Benchmark Specification

	United States		Japan		Germany	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration						
Final goods	-2.722***	-3.263***	-2.283*	-2.925**	-1.579***	-2.000***
(ΔIP^{FN})	(0.833)	(0.765)	(1.249)	(1.095)	(0.507)	(0.613)
Intermediate inputs	2.128	-3.084	4.977	6.408	7.134**	8.972**
(ΔIP^{IM})	(6.150)	(8.905)	(6.948)	(7.406)	(2.888)	(4.187)
Export-output ratio	1.530	5.285	0.350	1.149	-0.107	-0.393
(ΔEP)	(3.486)	(6.525)	(1.906)	(2.012)	(0.440)	(0.575)
N	38	38	36	36	38	38
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2						
ΔIP^{FN}		0.7363		0.7528		0.5401
ΔIP^{IM}		0.2153		0.5864		0.5435
ΔEP		0.1396		0.6143		0.5593
	United Kingdom		France		South Korea	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration						
Final goods	-2.719***	-2.680***	-1.888**	-2.950**	-1.705**	-1.056
(ΔIP^{FN})	(0.549)	(0.561)	(0.912)	(1.249)	(0.747)	(0.987)
Intermediate inputs	0.420	0.294	-3.513	1.045	0.716	1.457
(ΔIP^{IM})	(2.747)	(3.377)	(5.081)	(4.372)	(1.640)	(2.272)
Export-output ratio	0.009	0.451	1.599	0.783	0.002	0.217
(ΔEP)	(0.364)	(0.678)	(1.373)	(1.419)	(0.836)	(0.989)
N	38	38	38	38	36	36
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2						
ΔIP^{FN}		0.9130		0.7993		0.8662
ΔIP^{IM}		0.7126		0.6970		0.5965
ΔEP		0.7343		0.7754		0.6114

Notes: This table presents the estimation results of regression equation (3.4) with instruments (i.e., equations (3.7) and (3.9)) for 2SLS. ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses indicate heteroskedasticity robust standard errors. Observations are weighted by the 2000 employment level in the data set. The sample period consists of two sub-periods: 2000–2007 and 2007–2014. The number of industries thus is $N/2$. Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

the magnitude may be different across countries. In Section 3.3, the issue of magnitude is discussed further.

3.3.3 Counterfactual manufacturing employment

In Section 3.3.2, we found that the import penetration of final goods from China has significantly negative effects on employment while the import penetration of intermediate inputs from and exports to China commonly have weak positive effects across most of these countries. However, even if the results are similar across countries in terms of statistical significance, their economic significance may be different. To address this issue, we estimate changes in counterfactual employment when there is no increase in trade with China.[19]

The difference between actual and counterfactual manufacturing employment of country c, ΔL_{τ}^{cf}, is:

$$\Delta L_{\tau}^{cf} = -\sum_{j} L_{j,\tau}\left(1 - \exp\left(-\hat{\beta}_1 \Delta \widetilde{IP}_{j,\tau}^{IM} - \hat{\beta}_2 \Delta \widetilde{IP}_{j,\tau}^{FN} - \hat{\gamma} \Delta \widetilde{EP}_{j,\tau}\right)\right), \tag{3.10}$$

where $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\gamma}$ are the 2SLS coefficient estimates.[20] $\Delta \widetilde{IP}_{j,\tau}^{IM}$ and $\Delta \widetilde{IP}_{j,\tau}^{FN}$ indicate the increases in import penetration ratio from China for intermediate inputs and for final goods, respectively; $\Delta \widetilde{EP}_{j,\tau}$ indicates the increases in export–output ratio to China. Following Acemoglu et al. (2016), $\Delta \widetilde{IP}_{j,\tau}^{IM}$ is obtained by multiplying the observed increase in import penetration $\Delta IP_{j,\tau}^{IM}$ with the partial R-squared from the first-stage regression on the instrument. $\Delta \widetilde{IP}_{j,\tau}^{FN}$ and $\Delta \widetilde{EP}_{j,\tau}$ are estimated in a similar manner. As for time period τ, the estimation covers two periods. Changes in employment and ratios from 2000 to 2007 as well as changes from 2007 to 2014 are examined.

[19] This means that the counterfactual employment is estimated under the assumption that there is no change in imports of intermediate inputs, final goods, and exports.

[20] Unlike Acemoglu et al. (2016), we multiply the difference by -1 such that the sign of the difference becomes consistent with the sign of the effects of trade.

Table 3.5 presents the results. Each figure indicates the difference between actual and counterfactual employment. For example, the figure in the top-left corner in this table indicates -1237.6, which means that the US employment would have decreased by 1.2 million workers in comparison to the case where there was no increase in the imports of intermediate inputs and final goods from, as well as the exports to, China between 2000 and 2007.

The effect of the imports of final goods is generally negative on manufacturing employment while the effects of the imports of intermediate inputs and exports are generally positive. However, the magnitude is different across six countries. For the United Kingdom and the United States, the negative effects of the imports of final goods outweigh the positive effects of the imports of intermediate inputs and exports. These results suggest the significant negative effects of the China shock on manufacturing employment in these two countries, which may be consistent with the recent surge of anti-globalization activities in these two countries.

For France and Japan, in contrast, the negative effects of the imports of final goods offset the positive effects of the imports of intermediate inputs and exports. For example, negative effects are reduced to one-tenth for Japan if the effects of imports of intermediate inputs and exports are taken into account. Therefore, the effect of the China shock in France and Japan may be much smaller than in the United Kingdom and the United States.

For South Korea and Germany, positive effects outweigh negative effects. For example, for Germany, the employment would have *decreased* by 318 thousand workers if there were no imports from and exports to China. A similar finding is confirmed in South Korea. The China shock thus might have positive effects on manufacturing employment in these two countries. These results together imply that the effects of import competition from China vary across countries. Therefore, a careful interpretation is needed for the external validity of the results that are obtained in one country.

Table 3.5: Counterfactual Manufacturing Employment

	United States			Japan			Germany		
	2000-07	2007-14	2000-14	2000-07	2007-14	2000-14	2000-07	2007-14	2000-14
Imports: final goods	-1237.6	-316.7	-1554.4	-529.6	-398.3	-927.9	-215.0	-75.5	-290.5
Imports: intermediate inputs	-67.5	-72.5	-139.9	376.7	276.5	653.2	458.8	276.5	735.3
Exports	88.8	75.2	164.1	207.7	67.3	275.0	-61.4	-65.1	-126.4
Total	-1216.3	-314.0	-1530.2	54.8	-54.5	0.3	182.4	135.9	318.3
	United Kingdom			France			South Korea		
	2000-07	2007-14	2000-14	2000-07	2007-14	2000-14	2000-07	2007-14	2000-14
Imports: final goods	-284.6	-99.9	-384.5	-180.0	-8.6	-188.5	-133.6	-84.9	-218.5
Imports: intermediate inputs	4.6	4.8	9.4	18.6	13.3	31.9	127.6	204.6	332.2
Exports	9.9	12.8	22.7	28.7	16.8	45.6	34.6	57.3	91.9
Total	-270.1	-82.3	-352.4	-132.6	21.6	-111.0	28.6	177.0	205.6

Notes: The counterfactual employment is estimated from equation (3.10). The unit is thousand workers. ‘Imports’ means import penetration ratio while ‘exports’ means export–output ratio.
Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

It is important to note that the negative effects of the China shock could be overestimated if the analysis does not take into account exports as well as the imports of intermediate inputs. Table 3.6 presents the results of counterfactual employment, based on equation (3.1).[21] The results indicate negative employment effects in these six countries, which is consistent with the results of final good imports in Table 3.5. The results suggest that the negative effects of the China shock could be overemphasized without accounting for the effects of imports of intermediate inputs and those of exports.

It is also important to note that the negative effects of the imports of final goods from China declined from 2000–2007 period to 2007–2014 period in these six countries. These results suggest that the significantly negative effects of the China shock were mainly observed in the 2000s right after China's entry into the WTO. The negative shock seems to have declined in the 2010s. The recent decline in manufacturing employment may be attributable to other factors such as the substitution between capital and labor caused by the growing use of robots, although more detailed analysis is needed to determine the exact factors behind these changes.

3.4 Discussion

3.4.1 Alternative specifications

One may concern the consistency between the results of our study and those of the previous studies. Because none of the previous studies take into account the effects of exports and the difference between intermediate inputs and final goods simultaneously, we re-estimate our benchmark equation, dropping exports or using total (intermediate inputs + final goods) imports. Table 3.7 indicates the results without exports while Table 3.8 indicates the regression

[21]Counterfactual employment is computed from the 2SLS results and $\Delta L_{\tau}^{cf} = -\sum_j L_{j,\tau}\left(1-\exp\left(-\hat{\beta}\Delta\widetilde{IP}_{j,\tau}\right)\right)$.

Table 3.6: Counterfactual Manufacturing Employment: Alternative Specification

	United States			Japan			Germany		
	2000-07	2007-14	2000-14	2000-07	2007-14	2000-14	2000-07	2007-14	2000-14
Total imports	-1708.0	-671.7	-2379.7	-627.3	-468.0	-1095.3	-130.9	-55.9	-186.8
	United Kingdom			France			South Korea		
	2000-07	2007-14	2000-14	2000-07	2007-14	2000-14	2000-07	2007-14	2000-14
Total imports	-310.6	-140.8	-451.4	-221.1	-47.2	-268.3	-13.7	-14.9	-28.7

Notes: The counterfactual employment is estimated from equation (3.10). The unit is thousand workers. ‘Imports’ means import penetration ratio while ‘exports’ means export–output ratio.
Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

results of equation (3.4) without distinction between intermediate inputs and final goods, both of which are similar to the specifications employed by the previous studies.[22]

For the United States, if we drop exports from our benchmark equation, we can find a positive but insignificant coefficient for the imports of intermediate inputs (Table 3.7). Wang et al. (2018) also employed a similar specification and found the positive effects of imported intermediate inputs from China. Strictly speaking, however, our results are not directly comparable to their results because their positive effects are confirmed through downstream linkages, which we are unable to address due to the small sample size.

For Japan, even if we drop exports, we continue to find a positive but insignificant coefficient for the imports of intermediate inputs (Table 3.7). Taniguchi (2019) also found that the increases in the imports of intermediate inputs from China had positive effects on employment. Note, however, that her study is based on the regional variation (i.e., cross-region analysis) while our study is based on the industry variation (i.e., cross-industry analysis). It is therefore not surprising that our results are slightly different from her results.

For Germany, if we use total imports, we can confirm a significantly positive coefficient for exports (Table 3.8), which is consistent with the findings of Dauth, Findeisen, and Suedekum (2014) where they found significantly positive effects of trade exposure on employment in Germany. However, when they focus on trade with China, they find significantly negative effects of imports while insignificant effects on exports. Note that, like Taniguchi (2019), however, their study is based on the regional variation. Their sample period is also different from ours (Table 3.1). This may be one of the reasons why our results are slightly different from their results.

For South Korea, if we use total imports, we continue to find a positive

[22] For the first-stage results, see Tables B5 and B6.

Table 3.7: Estimation Results: Alternative Specification 1

	United States		Japan		Germany	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration						
Final goods	-2.683***	-3.099***	-2.283*	-2.807**	-1.541***	-1.971***
(ΔIP^{FN})	(0.814)	(0.776)	(1.244)	(1.147)	(0.462)	(0.535)
Intermediate inputs	3.991	3.063	5.744	8.665	6.705***	7.958***
(ΔIP^{IM})	(2.734)	(3.339)	(4.772)	(5.586)	(1.879)	(2.878)
N	38	38	36	36	38	38
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2						
ΔIP^{FN}		0.9008		0.7708		0.5053
ΔIP^{IM}		0.7523		0.6814		0.4896
	United Kingdom		France		South Korea	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration						
Final goods	-2.719***	-2.699***	-1.911*	-2.975**	-1.705**	-1.008
(ΔIP^{FN})	(0.541)	(0.552)	(0.992)	(1.307)	(0.717)	(1.075)
Intermediate inputs	0.428	0.295	-0.772	2.437	0.719	2.007
(ΔIP^{IM})	(2.826)	(3.366)	(3.072)	(2.944)	(0.845)	(1.615)
N	38	38	38	38	36	36
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2						
ΔIP^{FN}		0.9192		0.8045		0.8184
ΔIP^{IM}		0.6889		0.7363		0.7353

Notes: This table presents the estimation results of regression equation (3.4), dropping exports, with instruments (i.e., equations (3.7)) for 2SLS. ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses indicate heteroskedasticity robust standard errors. Observations are weighted by the 2000 employment level in the data set. The sample period consists of two sub-periods: 2000–2007 and 2007–2014. The number of industries thus is $N/2$.
Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

Table 3.8: Estimation Results: Alternative Specification 2

	United States		Japan		Germany	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration	-2.767***	-3.267***	-2.039	-2.892**	-0.600	-0.847
(ΔIP)	(0.811)	(0.703)	(1.204)	(1.058)	(0.557)	(0.648)
Export-output ratio	3.899**	5.379*	1.882	3.063*	0.846**	1.042**
(ΔEP)	(1.472)	(2.991)	(1.453)	(1.556)	(0.397)	(0.451)
N	38	38	36	36	38	38
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2						
ΔIP		0.8746		0.7156		0.7913
ΔEP		0.4428		0.7076		0.5577
	United Kingdom		France		South Korea	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration	-2.648***	-2.530***	-1.983**	-2.678**	-1.005	-0.702
(ΔIP)	(0.557)	(0.580)	(0.967)	(1.081)	(0.687)	(0.937)
Export-output ratio	0.150	0.587	1.254	1.471	0.496	0.677
(ΔEP)	(0.427)	(0.731)	(0.849)	(1.069)	(0.533)	(0.695)
N	38	38	38	38	36	36
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2						
ΔIP		0.8742		0.8491		0.7588
ΔEP		0.7539		0.7903		0.7540

Notes: This table presents the estimation results of regression equation (3.4), aggregating imports of intermediate inputs and final goods into total imports, with instruments (i.e., equations (3.3) and (3.9)) for 2SLS. ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses indicate heteroskedasticity robust standard errors. Observations are weighted by the 2000 employment level in the data set. The sample period consists of two sub-periods: 2000–2007 and 2007–2014. The number of industries thus is $N/2$. Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

but insignificant coefficient for exports (Table 3.8), which is consistent with the finding of Choi and Xu (2020) where they also found the positive effects of exports. Their analysis is based on more detailed industry-level data, which may allow them to capture the variations across industries more precisely.

3.4.2 Why is the impact so large in the United States?

Our estimation and counterfactual analysis suggest that the United States had the largest negative impact from the China shock in our six target countries. The coefficient of interest in our benchmark specification is the largest; as well, the number of counterfactual employment loss outweighs the numbers in the other five countries.

What causes this stronger "China shock" in the United States? A close look at industries shows that industry 6 (C13–C15 in ISIC) – Manufacture of textiles, wearing apparel and leather products, had a distinct behavior in changes in employment. In 2000, employment in the textile industry in the United States was over 1.2 million, but the number fell to almost one-half in 2007. During 2000–2007, this industry experienced the harshest employment decline as well as the largest increase in imports of final goods from China in the US manufacturing sector for the whole sample period. In the US textile industry, losses for the entire period from 2000 to 2014 were 744.5 thousand jobs.

Our benchmark estimation results show how much this single industry affected employment in the United States. To briefly look at this effect, we estimate our benchmark model excluding the textile industry. Without this industry, in the 2SLS estimation, the effect of a one-percent increase in the import penetration ratio of final goods from China on manufacturing employment is -1.38. This number is nearly one-third of the coefficient in the estimation including the textile industry. In addition, the coefficient of the import penetration ratio of intermediate inputs turns to positive, although it remains insignificant. This exercise suggests that the large employment decline in the US manufacturing in our benchmark results is largely attributable to the textile industry's experience.

The counterfactual employment change using the estimation result without the textile industry is also quite different from our main specification result for the United States. According to a new counterfactual exercise using the estimates without the textile industry, the decrease of employment caused by Chinese trade is 257.1 thousand workers during 2000–2014, which is almost one-sixth of 1,530.2 thousand, the number in the exercise that includes the textile industry. In particular, in 2007–2014, the counterfactual employment change is 1.44 thousand, which is small but positive in contrast to the number in our benchmark exercise. If we assume that all of the employment decline in the textile industry, 744.5 thousand, was attributable to the China shock, the sum of this decline and the employment loss estimated without the textile industry is approximately 1 million (= 257.1 + 744.5) during the sample period, which is almost two-thirds of the number in our benchmark exercise. Given these large differences, our results suggest that the import exposure in the textile industry would play an important role in the effect of the import penetration from China and the distinctive number of counterfactual employment change in the United States.

3.4.3 The small sample problem

We utilized the WIOD in our analysis. On the one hand, because the WIOD covers the same period based on the same industry classification, the use of it enables us to investigate the effects of the China shock in an internationally comparable manner. Besides, because the WIOD is based on the world input-output table, it allows us to distinguish the imports of intermediate inputs and those of final goods in a consistent way. Indeed, a number of studies utilized the WIOD in analyzing the effects of trade on employment.[23] For example, Feenstra and Sasahara (2018) utilized the WIOD to examine the effects of exports and imports on the US employment. Caliendo, Dvorkin, and Parro (2019) utilized the WIOD to examine the effects of trade on labor market dynamics, calibrating the model to 22 sectors. The wide use of the WIOD in the literature implies the relatively high reliability of the WIOD.

On the other hand, the use of the WIOD prevents us from using the detailed industry classification, which in turn leads to the small sample size, as was indicated in Table 3.1. This could cause the following two problems. One is the problem arises from the statistical aspect. The smaller the sample size, the less the precision of the statistical accuracy would be. Indeed, several studies such as Cravino and Sotelo (2019) also faced the problem of small sample, although their study did not discuss this problem explicitly. To address this issue, we use small option in Stata software to make degrees-of-freedom adjustments and report small-sample statistics, which would mitigate the problem. Nonetheless, a careful interpretation is needed for the results of our analysis. [24]

The other is the problem arises from the aggregation of industries. The WIOD is available only at the aggregated level. Because of the aggregation, there may be a large within-industry heterogeneity. For example, within Manufacture of chemicals and chemical products in the WIOD industry classification, there may be a huge variation of Chinese imports and exports. If one can utilize the data with more detailed industry classification, such problem could be alleviated. However, even when one can utilize firm-level

[23]For more detail, see the WIOD website (`http://www.wiod.org/published`)

[24]As a robustness check, we perform a regression with the benchmark specification that also includes non-manufacturing industries, following the previous studies such as Wang et al. (2018) and Caliendo, Dvorkin, and Parro (2019) (see Table 3.1). It has sample size of over one hundred. Our main messages from the benchmark results are unchanged: the coefficients of the imports of final goods from China are significantly negative in most countries while the imports of intermediate inputs do not show negative impacts. See Appendix B4 for the result.

data, international comparative analysis prevents us from the use of detailed industry classification because of, for example, differences in industry classification across countries. For example, Bellone et al. (2014) examined the cross-country productivity gap of exporters using firm-level data in France and Japan. For the comparison between countries, they aggregate the data into 18 manufacturing industries. Dobbelaere, Kiyota, and Mairesse (2015) estimated the productivity and markup of firms using the firm-level data in France, Japan, and the Netherlands. They aggregate the data into 30 manufacturing industries. For the international comparative studies, it is generally difficult to rely on the detailed industry-level classification at the current moment.

Note also that the problem of within-industry heterogeneity may not be solved even if the internationally comparable detailed product-level data (along with employment data) are available. For example, Schott (2004) found that the unit values of US manufacturing imports varied widely even within 10-digit Harmonized System (HS) product code. Similarly, Kiyota (2010) found such heterogeneity within 9-digit HS product code for the Japanese imports. These studies suggest that, even if we use the internationally comparable detailed product-level data, we may still face the same problem.

3.5 Conclusion

While in many advanced countries the increasing import competition from China on employment is a major concern for policymakers and the general public, its impact could be different across countries, depending upon the volume and composition of the products. This paper examines the impact of the China shock on employment in six advanced countries: France, Germany, Japan, South Korea, the United Kingdom, and the United States. One of the contributions of this paper is that we extend the previous studies to cross-country comparisons, based on the same analytical framework and the same dataset. We used the data from the WIOD between 2000 and 2014.

Our major findings are twofold. First, the import penetration of final goods from China has a negative effect on manufacturing employment in most of the six countries, whereas the import penetration of intermediate inputs from and the exports to China show positive coefficients while they are statistically insignificant in most countries. Second, in the counterfactual analysis, we show that such positive effects could offset or even outweigh the negative effects in some countries. For the United Kingdom and the United States, the negative effects of the imports of final goods outweigh the positive effects of the imports of intermediate inputs and exports. In contrast, for France and Japan, the negative effects of the imports of final goods offset the positive effects of the imports of intermediate inputs and exports. For South Korea and Germany, the positive effects outweigh the negative effects. These results together suggest that a careful interpretation is needed when evaluating the external validity of the China shock that is obtained in one country. It is also important for policymakers to focus on positive as well as negative aspects of trade with China. Furthermore, we should note that consumers generally receive benefits from the imports of low-priced goods, as standard trade theories suggest. Of course, the negative aspects of globalization should not be ignored, but they should not be overemphasized.

It is important to note that these results have an important caveat. Our analysis is based on small sample. This could cause the small sample problem, which results in the less precise estimates. Noting that the small sample is caused by the aggregation of industries, this could also magnify the problem of within-industry heterogeneity. Therefore, our estimation results should be interpreted with caution.

In conclusion, several future research issues are worth mentioning. First, further investigation of the China shock is an important extension. Recent studies have focused on the effects of Chinese import competition on various outcomes other than employment. For example, Autor, Dorn, and Hanson (2019) focused on the effects on mortality. Che, Xu, and Zhang (2018) focused on the effects on crime. However, to our knowledge, none of these studies distinguish between the imports of final goods and those of intermediate inputs. It is important to extend these studies to take into account such differences. Second, although our instrumental strategy followed Autor, Dorn, and Hanson (2013), some recent studies such as Goldsmith-Pinkham, Sorkin, and Swift (2020) and Jaeger, Ruist, and Stuhler (2018) point out potential problems of the use of such shift-share instrument. Exploring alternative instrumental strategy may be an interesting avenue for future research. Finally, it is also essential to extend the analysis to more detailed industry-level data. The use of more detailed industry-level analysis could mitigate the small sample problem. To conduct such analyses, it is imperative that the quality and coverage of the industry-level data must be improved and expanded.

Appendix A

Appendix to Chapter 1

A.1 Simulation and Estimation Process

1. Choose R (=the number of random draws to be taken from the different distribution functions).

2. Make $R \times F$ draws from exponential distribution (requires Poisson simulation) and $R \times F \times (I + N - 1) \times K$ draws from normal distribution. $I + N - 1$ is the number of random coefficients per establishment/task. K is a large number.

3. Plug D_f and the random draws obtained in 2. into the model, we get the predicted firm's purchases of workers. Since we want to choose integer X^*, compare two closest integers after solving FOC by their profits.[1]

4. Take an average of the predicted purchases of workers over all simulation draws.

5. Plug this simulated expected firm behavior into (1.15) and construct the moment conditions.

[1] In the preliminary analysis, I allow continuous values in X^* to simplify the algorithm.

6. Find the estimates for θ: minimize the objective function until the parameters converge.

A.2 Derivation of the wage effect

Assume that for each type i, labor market clearing applies at the aggregate level:

$$L_i^D(\boldsymbol{W}) = L_i^S \; \forall i = 1, ..., I, \tag{A.1}$$

where L_i^D, L_i^S denote labor demand and supply for type i workers, respectively. Taking the total derivative of the equations yields

$$\frac{\partial L_i^D}{\partial W_1} dW_1 + \cdots + \frac{\partial L_i^D}{\partial W_I} dW_I = dL_i^S$$

$$\Longrightarrow \epsilon_{i,1}^D d\ln W_1 + \cdots + \epsilon_{i,I}^D d\ln W_I = d\ln L_i^S, \; \forall i = 1, ..., I.$$

The last equal sign holds since $L_i^D = L_i^S$ holds $\forall i$. $\epsilon_{i,j}^D$ is type i's labor demand elasticity of wage for type j. Then we can write down in the matrix form

$$\begin{pmatrix} \epsilon_{1,1} & \cdots & \epsilon_{1,I} \\ \epsilon_{2,1} & \ddots & \vdots \\ \vdots & & \\ \epsilon_{I,1} & \cdots & \epsilon_{I,I} \end{pmatrix} \begin{bmatrix} d\ln W_1 \\ d\ln W_2 \\ \vdots \\ d\ln W_I \end{bmatrix} = \begin{bmatrix} d\ln L_1^S \\ d\ln L_2^S \\ \vdots \\ d\ln L_I^S \end{bmatrix} \tag{A.2}$$

$$\begin{aligned} \Longrightarrow \quad & \boldsymbol{\epsilon^D} d\ln \boldsymbol{W} = d\ln \boldsymbol{L^S} \\ \Longrightarrow \quad & d\ln \boldsymbol{W} = \left(\boldsymbol{\epsilon^D}\right)^{-1} d\ln \boldsymbol{L^S}. \end{aligned} \tag{A.3}$$

Equation (A.3) yields the equation (1.24).

Appendix B

Appendix to Chapter 3

B.1 Calculation using the WIOD

This paper uses data from the WIOD. The WIOD is useful to our analysis for the following reasons. First, the WIOD provides information on the use of imported goods. In the WIOD, data of imported intermediate input is separated from imported final demands. Second, the WIOD provides information on both source and destination industries. The latter is not obtained in standard trade data. The information of destination industry is used when we focus on manufacturing sector. Third, exports and imports are reported by country. In the national input-output tables, it is impossible to distinguish between imports from China and total imports. These features of the WIOD enable us to calculate the import penetration ratio from China, separating intermediate inputs and final goods. Meanwhile, 'imports' or 'exports' used in the calculation is not indicated explicitly in the WIOD, because there is no notation in the tables; therefore, this appendix aims to indicate components of calculations in the WIOD.

Suppose that there are S industries in N countries.[1] For ease of presen-

[1]In the WIOD, S equals to 56 including 23 manufacturing industries, and N equals to 44 including the rest of the world. In this paper, strictly speaking, goods include services.

tation, we omit time subscript t, unless otherwise noted. Note also that this subsection utilizes i and j for industry subscripts, following the standard notation in the IO analysis. Therefore, the subscripts below are not necessarily the same as those used in the main text.

As usual IO tables, transactions are divided into two broad sectors of 'intermediate demand sector' and 'final demand sector'. In the intermediate demand sector, an element of $x_{ji}^{m,n}$ indicates the value of transactions from industry j in country m to industry i in country n. The superscript m denotes the country of a source or a supplier, whereas n denotes a country of a destination or a user. A supplier industry is denoted as j, and a user industry is denoted as i. We regard imports in the intermediate demand sector as imports of intermediate inputs, and this is used in equation (3.5). Similarly, in the final demand sector, an element $f_j^{m,n}$ indicates the value of transactions in industry j provided from country m to country n. We regard imports in the final demand sector as imports of final goods which is used in equation (3.6). Total output of industry j in country m, Y_j^m, is produced to satisfy domestic and foreign final demands, or to be used as intermediate inputs in domestic and foreign production. Therefore, the sum of each row in a horizontal direction, adding elements in the intermediate demand sector and those in the final demand sector, equals to total output:

$$Y_j^m = \sum_{n=1}^{N} \sum_{i=1}^{S} x_{ji}^{m,n} + \sum_{n=1}^{N} f_j^{m,n}. \tag{B1}$$

For sake of simplicity, we construct three-country IO table, which consists of China (CHN), Japan (JPN), and the rest of the world (ROW) , see Figure A1. Total output in each industry is produced to satisfy domestic and foreign final demands or to be used as intermediate inputs in domestic and foreign production. Let Y_j^{JPN} denote the value of output of industry j in Japan.

For ease of explanation, however, this paper uses the word 'goods' rather than the word 'goods and services.'

Y_j^{JPN} consists of intermediate inputs used in China, Japan, and the ROW as well as final goods provided in China, Japan, and the ROW. Using the expressions of $x_{ji}^{m,n}$ for intermediate inputs and $f_j^{m,n}$ for final demands, Y_j^{JPN} is expressed as the sum of x-s and f-s in a horizontal direction in the following equation:

$$Y_j^{JPN} = \sum_{i=1}^{S} x_{ji}^{JPN,CHN} + \sum_{i=1}^{S} x_{ji}^{JPN,JPN} + \sum_{i=1}^{S} x_{ji}^{JPN,ROW} + f_j^{JPN,CHN} + f_j^{JPN,JPN} + f_j^{JPN,ROW}. \tag{B2}$$

Excluding domestic transactions from Y_j^{JPN}, we obtain exports from industry j in Japan to the world, E_j^{JPN}:

$$E_j^{JPN} = \sum_{i=1}^{S} x_{ji}^{JPN,CHN} + \sum_{i=1}^{S} x_{ji}^{JPN,ROW} + f_j^{JPN,CHN} + f_j^{JPN,ROW}. \tag{B3}$$

Exports in equation (B3) are used in the denominator of ΔIP and ΔEP in the equation (3.2). Similarly, exports from industry j in Japan to China, $E_j^{JPN,CHN}$, is:

$$E_j^{JPN,CHN} = \sum_{i=1}^{S} x_{ji}^{JPN,CHN} + f_j^{JPN,CHN}. \tag{B4}$$

Exports in equation (B4) are used in the numerator of ΔEP, expressed in equation (3.8). Imports from industry i (a supplier industry) in China to industry j (a user industry) in Japan is expressed as follows:

$$M_j^{CHN,JPN} = \sum_{i=1}^{S} x_{ij}^{CHN,JPN} + f_j^{CHN,JPN}. \tag{B5}$$

Note that industry j includes industries 5 to 23 of the WIOD industry code when exports or imports of intermediate inputs are limited to manufacturing. In order to calculate total imports from the world to Japan, add the value of imports from the ROW:

$$M_j^{JPN} = \sum_{i=1}^{S} x_{ij}^{CHN,JPN} + \sum_{i=1}^{S} x_{ij}^{ROW,JPN} + f_j^{CHN,JPN} + f_j^{ROW,JPN}. \tag{B6}$$

The import penetration ratio and export–output ratio of industry j in Japan from/to China are respectively calculated as follows:

$$IP_j^{JPN} = \frac{M_j^{CHN,JPN}}{Y_j^{JPN} - E_j^{JPN} + M_j^{JPN}} \quad \text{and} \quad EP_j^{JPN} = \frac{E_j^{JPN,CHN}}{Y_j^{JPN}}. \tag{B7}$$

Next, we extend it to many-country IO. In the regression analysis, we use the change of the import penetration ratio and export-output ratio from the initial period, as shown in Section 2.1. The change of the import penetration ratio at the period τ of a target country c such as Japan, $\Delta IP_{j,\tau}$, is derived as follows. The numerator of the ratio is a change in imports from the initial period 0 to the period τ, expressed as $\Delta M_{j,\tau}^{CHN}$. We omit the subscript c, unless otherwise noted. The denominator is the initial value of domestic absorption. Therefore, the change of the import penetration ratio from China to industry j in the target country, $\Delta IP_{j,\tau}$, is expressed as follows:

$$\Delta IP_{j,\tau} = \frac{\Delta M_{j,\tau}^{CHN}}{Y_{j,0} - E_{j,0} + M_{j,0}}, \tag{B8}$$

which corresponds to equation (3.2). As for an instrument variable, $\Delta IPO_{j,\tau}$ expressed in equation (3.3), we use data of other high-income countries as a target. Similarly, the change of the export-output ratio is calculated as follows:

$$\Delta EP_{j,\tau} = \frac{\Delta E_{j,\tau}^{CHN}}{Y_{j,0}}, \tag{B9}$$

where $\Delta E_{j,\tau}^{CHN}$ is the change in exports from 0 to τ. This corresponds to equation (3.8).As for an instrument variable, $\Delta EPO_{j,\tau}$ expressed in equation (3.9), we calculate it using data of other high-income countries as a target.

We further derive separate expressions of the import penetration ratio of intermediate inputs in equation (3.5) and final demands in equation (3.6). Let x_{ij}^{CHN} denote the value of imported intermediate inputs from China to the target country. The sum of imports of intermediate inputs from China to industry j in the target country is:

$$\sum_{i=1}^{S} x_{ij}^{CHN} = x_j^{CHN}. \tag{B10}$$

In IO tables, final demand sector does not provide the information of user industries. Therefore, we assume that imports from industry j in China satisfy demands in the same industry in the target country. Total imports from China to industry j in the target country are expressed as follows:

$$M_j^{CHN} = x_j^{CHN} + f_j^{CHN}, \tag{B11}$$

where M_j^{CHN} is utilized as a numerator of the import penetration ratio as noted below.

Domestic absorption of industry j, which is a denominator of the import penetration ratio, is $Y_j - E_j + M_j$, where Y_j indicates total output of industry j in country c; E_j is total exports to the world; and M_j is total imports from the world in the same industry. Total exports from the target country c to the world, E_j, is:

$$E_j = \sum_{n=1}^{N} \sum_{i=1}^{S} x_{ji}^{c,n} + \sum_{n=1}^{N} f_j^{c,n} \quad (n \neq c), \tag{B12}$$

where $x_{ji}^{c,n}$ denotes intermediate inputs from industry j in country c to industry i in country n. In a similar manner, M_j is expressed as the sum of imported intermediate inputs and imported final goods from all the N trade partners:

$$M_j = \sum_{n=1}^{N}\sum_{i=1}^{S} x_{ij}^{n,c} + \sum_{n=1}^{N} f_j^{n,c} \quad (n \neq c). \tag{B13}$$

Using these equations, the import penetration ratio of industry j is calculated as follows:

$$IP_j = \frac{M_j^{CHN}}{Y_j - E_j + M_j}. \tag{B14}$$

When we separate intermediate inputs from final goods, the first term of the right-hand side of equation (B13) is used as a numerator of the import penetration ratio. The second term, on the other hand, is used in the calculation of the import penetration ratio of final goods. The change of the import penetration ratio of intermediate inputs, $\Delta IP_{j,\tau}^{IM}$, is calculated as follows:

$$\Delta IP_{j,\tau}^{IM} = \frac{\Delta x_{j,\tau}^{CHN}}{Y_{j,0} - E_{j,0} + M_{j,0}}, \tag{B15}$$

where superscript IM denotes intermediate inputs. This corresponds to equation (3.5). Similarly, the change of the import penetration ratio of final goods is calculated as follows:

$$\Delta IP_{j,\tau}^{FN} = \frac{\Delta f_{j,\tau}^{CHN}}{Y_{j,0} - E_{j,0} + M_{j,0}}, \tag{B16}$$

where superscript FN denotes final goods. This corresponds to equation (3.6). We derive instrument variables $\Delta IPO_{j,\tau}^{IM}$ and $\Delta IPO_{j,\tau}^{FN}$ in equation (3.7) in a similar manner, using data of other high-income countries as a target.

Figure B1: An Example of A Three-Country Input-Output Table

		Intermediate demand sector			Final demand sector			Total output
		CHN	JPN	ROW	CHN	JPN	ROW	
		1 . . i . . 56	1 . . i . . 56	1 . . i . . 56				
CHN	1 : j : 56	$x_{ji}^{CHN,CHN}$	$x_{ji}^{CHN,JPN}$ [import of intermediate goods]	$x_{ji}^{CHN,ROW}$	$f_j^{CHN,CHN}$	$f_j^{CHN,JPN}$ [import of final goods]	$f_j^{CHN,ROW}$	Y_j^{CHN}
JPN	1 : j : 56	$x_{ji}^{JPN,CHN}$ [export]	$x_{ji}^{JPN,JPN}$	$x_{ji}^{JPN,ROW}$ [export]	$f_j^{JPN,CHN}$ [export]	$f_j^{JPN,JPN}$	$f_j^{JPN,ROW}$ [export]	Y_j^{JPN}
ROW	1 : j : 56	$x_{ji}^{ROW,CHN}$	$x_{ji}^{ROW,JPN}$ [import of intermediate goods]	$x_{ji}^{ROW,ROW}$	$f_j^{ROW,CHN}$	$f_j^{ROW,JPN}$ [import of final goods]	$f_j^{ROW,ROW}$	Y_j^{ROW}
Value added		v_i^{CHN}	v_i^{JPN}	v_i^{ROW}				
Total output		Y_i^{CHN}	Y_i^{JPN}	Y_i^{ROW}				

Notes: Blocks with a notation [export] are included in exports from Japan, whereas blocks with [import] are included in imports to Japan. The final demand sector is divided into five items, although they are omitted in this table for simplicity.

B.2 List of countries and industries in the WIOD

Table B1: Countries and Industries in the WIOD

Countries

Classification	Countries
Target of this paper	France, Germany, Japan, South Korea, the United Kingdom, the United States
Other OECD countries	Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, Greece, Hungary, Ireland, Italy, Latvia, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Taiwan, Turkey
Non-OECD countries	Bulgaria, Brazil, Cyprus, Croatia, India, Indonesia, Lithuania, Romania, Russia

Industries

WIOD Code	Name
5	Manufacture of food products, beverages and tobacco products
6	Manufacture of textiles, wearing apparel and leather products
7	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
8	Manufacture of paper and paper products
9	Printing and reproduction of recorded media
10	Manufacture of coke and refined petroleum products
11	Manufacture of chemicals and chemical products
12	Manufacture of basic pharmaceutical products and pharmaceutical preparations
13	Manufacture of rubber and plastic products
14	Manufacture of other non-metallic mineral products
15	Manufacture of basic metals
16	Manufacture of fabricated metal products, except machinery and equipment
17	Manufacture of computer, electronic and optical products
18	Manufacture of electrical equipment
19	Manufacture of machinery and equipment n.e.c.
20	Manufacture of motor vehicles, trailers and semi-trailers
21	Manufacture of other transport equipment
22	Manufacture of furniture; other manufacturing
23	Repair and installation of machinery and equipment

B.3 First-stage results

Table B2: List of IV Countries

Country	Variable	IV countries
US	Imports: intermediate inputs	France; Australia, Portugal
	Imports: final goods	France, Germany, Japan, South Korea, UK; Australia, Canada, Taiwan
	Exports	Germany, Japan; Belgium
Japan	Imports: intermediate inputs	UK; Australia, Italy, Portugal, Sweden
	Imports: final goods	South Korea, UK, US; Australia, Canada, Spain
	Exports	US; Belgium, Canada, Taiwan
Germany	Imports: intermediate inputs	Japan; Finland, Ireland, Portugal, Sweden
	Imports: final goods	France, Japan, South Korea, UK, US; Australia, Canada, Taiwan
	Exports	US; Australia, Finland, Italy, Sweden
UK	Imports: intermediate inputs	South Korea; Australia, Canada, Netherlands, Sweden, Taiwan
	Imports: final goods	France, Germany, Japan, South Korea, US; Australia, Canada, Taiwan
	Exports	US; Italy, Portugal
France	Imports: intermediate inputs	US; Portugal, Sweden
	Imports: final goods	Germany, Japan, US; Austria, Italy, Portugal
	Exports	US; Spain, Italy
South Korea	Imports: intermediate inputs	Germany, UK; Australia, Canada, Taiwan
	Imports: final goods	US; Italy, Portugal, Taiwan
	Exports	France, Germany, Japan, UK, US; Australia, Canada, Taiwan

Notes: Countries before a semicolon are chosen from other target countries, while countries after the semicolon are chosen from other OECD countries.

Table B3: First Stage Results: Preliminary Analysis

	United States	Japan	Germany
First-stage coefficient	ΔIP	ΔIP	ΔIP
ΔIP	0.596***	0.431***	0.814***
	(0.030)	(0.046)	(0.114)
F-value	201.64	50.94	25.61
Partial R^2	0.907	0.793	0.860
	United Kingdom	France	South Korea
First-stage coefficient	ΔIP	ΔIP	ΔIP
ΔIP	0.758***	1.348***	1.812***
	(0.088)	(0.120)	(0.283)
F-value	38.32	72.44	21.42
Partial R^2	0.883	0.889	0.739

Notes: ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses indicate heteroskedasticity robust standard errors. Observations are weighted by the 2000 employment level in the data set.

Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

Table B4: First Stage Results: Benchmark Specification

	United States			Japan			Germany		
First-stage coefficient	ΔIP^{FN}	ΔIP^{IM}	ΔEP	ΔIP^{FN}	ΔIP^{IM}	ΔEP	ΔIP^{FN}	ΔIP^{IM}	ΔEP
ΔIP^{FN}	0.612***	−0.026***	−0.017	0.425***	−0.013*	−0.019	0.674***	0.039**	0.159*
	(0.025)	(0.009)	(0.013)	(0.026)	(0.007)	(0.013)	(0.060)	(0.015)	(0.093)
ΔIP^{IM}	−0.227	0.650***	0.522	0.455	0.838***	0.450	1.039**	0.473***	−0.368
	(0.210)	(0.140)	(0.383)	(0.524)	(0.097)	(0.434)	(0.406)	(0.047)	(0.312)
ΔEP	0.164*	0.071*	0.277***	−0.067	0.034*	0.468***	−0.383*	0.067***	1.768***
	(0.091)	(0.035)	(0.047)	(0.131)	(0.019)	(0.052)	(0.205)	(0.024)	(0.232)
F-value	156.08	15.72	28.57	213.51	34.39	33.92	34.29	127.30	44.16
Shea's adjusted partial R^2	0.736	0.215	0.140	0.753	0.586	0.614	0.540	0.544	0.559
	United Kingdom			France			South Korea		
First-stage coefficient	ΔIP^{FN}	ΔIP^{IM}	ΔEP	ΔIP^{FN}	ΔIP^{IM}	ΔEP	ΔIP^{FN}	ΔIP^{IM}	ΔEP
ΔIP^{FN}	0.835***	0.001	−0.051	1.315***	0.010	−0.032	1.814***	−0.116	0.084
	(0.057)	(0.010)	(0.047)	(0.167)	(0.047)	(0.032)	(0.194)	(0.093)	(0.226)
ΔIP^{IM}	−0.175	0.311***	−0.002	−0.118	1.483***	0.619**	0.080	3.494***	3.830***
	(0.114)	(0.018)	(0.162)	(0.482)	(0.303)	(0.265)	(0.301)	(0.331)	(1.009)
ΔEP	0.071	0.099***	1.931***	0.167	0.034	1.673***	−0.350**	−0.470***	1.700***
	(0.118)	(0.017)	(0.278)	(0.197)	(0.085)	(0.337)	(0.149)	(0.077)	(0.253)
F-value	56.37	98.18	16.50	22.38	12.70	10.25	44.70	29.31	51.17
Shea's adjusted partial R^2	0.913	0.713	0.734	0.799	0.697	0.775	0.866	0.597	0.611

Notes: ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses indicate heteroskedasticity robust standard errors. Observations are weighted by the 2000 employment level in the data set.

Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

Table B5: First Stage results: Alternative Specification 1

	United States		Japan		Germany	
First-stage coefficient	ΔIP^{FN}	ΔIP^{IM}	ΔIP^{FN}	ΔIP^{IM}	ΔIP^{FN}	ΔIP^{IM}
ΔIP	0.583***	−0.008	0.424***	−0.012	0.821***	0.088
	(0.019)	(0.010)	(0.029)	(0.016)	(0.122)	(0.058)
ΔEP	0.206**	0.374***	0.040	0.507***	−0.066	1.602***
	(0.079)	(0.064)	(0.133)	(0.048)	(0.173)	(0.202)
F-value	305.01	15.86	206.59	40.23	18.41	52.51
Shea's adjusted partial R^2	0.875	0.443	0.716	0.708	0.791	0.558
	United Kingdom		France		South Korea	
First-stage coefficient	ΔIP^{FN}	ΔIP^{IM}	ΔIP^{FN}	ΔIP^{IM}	ΔIP^{FN}	ΔIP^{IM}
ΔIP	0.757***	−0.045	1.328***	0.004	1.959***	0.605
	(0.092)	(0.042)	(0.124)	(0.026)	(0.223)	(0.398)
ΔEP	0.173	1.931***	0.209	1.801***	−0.351*	2.638***
	(0.216)	(0.274)	(0.163)	(0.342)	(0.193)	(0.355)
F-value	33.62	17.32	62.16	14.85	37.52	18.49
Shea's adjusted partial R^2	0.874	0.754	0.849	0.790	0.759	0.754

Notes: ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses indicate heteroskedasticity robust standard errors. Observations are weighted by the 2000 employment level in the data set. Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

Table B6: First Stage Results: Alternative Specification 2

	United States		Japan		Germany	
First-stage coefficient	ΔIP^{FN}	ΔIP^{IM}	ΔIP^{FN}	ΔIP^{IM}	ΔIP^{FN}	ΔIP^{IM}
ΔIP^{FN}	0.617***	−0.024***	0.419***	−0.010	0.700***	0.035**
	(0.031)	(0.007)	(0.043)	(0.007)	(0.067)	(0.016)
ΔIP^{IM}	−0.029	0.735***	0.251	0.944***	0.670*	0.537***
	(0.187)	(0.108)	(0.540)	(0.110)	(0.389)	(0.049)
F-value	131.17	18.22	35.08	26.85	41.72	101.61
Shea's adjusted partial R^2	0.901	0.752	0.771	0.681	0.505	0.490
	United Kingdom		France		South Korea	
First-stage coefficient	ΔIP^{FN}	ΔIP^{IM}	ΔIP^{FN}	ΔIP^{IM}	ΔIP^{FN}	ΔIP^{IM}
ΔIP^{FN}	0.835***	0.002	1.316***	0.011	1.812***	−0.119
	(0.055)	(0.010)	(0.167)	(0.045)	(0.205)	(0.152)
ΔIP^{IM}	−0.174	0.312***	0.091	1.526***	−0.514	2.696***
	(0.119)	(0.020)	(0.417)	(0.263)	(0.322)	(0.351)
F-value	81.41	99.98	27.36	17.11	33.16	19.84
Shea's adjusted partial R^2	0.919	0.689	0.805	0.736	0.818	0.735

Notes: ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses indicate heteroskedasticity robust standard errors. Observations are weighted by the 2000 employment level in the data set. Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

B.4

Table B7: Estimation Results: Benchmark Specification with All Industries

	United States		Japan		Germany	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration						
Final goods	-2.603***	-3.066***	-2.182*	-2.999**	-1.188*	-2.170***
(ΔIP^{FN})	(0.803)	(0.926)	(1.276)	(1.348)	(0.666)	(0.819)
Intermediate inputs	8.910**	5.859	-3.823	5.545	3.149	9.774
(ΔIP^{IM})	(4.256)	(18.654)	(7.716)	(13.089)	(3.809)	(6.339)
Export–output ratio	-1.415	-1.116	1.985	1.477	0.574	0.073
(ΔEP)	(1.202)	(4.552)	(1.995)	(4.178)	(0.554)	(0.885)
N	110	110	102	102	110	110
Sector*Period Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2						
ΔIP^{FN}		0.8521		0.5486		0.5870
ΔIP^{IM}		0.2826		0.5169		0.5112
ΔEP		0.1098		0.3940		0.6034
	United Kingdom		France		South Korea	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Import penetration						
Final goods	-2.724***	-2.664***	-2.023*	-4.181***	-1.507*	-1.315
(ΔIP^{FN})	(0.522)	(0.589)	(1.056)	(1.356)	(0.884)	(1.308)
Intermediate inputs	1.176	6.362	3.922	7.390	1.714	2.028
(ΔIP^{IM})	(5.243)	(5.840)	(3.645)	(7.629)	(1.247)	(1.760)
Export–output ratio	0.108	-2.646	0.469	1.547	-0.129	-0.228
(ΔEP)	(0.621)	(2.785)	(0.978)	(2.322)	(0.518)	(0.742)
N	110	110	110	110	106	106
Sector*Period Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage partial R^2						
ΔIP^{FN}		0.8779		0.5415		0.6534
ΔIP^{IM}		0.4131		0.3794		0.6233
ΔEP		0.0764		0.2508		0.5976

Notes: ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses indicate heteroskedasticity robust standard errors. Observations are weighted by the 2000 employment level in the data set.

Sources: World IO Tables released in November 2016 and Social Economic Accounts data released in February 2018.

Table B8: List of IV Countries (All Industries)

Country	Variable	IV countries
US	Imports: intermediate inputs	France, Germany, Japan, South Korea, UK; Australia, Canada, Taiwan
	Imports: final goods	France, Germany, Japan, South Korea, UK; Australia, Canada, Taiwan
	Exports	France, South Korea, UK; Australia, Italy
Japan	Imports: intermediate inputs	UK; Italy, Portugal
	Imports: final goods	France, Germany, South Korea, UK, US; Australia, Canada, Taiwan
	Exports	Germany, South Korea; Italy, Taiwan
Germany	Imports: intermediate inputs	Finland, Italy, Mexico, Portugal
	Imports: final goods	France, Japan, South Korea, UK, US; Australia, Canada, Taiwan
	Exports	Japan, South Korea, UK
UK	Imports: intermediate inputs	South Korea; Italy, Taiwan
	Imports: final goods	France, Germany, Japan, South Korea, US; Australia, Canada, Taiwan
	Exports	South Korea, US; Italy, Australia
France	Imports: intermediate inputs	Germany, Japan, South Korea, UK, US; Australia, Canada, Taiwan
	Imports: final goods	Germany, Japan, South Korea, UK, US; Australia, Canada, Taiwan
	Exports	Germany, Japan, South Korea, UK, US; Australia, Canada, Taiwan
South Korea	Imports: intermediate inputs	US; Italy, Netherlands, Portugal, Taiwan
	Imports: final goods	France, Germany, Japan, UK, US; Australia, Canada, Taiwan
	Exports	France, Germany, Japan, UK, US; Australia, Canada, Taiwan

Notes: Countries before a semicolon are chosen from other target countries, while countries after the semicolon are chosen from other OECD countries.

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Eidesstattliche Versicherung

Ich versichere hiermit eidesstattlich, dass ich die vorliegende Arbeit selbstständig und ohne fremde Hilfe verfasst habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sowie mir gegebene Anregungen sind als solche kenntlich gemacht. Die Arbeit wurde bisher keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht. Sofern ein Teil der Arbeit aus bereits veröffentlichten Papers besteht, habe ich dies ausdrücklich angegeben.

16.03.2023

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