Supply Function Competition and Exporters: Nonparametric Identification and Estimation of Productivity Distributions and Marginal Costs *

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Abstract

In this paper we develop a structural model in which exporters are competing in supply functions and study the nonparametric identification and estimation of productivity distributions and marginal costs in this framework. Our model is able to reconcile the existence of multiple sellers, multiple prices, and variable markups that we observe in disaggregated bilateral trade data while also incorporating features such as strategic pricing and incomplete information, which are usually missing in models of exporter behavior. Our identification and estimation methodology makes an important contribution to the empirical share auction literature by showing that the underlying structure is identified nonparametrically even if we do not observe the entire schedules, but only the transaction points instead; whereas the methodology in the literature of empirical share auctions depends heavily on the fact that the entire bid/supply schedule is observed. Moreover, in view of the recent studies in international trade that have shown the sensitivity of the gains from trade estimates to the parametrization of productivity distributions, we maintain a flexible structure for productivity distributions and also marginal costs. We apply our model to the German market for manufacturing imports for 1990 using disaggregated bilateral trade data, which consists only of trade values and traded quantities. We recover the destination-source specific productivity distributions and destination-source specific marginal cost functions nonparametrically. Our empirical results do not support the distributional assumptions that are commonly made in the international trade literature such as Fréchet and Pareto. In particular, we find that the productivity distributions are not unimodal; low productivities are more likely to occur as expected, but there is not a single mode. Our results provide important insights about cross country and cross destination differences in productivity distributions, trade costs and markups.

Keywords: trade, technology, supply function competition, nonparametric identification and estimation, divisible good or share auctions

1 Introduction

In most of the recent papers in international trade literature using Ricardian or heterogeneous firm models with a probabilistic representation of technologies, which allows for technological differences across countries/firms, either perfect competition, Bertrand competition or monopolistic competition is assumed. Looking at the bilateral trade data that have been used in some of these models, which consists of trade values and traded quantities, even in the least aggregated level we observe the following: First, within the same product category we see many exporters for a given destination. Each supplies a share of that market, thus one exporter does not swipe the whole market. Baldwin and Harrigan (2011) reports that for US imports even in the 10-digit Harmonized System Codes, which is the least aggregated data publicly available, the median number of countries is 12. Second, again within the same product category and for a given destination, for all the exporters we see different unit values, which are the ratio of the trade value to traded quantity. This suggests the existence of different prices.

In Eaton and Kortum (2002), the underlying market structure is perfect competition. This implies the lowest cost exporter should supply the whole import market which is not consistent with the first feature of the data. Since perfect competition also implies marginal cost pricing, Bernard, Eaton, Jensen and Kortum (2003) assume Bertrand competition in an attempt to improve on this to allow for variable markups. This still suggests, however, that the lowest cost exporter supplies the whole market. One possible explanation for both of the features of trade data mentioned above is a market structure where there is monopolistic competition, where each firm produces a differentiated product.[1] In Melitz (2003), Helpman, Melitz and Yeaple (2004), Chaney (2008), Helpman, Melitz and Rubinstein (2008) and many other heterogeneous firm models, we see this type of structure which has the following implications: First, monopolistic competition with Dixit-Stiglitz preferences implies standard

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[1]For the analysis of countries as exporters, one can interpret this as countries with technological differences producing differentiated goods.

mark-up pricing where markups are constant across exporters and markets. This implication has been questioned and there have been studies which attempt to account for variable markups such as Melitz and Ottaviano (2008) in which variable markups are obtained from the demand side by imposing a more specific structure on preferences or Bernard, Eaton, Jensen and Kortum (2003) in which they are obtained from the supply side à la Bertrand competition. Second, the usual implication of these monopolistic competition models is that the pricing decision of one exporter does not influence the pricing decision of the others.

In this paper we propose an alternative way of modelling the exporting behavior of countries/firms which can explain the aforementioned features of data while still allowing for variable markups and the fact that the pricing decision of a country/firm can actually influence the decision of the others. Inspired by both Eaton and Kortum (2002) and Klemperer and Meyer (1989) we propose a model in which exporters compete in supply functions/schedules. According to Klemperer and Meyer (1989) in the presence of any uncertainty, firms might not want to commit to a fixed price or a fixed quantity.[2] Some decisions, however, such as size and structure, have to be made well in advance before this uncertainty is resolved. Such decisions, as indicated by Klemperer and Meyer (1989) , would implicitly determine a supply function relating the quantity that will be sold at any given price. They further argue that by offering supply functions, firms can make higher expected profits since it provides a better adaptation to uncertainty. In the context of international trade, it is even more likely that the exporters will face a lot of uncertainty since trade involve relations beyond the national borders. In supply function competition, each country/firm offers a supply schedule, which are horizontally added to obtain the aggreagte supply. Market clearing price is determined where this aggregate supply meets aggregate demand. The intersection of the market clearing price with the individual supply function gives how many units will be supplied by that country/firm. If there is uniform pricing, the revenue is this quantity multiplied by market clearing price whereas if there is discriminatory pricing the revenue is the area under the

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[2]Our model differs from Atkeson and Burstein (2008) in this aspect since their model, in which they have variable markups and quantity competition à la Cournot, implies committing to a fixed quantity.

supply schedule upto this quantity. Since we observe multiple unit values across exporters for a given product in a given destination, we assume discriminatory pricing.

Following the probabilistic representation of technologies in Eaton and Kortum (2002), countries/firms draw their productivity from some productivity distribution. In our case, however, this information will be private so that countries can only observe their own productivity but not the others'. Even with the advanced information technologies of today, monitoring the behavior of all the rival countries in the production of every single industry would be extremely costly and still might not even be possible. In this aspect our model differs from Klemperer and Meyer (1989) in which there is complete information about costs. We follow Wilson (1979) to introduce incomplete information. Hortacsu and Puller (2008) and Vives (2011) also follow Wilson (1979) to study supply function competition with private information under uniform pricing.

The structure in our model (other than supply function competition environment) is similar to Eaton and Kortum (2002). Countries are assumed to draw their productivities for each good from a source-destination specific productivity distribution.[3] Similar to their model, marginal cost is also source-destination specific. In almost all of the Ricardian and heterogeneous firm models, strong parametric assumptions are made on these productivity distributions and marginal costs which provide analytical solutions and tractable equations, making these models empirically relevant in explaining various factors affecting trade flows.[4] In contrast to the existing literature, we will not make any parametric assumptions on the productivity distribution and marginal cost function.

Why is this important ? This will allow us to check the adequacy of the parametric assumptions in the existing trade literature, which naturally affects the predictions of those models such as gains from trade and related policy questions. For instance, Arkolakis, Costinot and Rodriguez-Clare (2012) argue that one parameter of the productivity distrib-

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[3]In Eaton and Kortum (2002) this distribution is only source country specific.
[4]Because there is no empirical application in Melitz (2003), his theoretical results are derived for a general productivity distribution.

ution is actually one of the only two statistics governing gains from trade in most of these models. In a recent study, Simonovska and Waugh (2013) show that incorrect estimates of that parameter causes the gains from trade to be estimated half of what it should be. If we can recover the underlying structure (productivity distribution and marginal cost) from data with minimal parametric assumptions this might shed light on such concerns.

Recent literature of empirical share auctions provides insights about how to recover the productivity distributions and marginal costs nonparametrically. Note that our environment is very similar to the divisible good auction (share auction) environment in which instead of sellers, buyers compete. In a share auction there is a divisible item (or identical units of the same item) and each bidder submits a bid schedule (demand schedule) which shows at every price how many units (what share) she wants to have. Just as there is an underlying marginal cost determining the supply schedule in our model, there is an underlying marginal valuation determining this demand schedule. Some part or all of this marginal valuation can be private information just as productivities as part of marginal cost are private information in our model. Hortacsu (2002) studies discriminatory share auction of treasury bills, whereas Hortacsu and Kastl (2012), Kastl (2011) consider uniform pricing and recover the unknown marginal valuations following the approach in Guerre, Perrigne and Vuong (2000).

In this paper, we show that we can identify the productivity distributions and the marginal cost nonparametrically. Our methodology contributes to the literature of empirical share auctions in two important aspects: First, in Hortacsu (2002), Kastl (2011) and others, they usually have data on the bid schedules of the bidders whereas this is not the case in our data. In our data we can only observe the transaction/equilibrium points. Nevertheless, we show that the underlying structure, namely productivity distribution and cost function is identified, when one observes only the transaction/equilibrium points. Second, those papers deal with the asymmetry among the bidders by creating groups in which bidders in the same group are considered to be symmetric. In this paper, we allow for asymmetry without defining groups. In empirical applications of supply function competition model as in Wolak

(2003a, 2003b) and Hortacsu and Puller (2008) where they study competition in electricity markets they also observe the supply schedule of the firms. Availability of the individual demand/supply schedule, however, is a very specific characteristic of these type of markets. The fact that we can identify the underlying structure by observing only the transaction points makes the supply function competition model applicable to other markets as well.

In Eaton and Kortum (2002) and Bernard, Eaton, Jensen and Kortum (2003), the productivity distributions are assumed to be Fréchet. In others such as Helpman, Melitz and Yeaple (2004), Melitz and Ottaviano (2008), Helpman, Melitz and Rubinstein (2008), Eaton, Kortum and Kramarz (2010) and many others the productivity distribution is assumed to be Pareto. Fréchet distribution is also called the Type II extreme value distribution since it is related to the asymptotic distribution of the largest value. Eaton and Kortum (2002) refers to Kortum (1997) and Eaton and Kortum (1999) where they show how certain processes of innovation and diffusion give rise to this type of distribution. They argue that while producing any good, the actual technique that would ever be used in a country represents the best discovered one to date so it is reasonable to represent technology with an extreme value distribution. The models in Eaton and Kortum (2002) and Bernard, Eaton, Jensen and Kortum (2003), are mainly concerned with the best producers of a country for each good, which is considered as the explanation of the choice of an extreme value type for a country's productivity distribution. On the other hand, in Helpman, Melitz and Yeaple (2004), Melitz and Ottaviano (2008), Helpman, Melitz and Rubinstein (2008), Eaton, Kortum and Kramarz (2010) the main concern is not necessarily the best producers, which justifies the choice of an "non-extreme" value type of distribution such as Pareto. Helpman, Melitz and Yeaple (2004) refer to Axtell (2001) for justification, where he shows that US firm size distribution closely follows a Pareto distribution. This, however, does not say much about the underlying productivity distribution.[5] Both distributional assumptions provide great analytical

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[5]It is worth mentioning the link between Pareto and Fréchet: The limiting distribution of the maximum of independent random variables having Pareto distribution is Frechet which suggests that when all firms draw from Pareto the distribution of the best can be represented as Fréchet.

convenience in these models.

We apply our model to German market for manufacturing imports for 1990. We use the same year as Eaton and Kortum (2002). Our empirical results do not support those distributional assumptions. Another important observation is that the productivity distributions are not unimodal. Low productivities are more likely to occur as expected, but there is not a single mode. This is important to consider from a policy perspective since it suggests certain industries have certain types (levels) of productivity. Policy makers might want to distinguish between less productive and more productive types. In addition, in contrast to the monopolistic competition models with Dixit Stiglitz preferences, which implies constant markups across exporters, our empirical results suggest that they are not constant.

The paper is organized as follows: Section 2 introduces our model. Section 3 establishes the nonparametric identification of productivity distributions and the marginal cost functions. Section 4 introduces data and explains how to control for differences in measurement units and heterogeneity across goods. Also, in Section 4 we explain how to construct the market clearing prices. Section 5 describes our estimation procedure. Readers who are interested in the empirical results may skip Section 3 and Section 5 and move directly to Section 6, which provides our empirical results. The appendix contains the proof of some results.

2   The Model

Consider a world with N countries, indexed by $n = 1, 2, ..., N$ and a finite number, J, of goods indexed by $j = 1, 2, ..., J$. In each country n for any good j, the other $N-1$ countries, indexed by $i = 1, 2, .., n-1, n+1, .., N$, are competing with each other to export good j to country n. The index n will refer to destination/importer country or market whereas index i will refer to source/exporter country or seller.

Following the probabilistic representation of technologies in Eaton and Kortum (2002), country i's productivity, z_{ni}^{j}, in producing good j for destination n, is the realization of a

random variable Z_{ni}^j independently drawn across j from a destination-source specific distribution, $F_{ni}(\cdot)$ which is absolutely continuous with density $f_{ni}(\cdot)$ and support $[\underline{z}_{ni}, \overline{z}_{ni}] \subseteq \mathbb{R}_+$.[6] In Eaton and Kortum (2002), this distribution is only source country specific. Our model we allows for the more general case where this distribution is destination-source specific. This allows us to test whether a country's productivity distribution differs across destinations. For instance, if it differs checking the exporter composition of those destinations might provide valuable insights. Also, following the convention in the literature, these productivities are independent across countries. Thus, we make the following assumption.

Assumption A1 :

(i) *For any given n and i, Z_{ni}^j's are drawn independently from $F_{ni}(\cdot)$ across j.*

(ii) *For all n and for all $i, i', i \neq i'$, $\left\{Z_{ni}^j\right\}_{j=1}^J$ is independent of $\left\{Z_{ni'}^j\right\}_{j=1}^J$.*

In contrast to the conventional approach in the literature, we are not making any parametric assumptions on these productivity distributions.

For any country i, the marginal cost of producing the qth unit of good j for destination n is denoted by $c_{ni}^j(q, b^j, z_{ni}^j)$ where b^j is a vector of characteristics of good j such as being a high tech good, luxury good, unit of measure of the good, world price of the good, etc.

Assumption A2 : *For all n, i and j, marginal cost*

$$c_{ni}^j(q, b^j, z_{ni}^j) = \frac{c_{ni}^\circ(q, b^j)}{z_{ni}^j}$$

where $c_{ni}^\circ(\cdot, \cdot)$ is continuously differentiable and weakly increasing in q, for all $b^j \in \mathbb{R}^m$, $q \geq 0$.

Given good characteristics, the functional form $c_{ni}^\circ(\cdot, \cdot)$ does not depend on good j. It still depends, however, on source country i and the destination country n. This can be attributed

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[6]We use the convention that realization of random variables are denoted in lowercase letters whereas random variables are denoted in uppercase.

to factors such as transportation costs between source country and destination country and input costs in source country. The specification of marginal cost is similar to Eaton and Kortum (2002) as it is multiplicatively seperable in z_{ni}^j, though it does not have to be constant in our case. We will not make any further functional form assumption on marginal cost.[7] Hereafter, we will call $c_{ni}^{\circ}(\cdot, \cdot)$ the base marginal cost.

The total demand for imports of good j in destination n is denoted by Q_n^j.

Assumption A3 :

(i) *For any given n, Q_n^j is drawn independently from $F_{Q_n}(\cdot|b^j)$ for each j where $F_{Q_n}(\cdot|b^j)$ is absolutely continuous with strictly positive density, $f_{Q_n}(\cdot|b^j) > 0$, over its support, $\mathcal{S}_{Qn} = [0, \infty)$.*

(ii) *For all n and j, $\left\{Z_{n1}^j, ., Z_{ni}^j, ., Z_{nN}^j; i \neq n\right\}_{j=1}^J$ and $\{Q_n^j\}_{j=1}^J$ are independent given b^j.*

Note that given the good characteristics distribution $F_{Q_n}(\cdot|\cdot)$ does not depend on good j. However, it depends on destination country n which might be attributed to factors such as income, special tastes of destination country n. Also, Assumption A3 states that given good characteristics, demand for imports is independent of the productivities of the exporter countries. One implication is that the demand in the market for imports does not depend on the clearing price in the import market. The theoretical model below can be extended to the general case where Q_n^j is a function of the clearing price in the import market and some demand shock. For the time being, however, our identification results are for the special case where Q_n^j is exogenous.

In our model, countries can only observe their own productivity but not the others', in other words, z_{ni}^j is private information. The productivity distributions, $F_{ni}(\cdot)$'s, however, are common knowledge to all countries in the sense that even though countries do not know what the actual productivities of other countries are; they have at least some idea about the

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[7]In Eaton and Kortum (2002) and others we also see Samuelson's iceberg transportation costs assumption which is a special case of transportation costs entering marginal cost multiplicatively. The idea is that in order to supply one unit of any good j in country n, country i needs to produce $d_{ni} > 1$ units of good j since $(d_{ni} - 1) > 0$ "melts away" while being transported.

productivities of the others'. Exporting countries make their decisions about their supply before demand for imports is realized.

In the presence of uncertainty, as Klemperer and Meyer (1989) argue, agents might not want to commit to a fixed price or a fixed quantity and all decisions cannot be deferred until the uncertainty is resolved. For instance decisions about size and structure of an industry that produces a certain good have to be made well in advance. According to Klemperer and Meyer (1989) such decisions implicitly determine a supply function relating the quantity that will be sold at any given price. They further argue that instead of committing to a fixed price or a fixed quantity, committing to supply functions, will provide higher expected profits since it allows better adaptation to uncertainty. In our model for any country i, there are actually two sources of uncertainty: One is due to the uncertain demand for imports and the second is due to the unknown productivities of the other countries. Thus, given this uncertain environment, countries find it their best interest to offer supply functions instead of a fixed price or a fixed quantity.

Our model, however, differs from the supply function competition model of Klemperer and Meyer (1989) since in their model there is complete information about costs whereas in our case there is incomplete information about productivities. Even with the advanced information technologies of today, monitoring the behavior of all the rival countries in the production of every single good or in every industry would be extremely costly and still might not be possible. We follow Wilson (1979) to incorporate incomplete information.

Each exporter country i is offering a supply function (schedule) which shows at every price what country i is willing to supply of good j. We denote the supply schedule of exporter country i for destination n for good j by $s_{ni}^j(p, z_{ni}^j)$. This supply function naturally depends on country i's productivity z_{ni}^j, which is private information, but not the productivities of the others, $z_{ni',i'\neq n}^j$. Once their productivities are realized and before the realization of demand for imports of good j, countries decide on their supply schedules.[8] These individual supply

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[8] For each market n, country i solves an independent problem in the sense that we do not deal with an allocation across markets problem.

schedules are horizontally added to get aggregate supply and once demand is realized the market clearing price is determined where this aggregate supply intersects aggregate demand. The intersection of the market clearing price with each individual supply schedule gives the market clearing quantity supplied by each seller.

Denote the market clearing price in market n for good j by $P_n^{c,j}$. Define the quantity supplied by country i at the market clearing price as $Q_{ni}^j = s_{ni}^j(P_n^{c,j}, Z_{ni}^j)$. Note that by definition $\sum_{i \neq n} Q_{ni}^j = Q_n^j$. Define the total quantity supplied by all countries but i at the market clearing price by $Q_{n,-i}^j$, where $Q_{n,-i}^j = \sum_{k \neq i,n} Q_{nk}^j$. Also, denote the revenue of country i at the market clearing price by X_{ni}^j. An important feature of bilateral trade data is that even at the most disaggregated level, within the same product category unit values vary across exporters, i.e. $X_{ni}^j/Q_{ni}^j \neq X_{ni'}^j/Q_{ni'}^j$ for all $i \neq i', n$. This suggests discriminatory pricing rather than uniform pricing. In the former case, countries can charge different prices for different units of the same good, whereas they charge the same price for every unit in the latter. Hortacsu and Puller (2008) and Vives (2011) study supply function competition with private information under uniform pricing.

In the discriminatory case, the revenue of country i in country n for good j or expenditure of country n on good j from country i will be the area under the supply schedule upto the equilibrium quantity, i.e.

$$X_{ni}^j = \int_0^{s_{ni}^j(P_n^{c,j}, Z_{ni}^j)} s_{ni}^{j\,-1}(q, Z_{ni}^j) \, dq = \int_0^{Q_{ni}^j} s_{ni}^{j\,-1}(q, Z_{ni}^j) \, dq$$

where $s_{ni}^{j\,-1}(q, Z_{ni}^j)$ is the inverse of $s_{ni}^j(p, Z_{ni}^j)$ with respect to the first argument, i.e., $s_{ni}^{j\,-1}(q, Z_{ni}^j) = p$.

Notice that this environment is very similar to the divisible good auction (share auction) environment introduced by Wilson (1979) in which buyers instead of sellers compete. In a share auction there is a divisible item (or identical units of the same item) and each bidder submits a bid schedule (demand schedule) which shows at every price how many

units (what share) she wants to have. This underlying marginal valuation determines the demand schedule the bidder offers, just as the underlying marginal cost determines the supply schedule in our model. Some part or all of this marginal valuation can be private information in the sense that bidders only know about their own but not the others'. This is again analogous to our case where productivities, which are part of marginal cost, are private information. Market clearing price is determined in a similar fashion: Individual bid schedules are horizontally added to get aggregate demand and the market clearing price is where this aggregate demand meets aggregate supply. The intersection of the market clearing price with the individual bid function gives the number of units won by that bidder and in the case of discriminatory pricing the area below the individual bid function up to this quantity will be the amount she has to pay. Hortacsu (2002) studies discriminatory share auction in his analysis of Turkish Treasury Bill Auctions wheras Hortacsu and Kastl (2012), Kastl (2011) consider uniform pricing.

For notational simplicity hereafter, we will drop hereafter index j and the conditioning on its characteristics b^j, as the analysis is performed for a given good j. Thus, market clearing price P_n^c is determined by:

$$\sum_{i \neq n} s_{ni}(P_n^c, Z_{ni}) = Q_n \tag{1}$$

which states that at the market clearing price, P_n^c, total supply of exporters should match the import demand in market n. Following Wilson (1979) and Hortacsu (2002), we define the probability distribution function of the market clearing price P_n^c in market n, from the point of view of country i as:

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\begin{aligned}
\widetilde{H}_{ni}(p_n|z_{ni}) &= \Pr[P_n^c \leq p_n | Z_{ni} = z_{ni}] & (2) \\
&= \Pr[s_{ni}(p_n, z_{ni}) + \sum_{k \neq i,n} s_{nk}(p_n, Z_{nk}) \geq Q_n | Z_{ni} = z_{ni}] \\
&\equiv H_{ni}(p_n, s_{ni}(p_n, z_{ni})) & (3)
\end{aligned}
$$

This distribution will be of crucial importance in our analysis.

Now, we can define country i's problem for market n.[9] Given a particular realization of market clearing price, p_n^c, the profit of country i when it serves market n is:

$$\pi\big(s_{ni}(p_n^c, z_{ni})\big) = \int_0^{s_{ni}(p_n^c, z_{ni})} \big[s_{ni}^{-1}(q, z_{ni}) - c_{ni}(q, z_{ni})\big] \ dq \tag{4}$$

That is the profit integrates the difference between the price and marginal cost for every quantity up to market clearing quantity $s_{ni}(p_n^c, z_{ni})$. This, however, is profit at a particular p_n^c. Since p_n^c can take any value in the support $[\underline{p}_n, \overline{p}_n]$, country i's expected profit maximization problem for market n is:

$$\max_{s_{ni}(\cdot, z_{ni})} \int_{\underline{p}_n}^{\overline{p}_n} \underbrace{\left\{ \int_0^{s_{ni}(p_n^c, z_{ni})} \big[s_{ni}^{-1}(q, z_{ni}) - c_{ni}(q, z_{ni})\big] \ dq \right\}}_{\pi(s_{ni}(p_n^c, z_{ni}))} \underbrace{d\widetilde{H}_{ni}(p_n^c | z_{ni})}_{dH_{ni}(p_n^c, s_{ni}(p_n^c, z_{ni}))} \tag{5}$$

Country i's strategy is its supply function $s_{ni}(\cdot, \cdot)$. Using calculus of variations, the necessary condition for this functional optimization problem which defines country i's optimal supply schedule in a Bayesian Nash equilibrium is given by:

$$p_n = c_{ni}\big(s_{ni}(p_n, z_{ni}), z_{ni}\big) + \frac{1 - H_{ni}\big(p_n, s_{ni}(p_n, z_{ni})\big)}{H_{ni,p}\big(p_n, s_{ni}(p_n, z_{ni})\big)} \tag{6}$$

for all p_n in the support, where $H_{ni,p}(\cdot, \cdot)$ is the (partial) derivative of $H_{ni}(\cdot, \cdot)$ with respect to the first argument. See also the Appendix. Plugging in our marginal cost specification, (6) becomes

$$p_n = \frac{c_{ni}^{\circ}\big(s_{ni}(p_n, z_{ni})\big)}{z_{ni}} + \frac{1 - H_{ni}\big(p_n, s_{ni}(p_n, z_{ni})\big)}{H_{ni,p}\big(p_n, s_{ni}(p_n, z_{ni})\big)} \tag{7}$$

for all p_n in its support. The necessary condition (7) above has an intuitive meaning. It says that the optimum price that country i charges for the $s_{ni}(p_n, z_{ni})$th unit in market n is the sum of marginal cost of that unit and some markup since $\frac{1 - H_{ni}(p_n, s_{ni}(p_n, z_{ni}))}{H_{ni,p}(p_n, s_{ni}(p_n, z_{ni}))} \geq 0$.[10] Note

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[9]For any market n, country i solves an independent problem in the sense that we do not deal with an allocation across markets problem.

[10]Reny (1999) shows the existence of a Bayesian Nash Equilibrium in pure strategies in which bidders

that this markup is not necessarily constant across units or exporters or destinations.

For identification purposes, which is the topic of the next section; we need a normalization to separate the effect of $c_{ni}^{\circ}(\cdot)$ and z_{ni}.

Assumption A4 : *For all n and i, $\overline{z}_{ni}$ is normalized to be $\overline{z} = 1$.*

In this case the base marginal cost function $c_{ni}^{\circ}(\cdot)$ can also be viewed as the marginal cost frontier of country i exporting to country n.

Lastly, we make the following assumption:

Assumption A5 : *For all n,i and j, $Q_{ni}^{j} = s_{ni}^{j}(P_{n}^{c,j}, Z_{ni}^{j}) > 0$.*

This assumption ensures that at equilibrium, every country has a strictly positive supply of good j in every market n.[11] It is important to mention that this assumption is required only for nonparametric identification which is the topic of the next section.

3   Nonparametric Identification

In this section we investigate whether we can recover uniquely the structure of the model from the observables. The structure we are after are the productivity distribution and the base marginal cost $[F_{ni}(\cdot), c_{ni}^{\circ}(\cdot)]$ for each n and i. The observables are the bilateral trade quantities between countries and the market clearing price $\left\{Q_{ni}^{j}, (P^{c})_{n}^{j}\right\}_{j=1}^{J}$ for each n and i as well as the good characteristics $\{b^{j}\}_{j=1}^{J}$. Hence, the problem of identification is whether we can recover these unobservable productivity distributions and costs using observables from the data.

Bilateral trade data usually consists of bilateral trade quantities and expenditures between countries $\left\{Q_{ni}^{j}, X_{ni}^{j}\right\}_{j=1}^{J}$ for each n and i. Pehlivan and Vuong (2010) show how to obtain market clearing price under discriminatory pricing when only revenue and quantity

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employ nondecreasing functions for the asymmetric discriminatory share auction.

[11]Note that this is an assumption on the equilibrium quantity and not on the primitives. A case when it is satisfied is when $c_{ni}^{\circ}(0) = c_o$, $c_o \geq 0$ across $i \neq n$. It, however, can be also satisfied in other cases.

data are available.[12] We follow that approach to obtain market clearing prices $\{(P^c)_n^j\}_{j=1}^J$ for each n as is explained in detail in Section 4.3.

It is important to note that unlike Hortacsu (2002), Kastl (2011) and others, we do not observe the whole price-quantity schedules of players but observe *only the transaction/equilibrium points*. Basically, for any given n, i, and j only *one point* on the supply schedule is observed. The identification strategy proposed in this section, however, identifies the structure when only the transaction points are observed.

Our identification strategy basically follows Guerre, Perrigne and Vuong (2000) where they use the necessary condition of a first-price auction which characterizes the optimal bid function to identify the distribution of valuations in the case of a first-price auction. In their case, bids can be observed but the underlying private valuations cannot. In our case prices can be observed but the underlying productivities cannot. They use the necessary condition which characterizes the optimal bid and rewrite it in a way that everything except the private valuation term can be expressed in terms of the observables (either the bid itself, distribution of bids or density of bids which are observed from data). What they call *pseudo-valuations* can, then, be obtained and hence their distribution. In our case, the idea is very similar as we express the necessary condition (7) in terms of the observables, with two differences: First, obtaining the distribution of market clearing price from i's point of view is not as trivial as obtaining the distribution of bids and second, we also need to obtain the marginal cost from the observables before obtaining what we can call *pseudo-productivities*.

In this section, for any good j, we take the joint distribution $F_{Q_{ni}^j,(Q_{nk}^j)_{k\neq i,n},Q_n^j,P_n^{c,j}}(\cdot,...,\cdot)$ of the observables as known. Hence, all the marginals and conditionals are known. In Section 5, we discuss how such a distribution can be estimated from bilateral trade data.[13]

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[12] They basically use the simple fact that the market clearing price is the derivative of the revenue with respect to the quantity in discriminatory pricing.

[13] The fact that our observations are coming from a cross section and that we have only one observation for good j might be confusing at this stage. For now, it might be helpful to think we have many observations for good j such as in a time series fashion and that is how the joint distribution of the observables is obtained.

Dropping again the index j and the conditioning on b^j, identification is performed for a given good j, we proceed as follows: We first identify $H_{ni}(\cdot,\cdot)$ and then we identify $c_{ni}^{\circ}(\cdot)$. Lastly, we will identify $F_{ni}(\cdot)$.

3.1 Identification of $H_{ni}(\cdot,\cdot)$

For each i, define the random variable $S_{ni,p_n} = s_{ni}(p_n, Z_{ni})$ for any arbitrary p_n. By Assumption A1, S_{ni,p_n}'s are also mutually independent across i. Note that this p_n is a generic price, not the market clearing price. If it were market clearing price, then they would not be independent. Define the total quantity supplied by all exporters, $i \neq n$, at an arbitrary p_n as $\Sigma_{n,p_n} = \sum_{i \neq n} s_{ni}(p_n, Z_{ni})$, the total quantity supplied by all the other exporters but i at an arbitrary p_n as $\Sigma_{n,-i,p_n} = \sum_{k \neq n,i} s_{nk}(p_n, Z_{nk})$. Also, define $XD_{n,p_n} = Q_n - \sum_{i \neq n} s_{ni}(p_n, Z_{ni})$ which is the excess demand for any arbitrary p_n.

Let $q_{ni} = s_{ni}(p_n, z_{ni})$. Using (2) and by Assumption A1 and A3 we get[14]

$$H_{ni}(p_n, s_{ni}(p_n, z_{ni})) = \int_0^{\infty} \Pr[\Sigma_{n,-i,p_n} \geq q_n - q_{ni}] f_{Q_n}(q_n) dq_n \tag{8}$$

Define $f_{\Sigma_{n,p_n}}(\cdot)$ as the density of Σ_{n,p_n} and define $f_{\Sigma_{n,-i,p_n}}(\cdot)$ as the density of $\Sigma_{n,-i,p_n}$ for all i and for all n. Thus,

$$H_{ni}(p_n, q_{ni}) = \int_0^{\infty} \left[\int_{q_n - q_{ni}}^{\infty} f_{\Sigma_{n,-i,p_n}}(q_{n,-i}) dq_{n,-i} \right] f_{Q_n}(q_n) dq_n \tag{9}$$

Noting that $f_{Q_n}(\cdot)$ is observed from the data, if we can get $f_{\Sigma_{n,-i,p_n}}(\cdot)$ from the observables, then we can identify $H_{ni}(p_n, q_{ni})$ for all (p_n, q_{ni}). In order to express $f_{\Sigma_{n,-i,p_n}}(\cdot)$ in terms of observables consider the following relationships:

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[14]We obtain this using $H_{ni}(p_n, s_{ni}(p_n, z_{ni})) = \Pr[P_n^c \leq p_n | Z_{ni} = z_{ni}] = \Pr[S_{ni,p_n} + \Sigma_{n,-i,p_n} \geq Q_n | Z_{ni} = z_{ni}] = \Pr[q_{ni} + \Sigma_{n,-i,p_n} \geq Q_n | Z_{ni} = z_{ni}] = \Pr[\Sigma_{n,-i,p_n} \geq Q_n - q_{ni}] = \int_0^{\infty} \Pr[\Sigma_{n,-i,p_n} \geq q_n - q_{ni} | Q_n = q_n] f_{Q_n}(q_n) dq_n = \int_0^{\infty} \Pr[\Sigma_{n,-i,p_n} \geq q_n - q_{ni}] f_{Q_n}(q_n) dq_n$

First, note that $\Pr\left[Q_n \leq q_n | P_n^c = p_n\right] = \Pr\left[\Sigma_{n,p_n} \leq q_n | XD_{n,p_n} = 0\right]$.[15] By using Assumption A3 and relevant transformations, we get for any (p_n, q_n):

$$f_{\Sigma_{n,p_n}}(q_n) = \frac{f_{P_n^c | Q_n}(p_n | q_n)}{\int_0^\infty f_{P_n^c | Q_n}(p_n | \widetilde{q}_n) \, d\widetilde{q}_n} \tag{10}$$

See Appendix. Using Bayes' Rule, (10) can be written as

$$f_{\Sigma_{n,p_n}}(q_n) = \frac{f_{Q_n | P_n^c}(q_n | p_n)}{f_{Q_n}(q_n) \int_0^\infty \frac{f_{Q_n | P_n^c}(\widetilde{q}_n | p_n)}{f_{Q_n}(\widetilde{q}_n)} d\widetilde{q}_n} \tag{11}$$

Thus, (11) can be interpreted as follows: What would be our initial guess for the density of total supply given some p_n ? At first glance, one may think it is $f_{Q_n | P_n^c}(q_n | p_n)$. This would be incorrect because we are looking for the density of total supply at some arbitrary p_n which is not necessarily the market clearing price for that particular total demand $Q_n = q_n$. In other words, the total supply Σ_{n,p_n} might not match the total demand Q_n at that arbitrary p_n. Consequently, (Σ_{n,p_n}, p_n) might not be the equilibrium pair. In $f_{Q_n | P_n^c}(q_n | p_n)$, however, p_n is the market clearing price for that particular total demand Q_n. The expression in the denominator of (11) is actually the term that corrects our initial guess for the fact that p_n might not necessarily be the market clearing price when $Q_n = q_n$. On the other hand, note that $f_{Q_n | P_n^c}(q_n | p_n) = f_{\Sigma_{n,p_n} | P_n^c}(q_n | p_n)$ which is the conditional density of total supply given market clearing price but we are looking for the marginal density.

Second, we note that $\Pr[Q_{n,-i} \leq q_{n,-i} | P_n^c = p_n, \ Q_n = q_n] = \Pr[\Sigma_{n,-i,p_n} \leq q_{n,-i} | \Sigma_{n,p_n} = q_n, Q_n = q_n]$.[16] Similarly, using Assumption A3, A5 and relevant transformations, we get for

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[15] This follows from $\Pr[Q_n \leq q_n | P_n^c = p_n] = \Pr[Q_n \leq q_n | \Sigma_{n,p_n} = Q_n] = \Pr[\Sigma_{n,p_n} \leq q_n | XD_{p_n} = 0]$.

[16] This follows from $\Pr[Q_{n,-i} \leq q_{n,-i} | P_n^c = p_n, \ Q_n = q_n] = \Pr[\Sigma_{n,-i,p_n} \leq q_{n,-i} | P_n^c = p_n, \ Q_n = q_n] = \Pr[\Sigma_{n,-i,p_n} \leq q_{n,-i} | \Sigma_{n,p_n} = q_n, \ Q_n = q_n]$.

any $(p_n, q_{n,-i})$:[17]

$$f_{\Sigma_{n,-i,p_n}}(q_{n,-i}) = \int\limits_0^\infty f_{\Sigma_{n,p_n}}(q_n) f_{Q_{n,-i}|P_n^c,Q_n}(q_{n,-i}|p_n, q_n) \, dq_n \qquad (12)$$

See Appendix. Equation (12) can be interpreted in a similar fashion. What would be our initial guess for the density of total quantity supplied by the others, $\Sigma_{n,-i,p_n}$, given some p_n? A first but incorrect guess would be:

$$f_{Q_{n,-i}|P_n^c}(q_{n,-i}|p_n) = \int\limits_0^\infty f_{Q_n|P_n^c}(q_n|p_n) f_{Q_{n,-i}|P_n^c,Q_n}(q_{n,-i}|p_n, q_n) \, dq_n. \qquad (13)$$

When we substitute for (11) for $f_{\Sigma_{n,p_n}}(q_n)$ into (12), we have

$$f_{\Sigma_{n,-i,p_n}}(q_{n,-i}) = \int\limits_0^\infty \frac{f_{Q_n|P_n^c}(q_n|p_n) f_{Q_{n,-i}|P_n^c,Q_n}(q_{n,-i}|p_n, q_n)}{f_{Q_n}(q_n) \int\limits_0^\infty \frac{f_{Q_n|P_n^c}(\widetilde{q_n}|p_n)}{f_{Q_n}(\widetilde{q_n})} d\widetilde{q_n}} dq_n \qquad (14)$$

Note that the weights used in (13) are $f_{Q_n|P_n^c}(q_n|p_n)$ whereas the weights used in (14) are $\frac{f_{Q_n|P_n^c}(q_n|p_n)}{f_{Q_n}(q_n) \int\limits_0^\infty \frac{f_{Q_n|P_n^c}(\widetilde{q_n}|p_n)}{f_{Q_n}(\widetilde{q_n})} d\widetilde{q_n}}$ which correct $f_{Q_n|P_n^c}(q_n|p_n)$ similarly as in (11). Again this is due to the fact that we would like to know the density of $\Sigma_{n,-i,p_n}$, at an arbitrary p_n.

The next lemma provides an alternative expression for (14) which is more suitable for estimation:

Lemma 1: *Under Assumption A1, A3 and A5, the density $f_{\Sigma_{n,-i,p_n}}(\cdot)$ of $\Sigma_{n,-i,p_n}$, is identified by*

$$f_{\Sigma_{n,-i,p_n}}(q_{n,-i}) = \frac{\int\limits_0^\infty f_{Q_{n,-i},P_n^c|Q_n}(q_{n,-i}, p_n|q_n) \, dq_n}{\int\limits_0^\infty f_{P_n^c|Q_n}(p_n|q_n) \, dq_n} \qquad (15)$$

for all $(p_n, q_{n,-i})$ and for all n and i.

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[17]Unlike (10), however, (12) requires Assumption A5 which prevents any mass point in the distribution of $Q_{n,-i}$, a case we would have if some country is not serving market n.

Equation (15) follows from (14) by straight application of Bayes' Rule. Lemma 1 shows that the (marginal) density of $\Sigma_{n,-i,p_n}$, $f_{\Sigma_{n,-i,p_n}}(\cdot)$ is identified since everything on the right hand side can be estimated from the data.

Once we identify $f_{\Sigma_{n,-i,p_n}}(\cdot)$, everything on the right hand side of (9) is also known from the data. Hence, $H_{ni}(\cdot,\cdot)$ is identified. Moreover, its derivative $H_{ni,p}(\cdot,\cdot)$ is also identified. The next lemma states this result and gives an expression for this derivative.

Lemma 2: *The function $H_{ni}(\cdot,\cdot)$ is identified by (9) and (15) while its derivative $H_{ni,p}(\cdot,\cdot)$ is identified by*

$$H_{ni,p}(p_n, q_{ni}) = \int\limits_0^\infty \left[\int\limits_{q_n - q_{ni}}^\infty \frac{\partial\{f_{\Sigma_{n,-i,p_n}}(q_{n,-i})\}}{\partial p_n} dq_{n,-i} \right] f_{Q_n}(q_n) dq_n \qquad (16)$$

for all (p_n, q_{ni}) and for all n and i.

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Equation (16) follows from differentiating (9) with respect to the first argument.

3.2 Identification of $c_{ni}^\circ(\cdot)$

Denote the support of Q_{ni} by $\mathcal{S}_{Qni}$ for all n and for all i.

Proposition 1 : *Under Assumption A1-A5 and by necessary condition (7), $c_{ni}^\circ(\cdot)$ is identified on $S_{Qni} = [0, \overline{q}_{ni}]$, for all n and for all i.*

The identification argument is as follows: For a given market n, for a given i and for a given $q_o \in \mathcal{S}_{Qn}$, the support $\mathcal{S}_{Qni, P_n^c | Q_n = q_o}$ of (Q_{ni}, P_n^c) conditional on $Q_n = q_o$ is known. This corresponds to the area ABCD in Figure 1.[18] Define $\Sigma_{n,-i}(\cdot, \overline{z})$ to be total quantity supplied at any p_n by all exporters other than i, when all exporters other than i have the

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[18]Without loss of generality, the strategies of countries are positioned as in Figure 1. Our identification argument, however, would work in any other case such as when strategies of countries intersect each other.

best productivity draws $\overline{z}$, i.e., $\Sigma_{n,-i}(\cdot,\overline{z}) = \sum_{k\neq n,i} s_{nk}(\cdot,\overline{z})$ and $\Sigma_{n,-i}^{-1}(\cdot,\overline{z})$ is the inverse of it with respect to the first argument. Similarly, define $\underline{z} = (\underline{z}_{nk})_{k\neq n,i}$. The curves with tildas in Figure 1, e.g., $\widetilde{\Sigma}_{n,-i}^{-1}(\cdot,\overline{z},q_o)$, are the symmetries of the original ones, e.g., $\Sigma_{ni}^{-1}(\cdot,\overline{z})$, with respect to $q_o/2$. Hence, $\widetilde{\Sigma}_{n,-i}^{-1}(\cdot,\overline{z},q_o)$ can be thought of as the residual demand for i, when all her rivals have the best productivity draws. It is important to note that the optimal strategies will not depend on the realized value q_o of Q_n as Q_n is random by Assumption A3-(i), the residual demands, however, will depend on q_o.

Note that the minimum price, given $Q_n = q_o$, denoted $\underline{p}_n(q_o)$, is achieved at point A, since at point A all exporters have their best draws. Similarly, the maximum price, given $Q_n = q_o$, denoted $\overline{p}_n(q_o)$, is achieved at point C, since at point C, all countries have their worst draws. In market n, the minimum quantity supplied by i, given $Q_n = q_o$, denoted $\underline{q}_{ni}(q_o)$, is achieved at point D, since at point D, country i has her worst draw while her rivals all have their best draws. By a similar argument, in market n, the maximum quantity supplied by i, given $Q_n = q_o$, denoted $\overline{q}_{ni}(q_o)$, is achieved at point B.

As the optimal strategy will not depend on the realized value q_o of Q_n since Q_n is random by Assumption A3-(i), due to variations in Q_n, the support $\mathcal{S}_{Q_{ni},P_n^c|Q_n=q_o}$ of (Q_{ni}, P_n^c) conditional on Q_n (area ABCD in Figure 1) will move to cover an area between the supply schedules $s_{ni}^{-1}(\cdot,\underline{z})$ and $s_{ni}^{-1}(\cdot,\overline{z})$, thereby providing the unconditional support $\mathcal{S}_{Q_{ni},P_n^c}$. As $\mathcal{S}_{Qn} = [0,\infty)$ by Assumption A3-(i) the other two boundaries of the unconditional support $\mathcal{S}_{Q_{ni},P_n^c}$ of (Q_{ni}, P_n^c) are given by $Q_{ni} = 0$ and the highest possible residual demand, $\sup_{q_o\in[0,\infty)}\widetilde{\Sigma}_{n,-i}^{-1}(\cdot,\underline{z},q_o)$. In particular, the support $\mathcal{S}_{Q_{ni}}$ of Q_{ni} is $[0, \sup_{q_o\in[0,\infty)}\overline{q}_{ni}(q_o)]$.

Since the support $\mathcal{S}_{Q_{ni},P_n^c}$ is known, its lower boundary is also known, hence $s_{ni}^{-1}(\cdot,\overline{z})$ is known on $\mathcal{S}_{Q_{ni}}$. By the necessary condition (7) and Assumption A4 which sets $\overline{z} = 1$, $c_{ni}^{\circ}(\cdot)$ is identified over $\mathcal{S}_{Q_{ni}}$ by

$$c_{ni}^{\circ}(\cdot) = s_{ni}^{-1}(\cdot,1) - \frac{1 - H_{ni}\big(s_{ni}^{-1}(\cdot,1),\cdot\big)}{H_{ni,p}\big(s_{ni}^{-1}(\cdot,1),\cdot\big)} \tag{17}$$

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where $H_{ni}(\cdot, \cdot)$ and $H_{ni,p}(\cdot, \cdot)$ are identified by Lemma 2.

3.3   Identification of $F_{ni}(\cdot)$

The next proposition establishes identification of the productivity distribution $F_{ni}(\cdot)$ for any n and for any i.

Proposition 2 : *Under Assumption A1-A5 and by necessary condition (7), $F_{ni}(\cdot)$ and $\underline{z}_{ni}$ are identified for all n and for all i.*

Once we identify $c_{ni}^{\circ}(\cdot)$, now we know the base marginal cost for any possible q_{ni}. Hence, for any (q_{ni}, p_n^c) observation, we can now use our necessary condition to recover z_{ni}. Namely from (7) we have:

$$p_n^c = \frac{c_{ni}^{\circ}(q_{ni})}{z_{ni}} + \frac{1 - H_{ni}(p_n^c, q_{ni})}{H_{ni,p}(p_n^c, q_{ni})}$$

which gives

$$z_{ni} = \frac{c_{ni}^{\circ}(q_{ni})}{p_n^c - \frac{1 - H_{ni}(p_n^c, q_{ni})}{H_{ni,p}(p_n^c, q_{ni})}} \tag{18}$$

where everything on the right hand side of (18) is known. Once we know z_{ni}'s their distribution is also identified. Thus, $F_{ni}(\cdot)$ is identified.

In particular, the lower bound $\underline{z}_{ni}$ is identified by

$$\underline{z}_{ni} = \frac{c_{ni}^{\circ}(\cdot)}{s_{ni}^{-1}(\cdot, \underline{z}) - \frac{1 - H_{ni}(s_{ni}^{-1}(\cdot, \underline{z}), \cdot)}{H_{ni,p}(s_{ni}^{-1}(\cdot, \underline{z}), \cdot)}} \tag{19}$$

4   Data

In this section we first describe our data. We, then, introduce a hypothetical good to deal with the cross section nature of the data and in particular, the heterogenity across goods and the difference in measurement units. The last section deals with the construction of the market clearing price.

4.1   Data description

Our source of trade data is the United Nations Commodity Trade Statistics Database (COMTRADE) which is accessible online. As in Eaton and Kortum (2002) we use bilateral trade data for manufacturing imports in 1990. Bilateral trade data consists of traded quantity and trade values (in dollars) between countries and is available on disaggragated level according to different classifications. The disaggregation level is indicated by digits and higher digits correspond to more disaggregated product categories. Eaton and Kortum (2002) look at 19 OECD countries and use 4-digit SITC (Standard International Trade Classification) Revision2 data.[19] To determine which product categories correspond to the Bureau of Economic Analysis (BEA) manufacturing industry codes they use Maskus (1991) concordance. They, then aggregate to obtain total manufacturing imports between countries. In contrast to Eaton and Kortum (2002), we use the data at the disaggregated level, in particular, 5-digit SITC Revision 2, and the categories corresponding to BEA manufacturing industries according to the concordance provided by Feenstra, Lipsey and Bowen (1997).[20,21]

For this particular application we look at the German market, i.e. $n =$ Germany.[22]. Our sample consists of the 7 largest (in value) exporters listed in Table 1. Out of 19 countries in the Eaton and Kortum (2002) sample, the value of manufacturing imports from these 7 exporters constitute almost 80% of value of total manufacturing imports of Germany as shown in Table 1. Also, in our sample, the total value of manufacturing imports in product categories where we observe zeros (cases when at least one country is not exporting to

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[19]Those 19 countries are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, United Kingdom, United States. Also, Eaton and Kortum (2002) uses United Nations-Statistics Canada data (World Trade Database) as explained by Feenstra, Lipsey and Bowen (1997) which is a slightly modified version of United Nations Commodity Trade Statistics Data.

[20]Whenever 5 digit level is available we use data at this level. For some categories no further classification was available after 4 digits. In those cases we use the 4 digit level.

[21]Eaton and Kortum (2002) mention that using the concordance by Feenstra, Lipsey and Bowen (1997) made no difference in their case.

[22]This is actually the Federal Republic of Germany according to the United Nations Commodity Trade Statistics Database. Also, Belgium in their sample is actually Belgium and Luxembourg since they were still reporting together. We, however, follow the convention in Eaton and Kortum (2002) and call them Germany and Belgium, respectively.

Germany), constitute only 9% of the total value of manufacturing imports in our sample. When we drop those, we have $J = 969$ products where all the exporters in our sample export some positive amounts. Hence, we have $\left\{ Q_{ni}^{j}, X_{ni}^{j} \right\}_{j=1}^{J}$, where $n =$ Germany, $i = 1, ..., 7$ and $J = 969$.

One important thing to notice is that within a given product category j, the unit values X_{ni}^{j}/Q_{ni}^{j} vary across i, which justifies our discriminatory pricing assumption. Table 2 provides summary statistics for the coefficient of variation of unit values across exporters within a given product category. The mean is 0.67 indicating that the standard deviation of unit values across exporters within a given product category is more than half of the mean of unit values across exporters in that category. This indicates that there is significant amount of variations in unit values across exporters on average.

Another issue with this data is that trade quantities and unit prices depend on the unit of measurement. Some goods are measured in kilograms, some are measured in liters, some are measured in units, etc. Therefore, when units of measurement are changed, the same information can be represented in totally different quantities and unit prices. Obviously, this is not going to be the case for trade value since it is in dollars. The next section explains how we deal with this issue.

4.2   Introducing Hypothetical Good A

The observed bilateral trade quantities and the unit prices depend on the measurement unit of each good. To control for the differences in measurement units, we introduce a hypothetical good A. The idea is to express all data that depend on measurement units in terms of this hypothetical good A, so that we have repetitions of the same game for this hypothetical good A.[23]

For any country i and destination n, let the total cost of producing q units of good

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[23]If we had many observations on the same good such as in a time series situation or many observations for different goods having the same unit of measurement and similar characteristics, we would not need to consider this hypothetical good and make the assumptions below. Conditioning on b^{j} would be sufficient.

j be given by $TC_{ni}^j(q, b^j, z_{ni}^j)$ and the total cost of producing a units of the hypothetical good A at the productivity level realization z_{ni}^j be given by $TC_{ni}^A(a, z_{ni}^j)$. Let $\frac{\partial TC_{ni}^j(q, b^j, z_{ni}^j)}{\partial q} = c_{ni}^j(q, b^j, z_{ni}^j)$ and $\frac{\partial TC_{ni}^A(a, z_{ni}^j)}{\partial a} = c_{ni}^A(a, z_{ni}^j)$ where $c_{ni}^A(a, z_{ni}^j)$ is the marginal cost of producing the ath unit of hypothetical good A at productivity level realization z_{ni}^j. Following Assumption A2-A3, we make the following assumptions:

Assumption A2′ :

(i) *For any good j and some $\lambda^j > 0$, $TC_{ni}^j(q, b^j, z_{ni}^j) = TC_{ni}^A(\lambda^j q, z_{ni}^j)$ where $TC_{ni}^A(\cdot, \cdot)$ is twice continuously differentiable in a, for all $a \geq 0$, for all n and for all i.*[24]

(ii) *For all $a \geq 0$ and for all n, i and j, $c_{ni}^A(a, z_{ni}^j) = \frac{c_{ni}^{\circ, A}(a)}{z_{ni}^j}$ where $c_{ni}^{\circ, A}(\cdot)$ is weakly increasing in a.*

Assumption A2′-(i) says that given any destination n and exporter i, for any good j the total cost of producing q_{ni}^j units of good j is the total cost of producing $\lambda^j q_{ni}^j$ units of the hypothetical good A. We denote that amount by A_{ni}^j, so $A_{ni}^j = \lambda^j Q_{ni}^j$. For any good j, A_{ni}^j may be interpreted as the quantity of the hypothetical good A that is cost equivalent to the quantity Q_{ni}^j of good j. Similarly, we can define $A_n^j = \lambda^j Q_n^j$ where Q_n^j was defined to be the total demand for imports in destination n for good j. Thus, A_n^j is the amount of total demand in terms of good A. An immediate implication of Assumption A2′ is that $c_{ni}^{\circ}(q, b^j) = \lambda^j c_{ni}^{\circ, A}(\lambda^j q)$.[25]

Assumption A3′ :

(i) *For any given n, A_n^j is drawn independently from $F_{A_n}(\cdot)$ for each j where $F_{A_n}(\cdot)$ is absolutely continuous with density $f_{A_n}(\cdot) > 0$ over the support $\mathcal{S}_{A_n}[0, \infty)$.*

(ii) *For all n and j, $\left\{ Z_{n1}^j, ., Z_{ni}^j, ., Z_{nN}^j; i \neq n \right\}_{j=1}^J$ and A_n^j are independent.*

A consequence of Assumption A3′, is that $F_{Q_n}(q|b^j) = F_{A_n}(\lambda^j q)$ for all $q \geq 0$.

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[24]More generally, we could have $TC_{ni}^j(q, b^j, z_{ni}^j) = TC_{ni}^A(\lambda^j q, z_{ni}^j) + \kappa^j$ instead of A2′-(i). This will not change our results.

[25]Since $TC_{ni}^j(q, b^j, z_{ni}^j) = TC_{ni}^A(\lambda^j q, z_{ni}^j)$, taking derivative with respect to q of both sides yields $c_{ni}^j(q, b^j, z_{ni}^j) = \lambda^j c_{ni}^A(\lambda^j q, z_{ni}^j)$. Thus, $c_{ni}^{\circ}(q) = \lambda^j c_{ni}^{\circ, A}(\lambda^j q)$.

Introducing this hypothetical good does not change the nature of the solution in our model as well as our identification argument. The only difference is that the quantities are expressed in terms of the hypothetical good A. Recall that the supply schedule of the exporter country i for destination n and good j was denoted by $s_{ni}^j(\cdot, z_{ni}^j)$. Now denote the supply schedule of exporter country i for destination n for good A for the same level of productivity realization z_{ni}^j by $s_{ni}^A(\cdot, z_{ni}^j)$. Under Assumption A2'-A3' and the first order condition for each problem for good j, we have the following relation between the optimal schedules in terms of good j and hypothetical good A:

$$s_{ni}^j(p, z_{ni}^j) = \frac{1}{\lambda^j} s_{ni}^A(\frac{p}{\lambda^j}, z_{ni}^j) \tag{20}$$

for any p.

The market clearing price in destination n for good j was denoted by $P_n^{c,j}$. This market clearing price is a function of productivity of all exporters, the import demand and the good characteristics, i.e. $P_n^{c,j} = P_n^c(Z_{-n}^j, Q_n^j, b^j)$ where $Z_{-n}^j = (Z_{n1}^j, .., Z_{nn-1}^j, Z_{nn+1}^j.., Z_{nN}^j)$. Now, let the market clearing price in destination n for good A at productivity Z_{-n} of all exporters where $Z_{-n} = (Z_1, .., Z_{nn-1}, Z_{nn+1}, .., Z_N)$ and import demand for A_n be given by $P_n^{c,A} = P_n^{c,A}(Z_{-n}, A_n)$. We, then, have the following relation between the market clearing price for good j and the hypothetical good A for any j:

$$P_n^{c,j} = \lambda^j P_n^{c,A,j} \tag{21}$$

where $P_n^{c,A,j} = P_n^{c,A}(Z_{n1}^j, .., Z_{ni}^j, .., Z_{nN}^j, \lambda^j Q_n^j)$. Let $A_{n,-i}^j$ be the total quantity of good A supplied by all countries but i, at the market clearing price $P_n^{c,A,j}$, i.e., $A_{n,-i}^j = \sum_{k \neq i,n} s_{nk}^A(P_n^{c,A,j}, Z_{nk}^j)$. We can replace any value in terms of good j with its good A analogue and all our analysis and results above follow. Note that expenditure in terms of good j, X_{ni}^j, and expenditure on the equivalent amount of good A are the same. Therefore, we will not differentiate between expenditures, it will be denoted by X_{ni}^j for both good j and good A.

Hereafter, we let $\lambda^j = \frac{\sum_n \sum_i X_{ni}^j}{\sum_n Q_n^j}$, where λ^j can be considered as the average unit value of good j across all import markets around the world. Thus, for any j, λ^j is observed. Converting the supply Q_{ni}^j of any good j to the supply $A_{ni}^j = \lambda^j Q_{ni}^j$ of the hypothetical good A can be viewed as providing the value for Q_{ni}^j at an average world price.[26] Moreover, with such a choice of λ^j, we can control for heterogeneity across goods. Note that we could control for differences in measurement units and heterogeneity across goods by conditioning on the good characteristics including the unit of measurement. Using λ^j, we address both problems and save on conditioning variable(s). Table 3 provides some summary statistics for the hypothetical good A. The highest values for A, usually correspond to cars, more specifically "passenger motor vehicles excluding buses". We also see motor vehicles for transport of goods or materials and aircraft parts for some countries. The smallest A values correspond to goods such as pen nibs or matches.

4.3 Construction of $\left\{P_n^{c,A,j}\right\}_{j=1}^J$

As we mentioned before, usually in typical bilateral trade data we observe bilateral trade quantities and expenditures between countries $\left\{Q_{ni}^j, X_{ni}^j\right\}_{j=1}^J$ for each n and i but not the price levels. For our analysis we need the market clearing prices for each n, $\{P_n^{c,j}\}_{j=1}^J$ Since in our estimation we use the values in terms of our hypothetical good A, we need to get $\left\{P_n^{c,A,j}\right\}_{j=1}^J$ for each n, using $\left\{A_{ni}^j, X_{ni}^j\right\}_{j=1}^J$ for each n and i.

Pehlivan and Vuong (2010) show how to estimate market clearing price under discriminatory pricing when only revenue and quantity data are available. Basically they make use of the simple fact that the market clearing price is the derivative of the revenue with respect to the quantity in discriminatory pricing. They use Matzkin (2003) and extend it

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[26]In our data, there are some markets in which goods in same categories are denominated in different units than other markets. Within the same market across exporters there is no difference, though, across markets there might be some difference. Thus, for the German market to calculate λ^j we use Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain, Sweden and United Kingdom markets.

to the multidimensional error case using Hoderlein, Su and White (2010) to show that this derivative is identified.

First, note that expenditure $X_{ni}^{A,j} = \int_0^{A_{ni}^j} s_{ni}^{A-1}(a, Z_{ni}^j) da$ in terms of the hypothetical good A is related to trade value X_{ni}^j through $X_{ni}^{A,j} = X_{ni}^j$ for all n, i and j. Second, we note that $X_{ni}^j = x_{ni}(Z_{-n}^j, A_n^j)$ and $A_{ni}^j = a_{ni}(Z_{-n}^j, A_n^j)$ for any n, i, and j. Since $X_{ni}^j = \int_0^{A_{ni}^j} s_{ni}^{A-1}(a, Z_{ni}^j) da \equiv \psi_{ni}(A_{ni}^j, Z_{ni}^j)$, we have

$$P_n^{c,A,j} = s_{ni}^{A-1}(A_{ni}^j, Z_{ni}^j) = \frac{\partial X_{ni}^j}{\partial A_{ni}^j} = \frac{\partial \psi_{ni}(A_{ni}^j, Z_{ni}^j)}{\partial A_{ni}^j} \tag{22}$$

This derivative is hard to get since A_{ni}^j and Z_{ni}^j are not independent as they are linked through the equilibrium condition. Nevertheless, from the chain rule we can write:

$$\frac{\partial x_{ni}(Z_{-n}^j, A_n^j)}{\partial A_n} = \underbrace{\frac{\partial \psi_{ni}(A_{ni}^j, Z_{ni}^j)}{\partial A_{ni}^j}}_{P_n^{c,A,j}} \times \frac{\partial a_{ni}(Z_{-n}^j, A_n^j)}{\partial A_n} \tag{23}$$

Thus, for any n, i, and j, we have

$$P_n^{c,A,j} = \frac{\frac{\partial x_{ni}(Z_{-n}^j, A_n^j)}{\partial A_n}}{\frac{\partial a_{ni}(Z_{-n}^j, A_n^j)}{\partial A_n}} \tag{24}$$

Moreover, when we add this ratio across $i \neq n$

$$P_n^{c,A,j} = \frac{\sum_{i \neq n} \frac{\partial x_{ni}(Z_{-n}^j, A_n^j)}{\partial A_n}}{\sum_{i \neq n} \frac{\partial a_{ni}(Z_{-n}^j, A_n^j)}{\partial A_n}} = \frac{\frac{\partial \left(\sum_{i \neq n} x_{ni}(Z_{-n}^j, A_n^j) \right)}{\partial A_n}}{\frac{\partial \left(\sum_{i \neq n} a_{ni}(Z_{-n}^j, A_n^j) \right)}{\partial A_n}} = \frac{\frac{\partial x_n(Z_{-n}^j, A_n^j)}{\partial A_n}}{\frac{\partial a_n(Z_{-n}^j, A_n^j)}{\partial A_n}} = \frac{\partial x_n(Z_{-n}^j, A_n^j)}{\partial A_n} \tag{25}$$

where $X_n^j = x_n(Z_{-n}^j, A_n^j)$ and $A_n^j = a_n(Z_{-n}^j, A_n^j)$ for any n and j.[27]

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[27] Note that the last equality in (25) follows from the fact that $\frac{\partial a_n(Z_{-n}^j, A_n^j)}{\partial A_n} = 1$.

Following Pehlivan and Vuong (2010) we have

$$P_n^{c,A,j} = \frac{\partial F_{X_n|A_n}^{-1}(u_n^j|A_n^j)}{\partial A_n} \tag{26}$$

where $u_n^j = F_{X_n|A_n}(X_n^j|A_n^j)$. Since our data is highly skewed we use a logarithmic transformation of our variables. Define $LX_n^j = \ln(X_n^j)$, $LA_{ni}^j = \ln(A_{ni}^j)$, and $LA_n^j = \ln(A_n^j)$ for all n, i, and j. Using these transformations, equation (26) can be written as:

$$P_n^{c,A,j} = \frac{X_n^j}{A_n^j} \frac{\partial F_{LX_n|LA_n}^{-1}(u_n^j|LA_n^j)}{\partial LA_n} \tag{27}$$

where $u_n^j = F_{LX_n|LA_n}(LX_n^j|LA_n^j)$. Manipulating the derivative in (27) we get

$$\frac{\partial F_{LX_n|LA_n}^{-1}(u_n^j|LA_n^j)}{\partial LA_n} = \frac{\left[F_{LX_n|LA_n}(LX_n^j|LA_n^j)\frac{\partial f_{LA_n}(LA_n^j)}{\partial LA_n} - \frac{\partial}{\partial LA_n}\left\{F_{LX_n|LA_n}(LX_n^j|LA_n^j)f_{LA_n}(LA_n^j)\right\}\right]}{f_{LX_n,LA_n}(LX_n^j,LA_n^j)} \tag{28}$$

Thus, an estimator $\frac{\partial \widehat{F}_{LX_n|LA_n}^{-1}(u_n^j|LA_n^j)}{\partial LA_n}$ is obtained by replacing the unknown quantities by their estimates, namely

$$\widehat{F}_{LX_n|LA_n}(LX_n^j|LA_n^j) = \frac{\frac{1}{Jh_1 s_{LA_n}}\sum_{j'=1}^{J}1(LX_n^{j'} \le LX_n^j)K\left(\frac{LA_n^j - LA_n^{j'}}{h_1 s_{LA_n}}\right)}{\frac{1}{Jh_1 s_{LA_n}}\sum_{j'=1}^{J}K\left(\frac{LA_n^j - LA_n^{j'}}{h_1 s_{LA_n}}\right)}$$

$$\frac{\partial \widehat{f}_{LA_n}(LA_n^j)}{\partial LA_n} = \frac{1}{Jh_1^2 s_{LA_n}^2}\sum_{j'=1}^{J}K'\left(\frac{LA_n^j - LA_n^{j'}}{h_1 s_{LA_n}}\right)$$

$$\frac{\partial}{\partial LA_n}\left(\widehat{F}_{LX_n|LA_n}(LX_n^j|LA_n^j)\widehat{f}_{LA_n}(LA_n^j)\right) = \frac{1}{Jh_1^2 s_{LA_n}^2}\sum_{j'=1}^{J}1(LX_{ni}^{j'} \le LX_{ni}^j)K'\left(\frac{LA_n^j - LA_n^{j'}}{h_1 s_{LA_n}}\right)$$

$$\widehat{f}_{LX_n,LA_n}(LX_n^j,LA_n^j) = \frac{1}{Jh_2^2 s_{LX_n}s_{LA_n}}\sum_{j'=1}^{J}K\left(\frac{LX_{ni}^j - LX_{ni}^{j'}}{h_2 s_{LX_{ni}}}\right)K\left(\frac{LA_n^j - LA_n^{j'}}{h_2 s_{LA_n}}\right)$$

where s_{LX_n} and s_{LA_n} are the standard errors of the random variables LX_n and LA_n, respec-

tively, h_1 and h_2 some bandwidth and $K(\cdot)$ some kernel with $K'(\cdot)$ its derivative.

Note that due to the discriminatory pricing one of the implications of our model is that for any given n and j, we have $\frac{X_n^j}{A_n^j} \leq P_n^{c,A,j}$, therefore whenever our estimate $\frac{\partial \widehat{F}^{-1}_{LX_n|LA_n}(u_n^j|LA_n^j)}{\partial LA_n} < 1$, we consider this as a violation. Setting $h_1 = cJ^{-1/5}$ and $h_2 = cJ^{-1/6}$, we pick c such that those violations are minimized. In our case that c is 1.4039, close to the rule of thumb case and we have 167 violations out of 969 cases.[28] We use a standard Gaussian kernel in our estimation.

5   Nonparametric Estimation

After introducing the hypothetical good A and constructing the market clearing prices, our observations are $\left\{A_{ni}^j, P_n^{c,A,j}\right\}_{j=1}^J$ for each n and i. All the identification results in Section 3 are valid for the hypothetical good A case as well and we are after the structure $[F_{ni}(\cdot), c_{ni}^{\circ,A}(\cdot)]$. Estimation follows the same steps as identification: We first estimate $H_{ni}^A(\cdot, \cdot)$, then estimate $c_{ni}^{\circ,A}(\cdot)$ and lastly, we estimate $F_{ni}(\cdot)$.

5.1   Estimation of $H_{ni}^A(\cdot, \cdot)$

Analogous to (9) we have

$$H_{ni}^A(p_n, a_{ni}) = \int_0^\infty \left[\int_{a_n-a_{ni}}^\infty f_{\Sigma_{n,-i,p}^A}(a_{n,-i}) da_{n,-i} \right] f_{A_n}(a_n) da_n \tag{29}$$

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[28]In this particular application, since we also have individual observations whenever our $P_n^{c,A,j}$ estimate is lower than $\max_{i \neq n} \left\{ \frac{X_{ni}^j}{A_{ni}^j} \right\}$ we take that max value.

Moreover, from Lemma 1, applied to the hypothetical good A, we have

$$H_{ni}^A(p_n, a_{ni}) = 1 - \frac{\int_0^\infty \left\{ \int_0^\infty F_{A_{n,-i}|P_n^{c,A},A_n}(a_n - a_{ni}|p_n, \widetilde{a}_n) dF_{A_n}(a_n) \frac{f_{P_n^{c,A},A_n}(p_n,\widetilde{a}_n)}{f_{A_n}^2(\widetilde{a}_n)} \right\} dF_{A_n}(\widetilde{a}_n)}{\int_0^\infty \frac{f_{P_n^{c,A},A_n}(p_n,\widetilde{a}_n)}{f_{A_n}^2(\widetilde{a}_n)} dF_{A_n}(\widetilde{a}_n)} \tag{30}$$

Expressing (30) in terms of expectations and our logarithmic transformations we get

$$H_{ni}^A(p_n, a_{ni}) = 1 - \frac{E_{\widetilde{A}_n}\left[\frac{f_{LP_n^{c,A},LA_n}(\ln p_n, \ln \widetilde{A}_n)}{f_{LA_n}^2(\ln \widetilde{A}_n)} \widetilde{A}_n E_{A_n}[F_{LA_{n,-i}|LP_n^{c,A},LA_n}(\ln(A_n - a_{ni})|\ln p_n, \ln \widetilde{A}_n)]\right]}{E_{\widetilde{A}_n}\left[\frac{f_{LP_n^{c,A},LA_n}(\ln p_n, \ln \widetilde{A}_n)}{f_{LA_n}^2(\ln \widetilde{A}_n)} \widetilde{A}_n\right]} \tag{31}$$

Denote the numerator in equation (31) by $N_{ni}(p_n, a_{ni})$ and the denominator by $D_n(p_n)$. We propose the following estimator for $N_{ni}(p_n, a_{ni})$:

$$\widehat{N}_{ni}(p_n, a_{ni}) = \frac{1}{J}\sum_{j'=1}^J \left[\frac{A_n^{j'}}{\widehat{f}_{LA_n}^2(\ln A_n^{j'})} \frac{1}{J}\sum_{j=1}^J \widehat{F}_{LA_{n,-i}|LP_n^{c,A},LA_n}(\ln(A_n^j - a_{ni})|\ln p_n, \ln A_n^{j'})\widehat{f}_{LP_n^{c,A},LA_n}(\ln p_n, \ln A_n^{j'}) \right] \tag{32}$$

where

$$\widehat{F}_{LA_{n,-i}|LP_n^{c,A},LA_n}(\ln(A_n^j - a_{ni})|\ln p_n, \ln A_n^{j'})\widehat{f}_{LP_n^{c,A},LA_n}(\ln p_n, \ln A_n^{j'}) \tag{33}$$

$$= \frac{1}{Jh_3^2 s_{LP_n^{c,A}} s_{LA_n}} \sum_{k=1}^J \mathbb{1}(\ln(A_{n,-i}^k) \le \ln(A_n^j - a_{ni}) K\left(\frac{\ln p_n - \ln(P_n^{c,A,k})}{h_3 s_{LP_n^{c,A}}}\right) K\left(\frac{\ln A_n^{j'} - \ln A_n^k}{h_3 s_{LA_n}}\right)$$

and

$$\widehat{f}_{LA_n}^2(\ln A_n^{j'}) = \frac{1}{Jh_4^2 s_{LA_n}^2}\left[\sum_{k=1}^J K\left(\frac{\ln A_n^{j'} - \ln A_n^k}{h_4 s_{LA_n}}\right)\right]^2 \tag{34}$$

Similarly, we propose the following estimator for $D_n(p_n)$

$$\widehat{D}_n(p_n) = \frac{1}{J}\sum_{j'=1}^J \frac{\widehat{f}_{LP_n^{c,A},LA_n}(\ln p_n, \ln A_n^{j'})}{\widehat{f}_{LA_n}^2(\ln A_n^{j'})} A_n^{j'} \tag{35}$$

31

where

$$\widehat{f}_{LP_n^{c,A},LA_n}(\ln p_n, \ln A_n^{j'}) = \frac{1}{Jh_3^2 s_{LP_n^{c,A}} s_{LA_n}} \sum_{k=1}^{J} K\left(\frac{\ln p_n - \ln(P_n^{c,A,k})}{h_3 s_{LP_n^{c,A}}}\right) K\left(\frac{\ln A_n^{j'} - \ln A_n^k}{h_3 s_{LA_n}}\right)$$

(36)

where h_3 and h_4 are some bandwidth and $K(\cdot)$ is some kernel.

For an estimate of $H_{ni,p}^A(\cdot, \cdot)$, we use the fact that

$$H_{ni,p}^A(p_n, a_{ni}) = \frac{\left[N_{ni}(p_n, a_{ni})\frac{\partial D_n(p_n)}{\partial p} - D_n(p_n)\frac{\partial N_{ni}(p_n, a_{ni})}{\partial p}\right]}{[D_n(p_n)]^2}$$

(37)

and replacing the numerator and denominator with their respective estimates proposed above, then, taking the derivative provides our estimator.

5.2   Estimation of $c_{ni}^{\circ,A}(\cdot)$

Estimation of $c_{ni}^{\circ,A}(\cdot)$ will be in two steps. First, we need to estimate the lower boundary of the support $\mathcal{S}_{A_{ni},P_n^c}$. We, then, estimate the cost frontier. In order to estimate the lower boundary $s_{ni}^{A,-1}(\cdot, \bar{z}) = s_{ni}^{A,-1}(\cdot, 1)$ of the support of (A_{ni}, P_n^c), we use splines. The supply schedules are weakly increasing in a_{ni}, the quantity of good A supplied by player i in any destination n. Using splines we can guarantee that our estimator is continuous and smooth but we also like to impose the (weak) monotonicity condition. Following DeVore(1977), we integrate lower degree splines which provides weakly increasing functions by construction.

For any $t \in [0, 1]$, we define

$$\widetilde{LB}(t) = \sum_{k=0}^{J_n+2} \psi_k B_k(t)$$

where $B_o(t) = 1$, $B_k(t) = \int_0^t b_k(u)du$ for $k = 1, ...J_n + 2$ and $b_k(\cdot)$'s are linear B-spline basis functions while J_n is the number of knots $\{t_l : t_o = 0 < t_1 < ... < t_{J_n+1} = 1, l = 0, 1, .., J_n+1\}$

in between the endpoints. Specifically, the $b_k(\cdot)$'s are as follows:

For $k = 1$, $\quad b_1(u) = \left[1 - \dfrac{u}{t_1}\right] 1(u \in [t_0, t_1])$

For $k = 2, ..., J_n + 1$, $\quad b_k(u) = \left[\dfrac{u - t_{k-2}}{t_{k-1} - t_{k-2}}\right] 1(u \in [t_{k-2}, t_{k-1})) + \left[\dfrac{t_k - u}{t_k - t_{k-1}}\right] 1(u \in [t_{k-1}, t_k))$

For $k = J_n + 2$, $\quad b_{J_n+2}(u) = \left[\dfrac{u - t_{J_n}}{t_{J_n+1} - t_{J_n}}\right] 1(u \in [t_{J_n}, t_{J_n+1}])$

We use "uniform B-splines" meaning that the knots are equally spaced, i.e. $t_{l-1} - t_{l-2} = t_l - t_{l-1} = \frac{1}{J_n+1}$ for any $l = 1, ..., J_n + 1$. We, then, have the following basis functions $B_k(t)$'s for all $t \in [0, 1]$:

For $k = 0$, $\quad B_0(t) = 1$

For $k = 1$, $\quad B_1(t) = \left[t - \dfrac{t^2(J_n+1)}{2}\right] 1(t \in [0, \frac{1}{J_n+1})) + \dfrac{1}{2(J_n+1)} 1(t \in [\frac{1}{J_n+1}, 1])$

For $k = 2, ..., J_n + 1$, $\quad B_k(t) = \left[\dfrac{(t - \frac{k-2}{J_n+1})^2(J_n+1)}{2}\right] 1(t \in [\frac{k-2}{J_n+1}, \frac{k-1}{J_n+1}))$

$+ \left[\dfrac{1}{(J_n+1)} - \dfrac{\left(\frac{k}{J_n+1} - t\right)^2(J_n+1)}{2}\right] 1(t \in [\frac{k-1}{J_n+1}, \frac{k}{J_n+1})) + \left[\dfrac{1}{J_n+1}\right] 1(t \in \frac{k}{J_n+1}, 1)$

For $k = J_n + 2$, $\quad B_{J_n+2}(t) = \left[\dfrac{(t - \frac{J_n}{J_n+1})^2(J_n+1)}{2}\right] 1(t \in [\frac{J_n}{J_n+1}, 1])$

In order for $\widetilde{LB}(t)$ to be weakly increasing over $t \in [0, 1]$, it is necessary and sufficient that $\psi_k \geq 0$ for $k = 1, ..., J_n + 2$.

We define $\widetilde{LA^j_{ni}} = \dfrac{LA^j_{ni} - \min_j(LA^j_{ni})}{\max_j(LA^j_{ni}) - \min_j(LA^j_{ni})}$ and $LB(A^j_{ni}) = \widetilde{LB}(\widetilde{LA^j_{ni}})$. Note that $\widetilde{LA^j_{ni}} \in [0, 1]$ so we can substitute $\widetilde{LA^j_{ni}}$ for t in the above equations. Since $\widetilde{LB}(\cdot)$ is the lower boundary, our estimator is the curve that maximizes the area under it while having all the observations above, following Tsybakov (1993). In Campo, Guerre, Perrigne and Vuong (2009), they also follow a similar approach to estimate the upper boundary of the bid distribution. Specifically,

we solve the following problem:

$$\max_{\{\psi_k\}_{k=0}^{J_n+2}} \int_0^1 \widetilde{LB}(\widetilde{LA_{ni}}) d\widetilde{LA}_{ni}$$

$$s.t. \ P_n^{c,A,j} \geq \widetilde{LB}(\widetilde{LA_{ni}^j}) \text{ for all } j = 1, ..., J$$

$$\psi_k \geq 0 \text{ for all } k = 1, ..., J_n + 2$$

The first constraint imposes that all the observations lie above our $\widetilde{LB}(\cdot)$ curve and the second one imposes (weak) monotonicity. Substituting the definition of $\widetilde{LB}(\cdot)$ into our objective function and the constraint, the problem becomes a simple linear programming problem since both the objective function and the constraints are linear in ψ_k's.

Once we have $\widehat{s}_{ni}^{A,-1}(\cdot, 1)$, our estimate of $c_{ni}^{\circ,A}(\cdot)$ is given by

$$\widehat{c}_{ni}^{\circ,A}(\cdot) = \widehat{s}_{ni}^{A,-1}(\cdot, 1) - \frac{1 - \widehat{H}_{ni}^A(\widehat{s}_{ni}^{A,-1}(\cdot, 1), \cdot)}{\widehat{H}_{ni,p}^A(\widehat{s}_{ni}^{A,-1}(\cdot, 1), \cdot)} \tag{38}$$

5.3 Estimation of $F_{ni}(\cdot)$

Once we estimate the marginal cost frontier by $\widehat{c}_{ni}^{\circ,A}(\cdot)$, we can estimate the *pseudo-productivities* for any $(A_{ni}^j, P_n^{c,A,j})$

$$\widehat{z}_{ni}^j = \frac{\widehat{c}_{ni}^{\circ,A}(A_{ni}^j)}{P_n^{c,A,j} - \frac{1 - \widehat{H}_{ni}^A(P_n^{c,A,j}, A_{ni}^j)}{\widehat{H}_{ni,p}^A(P_n^{c,A,j}, A_{ni}^j)}} \tag{39}$$

We, then, estimate the density $f_{ni}(\cdot)$ of productivities by

$$\widehat{f}_{ni}(z_{ni}) = \frac{1}{J h_5 s_{\widehat{z}_{ni}}} \sum_{j=1}^J K\left(\frac{z_{ni} - \widehat{z}_{ni}^j}{h_5 s_{\widehat{z}_{ni}}}\right) \tag{40}$$

where $s_{\widehat{z}_{ni}}$ is the standard error of $\widehat{z}_{ni}$, h_5 is some bandwidth and $K(\cdot)$ is some kernel.

6 Empirical Results

For this particular application, we look at the German market of manufacturing imports for 1990. Figures 2-8 show our estimates of the base marginal cost $\widehat{c}_{ni}^{\circ,A}(\cdot)$ and the associated markup for our 7 exporters when the exporters have the highest possible productivity, which is $\overline{z} = 1$. According to our estimates, the countries with the lowest base marginal cost are Italy and Belgium with Italy being the lowest as shown in Figure 4 and Figure 2, respectively. As mentioned before, base marginal cost is the cost frontier of these countries, i.e. they assumed to have the highest level of productivity, $\overline{z} = 1$. Thus, the difference in base marginal costs can solely be attributed to trade barriers or input costs. Actually, base marginal cost of Italy is the lowest which can be attributed to lower wages. In Eaton and Kortum (2002) they provide human capital adjusted manufacturing wages for 1990 and Italy has the lowest wage rate compared to the other 6 countries. On the other hand, Belgium is one of the countries with the highest wage rate. Its low marginal cost might be attributed to low trade barriers of Belgium. Note that from Table 1 we know that Italy and Belgium are the second and third largest exporter in terms of export shares. The ones with highest base marginal cost are Japan and US with Japan as being slightly lower as shown in Figure 5 and Figure 8, respectively. These high base marginal costs can be attributed to higher trade costs for these countries. Japan has a lower wage rate than US which can explain the relatively lower base marginal cost despite Japan being further away. Netherlands and UK, shown in Figure 6 and Figure 7, respectively, are in the middle range in terms of the base marginal costs. What is a bit surprising is that the largest exporter in terms of export shares, France, having higher base marginal cost, as shown in Figure 3, than countries such as Belgium even though they have very similar wage rate and proximity, which might be due to some other trade barriers.

In Figure 9, we display the markup to marginal cost ratio. The reason we are interested in this ratio instead of the markups represented in previous figures is that what we call markup and the standard markup in the monopolistic competition models are slightly different.

There, markup is price over marginal cost which is constant across units whereas in our case what we call markup is price minus marginal cost, which may or may not be constant across units. In those models markup is not only constant over units, but also constant across exporters and even sometimes across markets. Therefore, in order to see for instance whether the markup is indeed constant say across exporters, we need to look at whether markup to marginal cost ratio is constant across countries or not. In Figure 9, we see that markups are not fixed across exporters.[29]

Other than markups, another question which has become popular recently, is about the characteristics of the productivity distributions assumed in trade models and to what extent they effect the welfare gains. In Eaton and Kortum (2002) and many variants the distributional assumption is Fréchet. It has a key parameter θ that is used to measure the comparative advantage. Its estimation is very important for calculating welfare gains. Simonovska and Waugh (2013) claim that their estimate of θ is actually half of the conventional estimates of θ, which causes a doubling in estimation of the welfare costs of autarky in those models. Therefore, it is important to see how the distribution of productivities behave.

In Figures 10-16, we display the estimated denstiy $\widehat{f}_{ni}(\cdot)$ of estimated productivities for all exporters. Our first observation is that these distributions are not unimodal. It is almost a common assumption in the models that for any good, countries draw from the same distribution. Our result, however, suggests that certain industries have certain types (levels) of productivity. This is important from a policy perspective since policy makers might want to distinguish between less productive and more productive types. Figure 17 shows all productivity distributions in a single graph so that we can make an easier comparison. France and US seem to have the best productivity distributions as there is more dispersion and the concentration is not only around lower productivity levels. For instance for Belgium and Italy the productivity distributions seem to be concentrated more around lower productivity

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[29]Note that the markup to marginal cost ratio here is obtained when countries have the best productivity draw, i.e., $\bar{z} = 1$. Actually, providing this ratio at several other productivity levels would provide much better insights.

levels. The productivity distribution of Japan is also similar to that of France and US though slightly worse. Actually, in Eaton and Kortum (2002) under the Fréchet distribution assumption they estimate the state of technologies of the countries. In their ranking Belgium, Italy has lower state of technology than US, France and Japan as well. However, for instance we find Netherlands to have a better productivity distribution in terms of dispersion and concentration around lower productivity levels, hence better state of technology than Italy which is not the case in Eaton and Kortum (2002). One might claim that this is due to the fact that we only look at a particular market, Germany, whereas in their case they consider all markets in their sample. That is why our productivity distribution estimates are destination-source specific. Actually, when we extend this application to include other markets we can check whether the productivity distribution of countries vary across destinations. This might provide valuable insights into whether the composition of exporters change or not across different markets.

Now, the big question : Is it really Fréchet ? To get an idea, we will perform maximum likelihood estimation with the *pseudo-productivities* that we recovered. We will consider two extreme cases, namely Belgium and US, which are the countries with the worst and best productivity distributions, respectively. Similar analysis can be performed with the other countries as well. According to our maximum likelihood estimates, we find $\widehat{\theta}^*_{Bel} = 0.4036$ for Belgium whereas the estimates of θ in the literature range from 3 to 13. As it can be seen from Figure 18, the truncated Fréchet distribution with $\widehat{\theta}^*_{Bel} = 0.4036$ does not fit very well our nonparametric estimate. We also tried truncated Pareto case even though our analysis was at the country level, but the fit was too poor. Figure 19, shows the same two distributions for US. For US, our maximum likelihood estimates give $\widehat{\theta}^*_{US} = 0.2864$ and again the associated truncated Fréchet does not fit well to our nonparametric estimate.

7   Conclusion

In this paper, we introduce supply function competition to explain bilateral trade data. Unlike the convention in the existing literature in international trade, we keep a flexible structure for the productivity distributions and marginal costs. Next, we show that the productivity distributions and marginal costs can be identified nonparametrically. Due to the nature of the bilateral trade data only trade values and traded quantities can be observed, however, we show that the structure of our model can still be identified when only transaction points are observed instead of the whole schedule. Following the nonparametric identification we propose a nonparametric estimation procedure.

The 1990 German market for manufacturing imports was analyzed. Our empirical results show that markups are not constant across exporters, in contrast to monopolistic competition with Dixit-Stiglitz preferences, which implies a constant markup across exporters. In the recent literature there has been some attempts to introduce variable markups. Our model contributes to those attempts as well. Our results indicate that the productivity distributions are not unimodal and do not support the conventional distributional assumptions. Another interesting application would be to look at different markets. Again, we would like to know whether markups are constant across markets or whether in some markets markups are consistently high. By looking at how base marginal cost varies across destinations for a given country we can obtain an estimate for the trade costs. Extending this application to include more than one market would allow us to check also whether productivity distributions vary across destinations. This might provide important insights into whether the composition of exporters of a given country changes across different markets.

We consider the following possible extensions for future research : First, introducing zeros, i.e., cases when countries do not trade with each other. Our theoretical model allows for the fact that there can be zeros. Our identification argument, however, needs all countries in our sample to export a positive amount. Second, we would like to have a more general form of demand which allows for quantity demanded for imports to depend on the clearing

price. In that case, as long as we can find home production data at a disaggragated level that matches our bilateral trade data we can include also the home country in our analysis. Third, in our identification argument it was easier to do the analysis using market clearing prices and quantities. That is why we used Pehlivan and Vuong (2010) to construct market clearing prices. It might still be possible to obtain identification using only expenditures and quantities which is an open issue left for future research.

APPENDIX A

Derivation of the necessary condition

Similar to Hortacsu (2002), we will use calculus of variations to solve our functional optimization problem. For notational simplicity we will drop hereafter index j and n and the conditioning on its characteristics b^j, as the analysis is performed for a given good j and n.

Our expected profit maximization problem is defined as

$$\max_{s_i(\cdot, z_i)} \int_{\underline{p}}^{\overline{p}} \underbrace{\left\{ \int_0^{s_i(p^c, z_i)} \left[s_i^{-1}(q, z_i) - c_i(q, z_i) \right] \, dq \right\}}_{\pi(s_i(p^c, z_i))} \underbrace{d\widetilde{H}_i(p^c|z_i)}_{dH_i(p^c, s_i(p^c, z_i))}$$

Let $s_i(p^c, z_i)$ be defined over the support $[\underline{p}, \overline{p}]$

$$s_i(p^c, z_i) = \begin{cases} 0 & \text{if } \underline{p} \leq p^c \leq p_i^* \\ \widetilde{s}_i(p^c, z_i) & \text{if } p_i^* \leq p^c \leq \overline{p} \end{cases}$$

Let $I = \int_{\underline{p}}^{\overline{p}} \pi(s_i(p^c, z_i)) \, dH_i(p^c, s_i(p^c, z_i)) = \int_{p_i^*}^{\overline{p}} \pi(\widetilde{s}_i(p^c, z_i)) \, dH_i(p^c, \widetilde{s}_i(p^c, z_i))$ and note that by Leibnitz's Rule

$$\begin{aligned} \frac{d\pi}{dp^c} &= \left[\widetilde{s}_i^{-1}(\widetilde{s}_i(p^c, z_i), z_i) - c_i(q, z_i) \right] \widetilde{s}_i'(p^c, z_i) \\ &= \left[p^c - c_i(\widetilde{s}_i(p^c, z_i), z_i) \right] \widetilde{s}_i'(p^c, z_i) \end{aligned}$$

where $\widetilde{s}_i'(p^c, z_i)$ is the derivative of $\widetilde{s}_i(p^c, z_i)$ with respect to the first argument. Applying integration by parts and noting that $\pi(\widetilde{s}_i(p_i^*, z_i)) = 0$, we get

$$I = \pi(\widetilde{s}_i(\overline{p}, z_i)) - \int_{p_i^*}^{\overline{p}} H_i(p^c, \widetilde{s}_i(p^c, z_i)) \left[p^c - c_i(\widetilde{s}_i(p^c, z_i), z_i) \right] \widetilde{s}_i'(p^c, z_i) dp^c$$

Note that $\pi(\widetilde{s}_i(\overline{p}, z_i)) = \int\limits_0^{\widetilde{s}_i(\overline{p}, z_i)} \left[\widetilde{s}_i^{-1}(q, z_i) - c_i(q, z_i)\right] \, dq$. Applying change of variable and

setting $p_i^* = c_i(0, z_i)$, we have $\pi(\widetilde{s}_i(\overline{p}, z_i)) = \int\limits_{p_i^*}^{\overline{p}} \left[p^c - c_i(\widetilde{s}_i(p^c, z_i), z_i)\right] \widetilde{s}_i'(p^c, z_i) dp^c$. Then, our

maximization problem becomes

$$\max_{\widetilde{s}_i(\cdot, z_i)} \int\limits_{p_i^*}^{\overline{p}} \left(1 - H_i(p^c, \widetilde{s}_i(p^c, z_i))\right) \left[p^c - c_i(\widetilde{s}_i(p^c, z_i), z_i)\right] \widetilde{s}_i'(p^c, z_i) dp^c$$

Since the integrand is a function of $p^c, \widetilde{s}_i$ and $\widetilde{s}_i'$ denote the integrand by $F_i(p^c, \widetilde{s}_i, \widetilde{s}_i')$. From

Kamien and Schwartz (1993), the Euler equation which provides our necessary condition is

given by

$$F_{i,\widetilde{s}_i} = \frac{dF_{i,\widetilde{s}_i'}}{dp^c}$$

where $F_{i,\widetilde{s}_i}$ is the partial derivative of $F_i(p^c, \widetilde{s}_i, \widetilde{s}_i')$ with respect to the second variable and

$F_{i,\widetilde{s}_i'}$ is the partial derivative with respect to the third variable. Plugging in the respective

derivatives we get

$$-H_{i,p}(p^c, \widetilde{s}_i(p^c, z_i)) \left[p^c - c_i(\widetilde{s}_i(p^c, z_i), z_i)\right] + (1 - H_i(p^c, \widetilde{s}_i(p^c, z_i))) = 0$$

for $p_i^* \leq p^c \leq \overline{p}$. Rearranging it gives

$$p^c - c_i(\widetilde{s}_i(p^c, z_i), z_i) = \frac{(1 - H_i(p^c, \widetilde{s}_i(p^c, z_i)))}{H_{i,p}(p^c, \widetilde{s}_i(p^c, z_i))}$$

for $p_i^* \leq p^c \leq \overline{p}$.

APPENDIX B

Proof of Lemma 1

We will prove Lemma 1 by proving equations (10), (12) and (15).

Proof of (10) :

Since $\Pr\left[Q_n \leq q_n | P_n^c = p_n\right] = \Pr\left[\Sigma_{n,p_n} \leq q_n | XD_{n,p_n} = 0\right]$, we know that

$$f_{Q_n|P_n^c}\left(q_n|p_n\right) = f_{\Sigma_{n,p_n}|XD_{n,p_n}}\left(q_n|0\right) = \frac{f_{\Sigma_{n,p_n},XD_{n,p_n}}\left(q_n,0\right)}{f_{XD_{n,p_n}}\left(0\right)} \tag{41}$$

Now, consider the following transformation

$$\begin{pmatrix} \Sigma_{n,p_n} \\ Q_n \end{pmatrix} \longrightarrow \begin{pmatrix} \Sigma_{n,p_n} \\ XD_{n,p_n} \end{pmatrix}$$

since the Jacobian is 1 we get

$$f_{\Sigma_{n,p_n},XD_{n,p_n}}\left(\widetilde{q}_n,x_n\right) = f_{\Sigma_{n,p_n},Q_n}\left(\widetilde{q}_n,x_n+\widetilde{q}_n\right)$$

evaluating at $\widetilde{q}_n = q_n$ and $x_n = 0$ gives $f_{\Sigma_{n,p_n},XD_{n,p_n}}\left(q_n,0\right) = f_{\Sigma_{n,p_n},Q_n}\left(q_n,q_n\right)$. Plugging this back to (41) we obtain

$$f_{Q_n|P_n^c}\left(q_n|p_n\right) = \frac{f_{\Sigma_{n,p_n},XD_{n,p_n}}\left(q_n,0\right)}{f_{XD_{n,p_n}}\left(0\right)} = \frac{f_{\Sigma_{n,p_n},Q_n}\left(q_n,q_n\right)}{f_{XD_{n,p_n}}\left(0\right)} = \frac{f_{\Sigma_{n,p_n}}\left(q_n\right)f_{Q_n}\left(q_n\right)}{f_{XD_{n,p_n}}\left(0\right)} \tag{42}$$

where the last equality follows from independence of Σ_{n,p_n} and Q_n since for any arbitrary p_n they are independent by Assumption A3. Rewriting (42) we have

$$f_{Q_n|P_n^c}\left(q_n|p_n\right)f_{XD_{n,p}}\left(0\right) = f_{\Sigma_{n,p_n}}\left(q_n\right)f_{Q_n}\left(q_n\right) \tag{43}$$

for all $(q_n, p_n) \in \mathbb{R}_+ \times \mathcal{S}_{P_n^c}$. Let $C_{p_n} = f_{XD_{n,p}}(0)$ and apply Bayes' Rule in (43), then we get

$$\frac{f_{P_n^c|Q_n}(p_n|q_n) C_{p_n}}{f_{P_n^c}(p_n)} = f_{\Sigma_{n,p_n}}(q_n) \tag{44}$$

for all $(q_n, p_n) \in \mathbb{R}_+ \times \mathcal{S}_{P_n^c}$. To get the C_{p_n} integrate both sides over q_n, the RHS will be 1, thus we get

$$C_{p_n} = \frac{f_{P_n^c}(p_n)}{\int_{\mathcal{S}_{\Sigma_{n,p_n}}} f_{P_n^c|Q_n}(p_n|\widetilde{q}_n) d\widetilde{q}_n}$$

By Assumption A3 we have $\mathcal{S}_{\Sigma_{n,p_n}} = \mathcal{S}_{Q_n} = [0, \infty)$, hence

$$C_{p_n} = \frac{f_{P_n^c}(p_n)}{\int_0^\infty f_{P_n^c|Q_n}(p_n|\widetilde{q}_n) d\widetilde{q}_n}$$

for any $p_n \in \mathcal{S}_{P_n^c}$. Substituting C_{p_n} into (44) yields

$$f_{\Sigma_{n,p_n}}(q_n) = \frac{f_{P_n^c|Q_n}(p_n|q_n)}{\int_0^\infty f_{P_n^c|Q_n}(p_n|\widetilde{q}_n) d\widetilde{q}_n} \tag{45}$$

which is equation (10). $\square$

Proof of Equation (12) :

Since $\Pr[Q_{n,-i} \leq q_{n,-i} | P_n^c = p_n, \ Q_n = q_n] = \Pr[\Sigma_{n,-i,p_n} \leq q_{n,-i} | \Sigma_{n,p_n} = q_n, Q_n = q_n]$, it implies

$$f_{Q_{n,-i}|P_n^c, Q_n}(q_{n,-i}|p_n, q_n) = f_{\Sigma_{n,-i,p_n}|\Sigma_{n,p_n},Q_n}(q_{n,-i}|q_n, q_n) = \frac{f_{\Sigma_{n,-i,p_n},\Sigma_{n,p_n},Q_n}(q_{n,-i}, q_n, q_n)}{f_{\Sigma_{n,p_n},Q_n}(q_n, q_n)} \tag{46}$$

Now, consider the following transformation

$$
\begin{pmatrix} \Sigma_{n,-i,p_n} \\ S_{ni,p_n} \\ Q_n \end{pmatrix} \longrightarrow \begin{pmatrix} \Sigma_{n,-i,p_n} \\ \Sigma_{n,p_n} \\ Q_n \end{pmatrix}
$$

Since the Jacobian is 1 again, we have

$$
f_{\Sigma_{n,-i,p_n},\Sigma_{n,p_n},Q_n}(\widetilde{q}_{n,-i},\widetilde{q}_n,\widetilde{\widetilde{q}}_n) = f_{\Sigma_{n,-i,p_n},S_{ni,p_n},Q_n}(\widetilde{q}_{n,-i},\widetilde{q}_n - \widetilde{q}_{n,-i},\widetilde{\widetilde{q}}_n)
$$

evaluating at $\widetilde{q}_{n,-i} = q_{n,-i}$, $\widetilde{q}_n = q_n$ and $\widetilde{\widetilde{q}}_n = q_n$ we get

$$
f_{\Sigma_{n,-i,p_n},\Sigma_{n,p_n},Q_n}(q_{n,-i},q_n,q_n) = f_{\Sigma_{n,-i,p_n},S_{ni,p_n},Q_n}(q_{n,-i},q_n - q_{n,-i},q_n)
$$

When we plug this back into (46)

$$
\begin{aligned}
f_{Q_{n,-i}|P_n^c,Q_n}(q_{n,-i}|p_n,q_n) &= \frac{f_{\Sigma_{n,-i,p_n},\Sigma_{n,p_n},Q_n}(q_{n,-i},q_n,q_n)}{f_{\Sigma_{n,p_n},Q_n}(q_n,q_n)} \\
&= \frac{f_{\Sigma_{n,-i,p_n},S_{ni,p_n},Q_n}(q_{n,-i},q_n - q_{n,-i},q_n)}{f_{\Sigma_{n,p_n},Q_n}(q_n,q_n)} \\
&= \frac{f_{\Sigma_{n,-i,p_n}}(q_{n,-i})f_{S_{ni,p_n}}(q_n - q_{n,-i})}{f_{\Sigma_{n,p_n}}(q_n)}
\end{aligned} \tag{47}
$$

where the last equality follows from independence of $\Sigma_{n,-i,p_n}$, S_{ni,p_n} and Q_n for any arbitrary p_n they are independent by Assumption A3. Note that we need Assumption A5 for the existence of $f_{Q_{n,-i}|P_n^c,Q_n}(q_{n,-i}|p_n,q_n)$. Rewriting (47) we get

$$
f_{Q_{n,-i}|P_n^c,Q_n}(q_{n,-i}|p_n,q_n) f_{\Sigma_{n,p_n}}(q_n) = f_{\Sigma_{n,-i,p_n}}(q_{n,-i})f_{S_{ni,p_n}}(q_n - q_{n,-i}) \tag{48}
$$

for any $(q_{n,-i},p_n,q_n) \in \mathbb{R}_+ \times \mathcal{S}_{P_n^c} \times \mathcal{S}_{Q_n}$. Integrating both sides of (48) over q_n, remembering

44

$\mathcal{S}_{Q_n} = [0, \infty)$ yields

$$\int_0^\infty f_{Q_{n,-i}|P_n^c,Q_n}(q_{n,-i}|p_n, \widetilde{q}_n) f_{\Sigma_{n,p_n}}(\widetilde{q}_n) d\widetilde{q}_n = f_{\Sigma_{n,-i,p_n}}(q_{n,-i}) \int_0^\infty f_{S_{ni,p_n}}(\widetilde{q}_n - q_{n,-i}) d\widetilde{q}_n$$

for any $(q_{n,-i}, p_n) \in \mathbb{R}_+ \times \mathcal{S}_{P_n^c}$. Consider the integral on the RHS, using change of variable it can be shown that it adds up to 1. Hence, we have

$$f_{\Sigma_{n,-i,p_n}}(q_{n,-i}) = \int_0^\infty f_{Q_{n,-i}|P_n^c,Q_n}(q_{n,-i}|p_n, \widetilde{q}_n) f_{\Sigma_{n,p_n}}(\widetilde{q}_n) d\widetilde{q}_n \qquad (49)$$

for any $(q_{n,-i}, p_n) \in \mathbb{R}_+ \times \mathcal{S}_{P_n^c}$ which is equation (12). $\square$

Proof of Equation (15) :

From (45) plug the expression for $f_{\Sigma_{n,p_n}}(\cdot)$ into (49), then we get

$$f_{\Sigma_{n,-i,p_n}}(q_{n,-i}) = \int_0^\infty f_{Q_{n,-i}|P_n^c,Q_n}(q_{n,-i}|p_n, \widetilde{q}_n) \frac{f_{P_n^c|Q_n}(p_n|\widetilde{q}_n)}{\int_0^\infty f_{P_n^c|Q_n}(p_n|\widetilde{q}_n) d\widetilde{q}_n} d\widetilde{q}_n$$

rewriting yields

$$f_{\Sigma_{n,-i,p_n}}(q_{n,-i}) = \frac{\int_0^\infty f_{Q_{n,-i},P_n^c|Q_n}(q_{n,-i}|p_n, \widetilde{q}_n) d\widetilde{q}_n}{\int_0^\infty f_{P_n^c|Q_n}(p_n|\widetilde{q}_n) d\widetilde{q}_n}$$

for any $(q_{n,-i}, p_n) \in \mathbb{R}_+ \times \mathcal{S}_{P_n^c}$ which is equation (15). $\square$

REFERENCES

Arkolakis, Costas, Arnaud Costinot and Andrés Rodríguez-Clare, 2012. "New Trade Models, Same Old Gains?," American Economic Review, vol. 102(1), 94–130.

Atkeson, Andrew and Ariel Burstein, 2008. "Pricing-to-Market, Trade Costs, and International Relative Prices," American Economic Review, vol. 98(5), 1998-2031.

Axtell, Robert L. 2001. "Zipf Distribution of U.S. Firm Sizes." Science, 293, pp.1818–20.

Baldwin, Richard and James Harrigan, 2011. "Zeros, Quality and Space: Trade Theory and Trade Evidence," American Economic Journal: Microeconomics, vol. 3(2), 60-88.

Bernard, Andrew B., Jonathan Eaton, J. Bradford Jensen and Samuel Kortum, 2003. "Plants and Productivity in International Trade," American Economic Review, vol. 93(4), 1268-1290.

Campo, Sandra, Emmanuel Guerre, Isabelle Perrigne and Quang Vuong, 2011. "Semiparametric Estimation of First-Price Auctions with Risk Averse Bidders," Review of Economic Studies, vol. 78 (1), 112-147.

Chaney, Thomas 2008. "Distorted Gravity: The Intensive and Extensive Margins of International Trade," American Economic Review, vol. 98(4), 1707-21.

Das, Sanghamitra & Mark J. Roberts & James R. Tybout, 2007. "Market Entry Costs, Producer Heterogeneity, and Export Dynamics," Econometrica, vol. 75(3), 837-873.

Del Gatto, Massimo, G. Mion and GIP. Ottaviano, 2007. "Trade Integration, Firm Selection and the Costs of Non-Europe," Working Paper CRENoS 200703, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia.

DeVore, Ronald, 1977. "Monotone approximation by splines," SIAM J. Math. Anal. 8, pp. 891-905.

Eaton, Jonathan and Samuel Kortum, 1999. "International Technology Diffusion: Theory and Measurement", International Economic Review, 40, 537-570.

Eaton, Jonathan and Samuel Kortum, 2002. "Technology, Geography, and Trade," Econometrica, vol. 70(5), 1741-1779.

Eaton, Jonathan, Samuel Kortum and Francis Kramarz, 2011. "An Anatomy of International Trade: Evidence from French Firms," Econometrica, vol. 79(5), 1453–1498.

Engelbrecht-Wiggans, Richard and Charles Kahn, 1998. "Multi-Unit Pay-Your-Bid Auctions with Variable Awards," Games and Economic Behavior, 23, 25–42.

Feenstra, Robert C., Robert E. Lipsey and Harry P. Bowen, 1997. "World Trade Flows, 1970-1992, with Production and Tariff Data," NBER Working Paper 5910.

Flambard, Véronique and Isabelle Perrigne, 2006. "Asymmetry in Procurement Auctions: Evidence from Snow Removal Contracts," Economic Journal, vol. 116(514), 1014-1036.

Grossman, Sanford J., 1981. "Nash Equilibrium and the Industrial Organization of Markets with Large Fixed Costs," Econometrica, vol. 49(5), 1149-72.

Guerre, Emmanuel, Isabelle Perrigne and Quang Vuong, 2000. "Optimal Nonparametric Estimation of First-Price Auctions," Econometrica, vol. 68(3), 525-574.

Hardle, Wolfgang, 1990. Smoothing Techniques With Implementation in S, Springer-Verlag, New York.

Helpman, Elhanan and Paul Krugman, 1987. Market Structure and Foreign Trade: Increasing Returns, Imperfect Competition, and the International Economy, MIT Press Books, The MIT Press.

Helpman, Elhanan, Marc J. Melitz and Stephen R. Yeaple, 2004. "Export Versus FDI with Heterogeneous Firms," American Economic Review, vol. 94(1), 300-316.

Helpman, Elhanan, Marc Melitz and Yona Rubinstein, 2008. "Estimating Trade Flows: Trading Partners and Trading Volumes," The Quarterly Journal of Economics, vol. 123(2), 441-487.

Hoderlein,S., L. Su and Halbert White, 2010. "Testing monotonicity in Unobservables with Panel Data," Working Paper, University of California San Diego.

Hortaçsu, Ali, 2002. "Mechanism Choice and Strategic Bidding in Divisible Good Auctions: An Empirical Analysis of the Turkish Treasury Auction Market," Working Paper, University of Chicago.

Hortaçsu, Ali, and Jakub Kastl, 2012. "Valuing Dealers' Informational Advantage: A Study of Canadian Treasury Auctions" Econometrica , vol. 80(6), 2511-42.

Hortaçsu, Ali & Steven L. Puller, 2008. "Understanding strategic bidding in multi-unit auctions: a case study of the Texas electricity spot market," RAND Journal of Economics, vol. 39(1), 86-114.

Kastl, Jakub, 2011. "Discrete Bids and Empirical Inference in Divisible Good Auctions," Review of Economic Studies, vol. 78 (3), 974-1014.

Kamien, Morton I. and Nancy L. Schwartz, 1993. Dynamic Optimization, North Holland.

Klemperer, Paul D. and Margaret A. Meyer, 1989. "Supply Function Equilibria in Oligopoly under Uncertainty," Econometrica, vol. 57(6), 1243-77.

Korostelev, A.P., and Alexandre B.Tsybakov,1993. Minimax Theory of Image Reconstruction, Lecture Notes in Statistics, v.82. Springer, NY.

Kortum, Samuel, 1997. "Research, Patenting and Technological Change," Econometrica, vol. 65(6), 1389-1419.

Krishna, Vijay, 2002. Auction Theory, Academic Press, San Diego.

Laffont, Jean-Jacques and Quang Vuong, 1996. "Structural Analysis of Auction Data," American Economic Review, Papers and Proceedings, 86, 414-420.

Li, Tong, Isabelle Perrigne and Quang Vuong, 2000. "Conditionally Independent Private Information in OCS Wildcat Auctions," Journal of Econometrics, 98(1), 129-161.

Matzkin, Rosa L., 2003. "Nonparametric Estimation of Nonadditive Random Functions," Econometrica, vol. 71(5), 1339-1375.

Melitz, Marc J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," Econometrica, vol. 71(6), 1695-1725.

Melitz, Marc J. and Giancarlo I. P. Ottaviano, 2008. "Market Size, Trade, and Productivity," Review of Economic Studies, vol. 75(1), 295-316.

Pagan, Adrian and Aman Ullah, 1999. Nonparametric Econometrics, Cambridge University Press, Cambridge.

Pehlivan, Ayse O. and Quang Vuong, 2010. "Estimation of the Market Clearing Price Under Discriminatory Pricing," Working Paper, Pennsylvania State University.

Reny, Philip J., 1999. "On the Existence of Pure and Mixed Strategy Nash Equilibria in Discontinuous Games," Econometrica, vol. 67(5), 1029-1056.

Simonovska, Ina, 2013. "Income Differences and Prices of Tradables," Working Papers 1015, University of California, Davis, Department of Economics.

Simonovska, Ina and Michael E.Waugh, 2013. "The Elasticity of Trade: Estimates and Evidence," Journal of International Economics, forthcoming

Vives, Xavier, 2011. "Strategic Supply Function Competition with Private Information," Econometrica, 79: 1919–1966.

Waugh, Michael E., 2010. "International Trade and Income Differences," American Economic Review, vol. 100(5), 2093-2124.

Wilson, Robert, 1979. "Auctions of Shares," The Quarterly Journal of Economics, vol. 93(4), 675-89.

Wolak, Frank A, 2003a. "Identification and Estimation of Cost Functions Using Observed Bid Data: An Application to Electricity Markets," In M. Dewatripont, L.P. Hansen, and S.J. Turnovsky,eds., Advances in Economics and Econometrics: Theory and Applications, Eighth World Congress, Volume II. New York: Cambridge University Press.

Wolak, Frank A, 2003b. "Measuring Unilateral Market Power in Wholesale Electricity Markets: The California Market 1998 to 2000," American Economic Review, Vol. 93, 425–430.

Table 1. Percentage of Manufacturing Imports for n = Germany	
France	16.6
Italy	14.0
Belgium	10.5
Japan	9.8
Netherlands	9.5
United States	9.4
United Kingdom	8.8
TOTAL	78.6

Note: Percentage of value of total manufacturing imports in the Eaton and Kortum (2002) sample.

Table 2. Coefficient of Variation of Unit Values across Exporters	
Mean	0.67
St. Deviation	0.40
Min	0.04
Max	2.56

Note: Coefficient of Variation is the ratio of st. deviation

of unit values to mean of unit values across exporters.

Table 3. Summary Statistics for A_{ni} for $n =$ Germany (in dollars)				
	Mean	St.Dev.	Min	Max
A_{Bel}	24,778,078	240,691,924	233	7,302,002,850
A_{Fra}	31,232,944	170,209,649	20	4,830,644,752
A_{Ita}	32,687,539	131,568,945	48	2,966,307,956
A_{Jpn}	24,383,660	323,489,959	2	9,892,275,446
A_{Ned}	21,252,720	51,390,764	93	680,094,647
A_{UK}	17,793,301	82,934,322	110	1,216,429,607
A_{US}	12,376,996	65,115,838	11	1,307,815,373
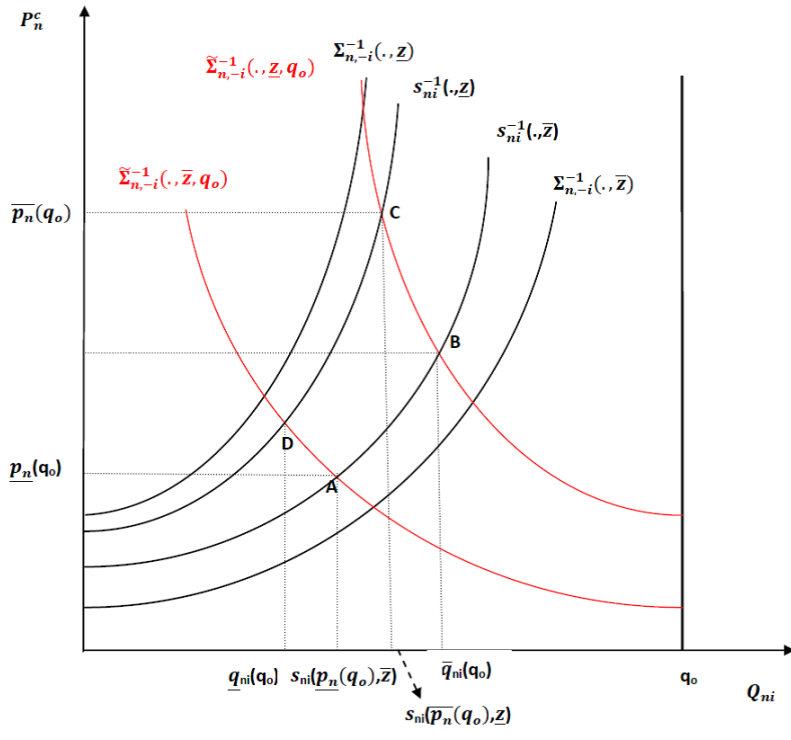
FIGURE 1: Identification of $c_{ni}^{\circ}(\cdot)$
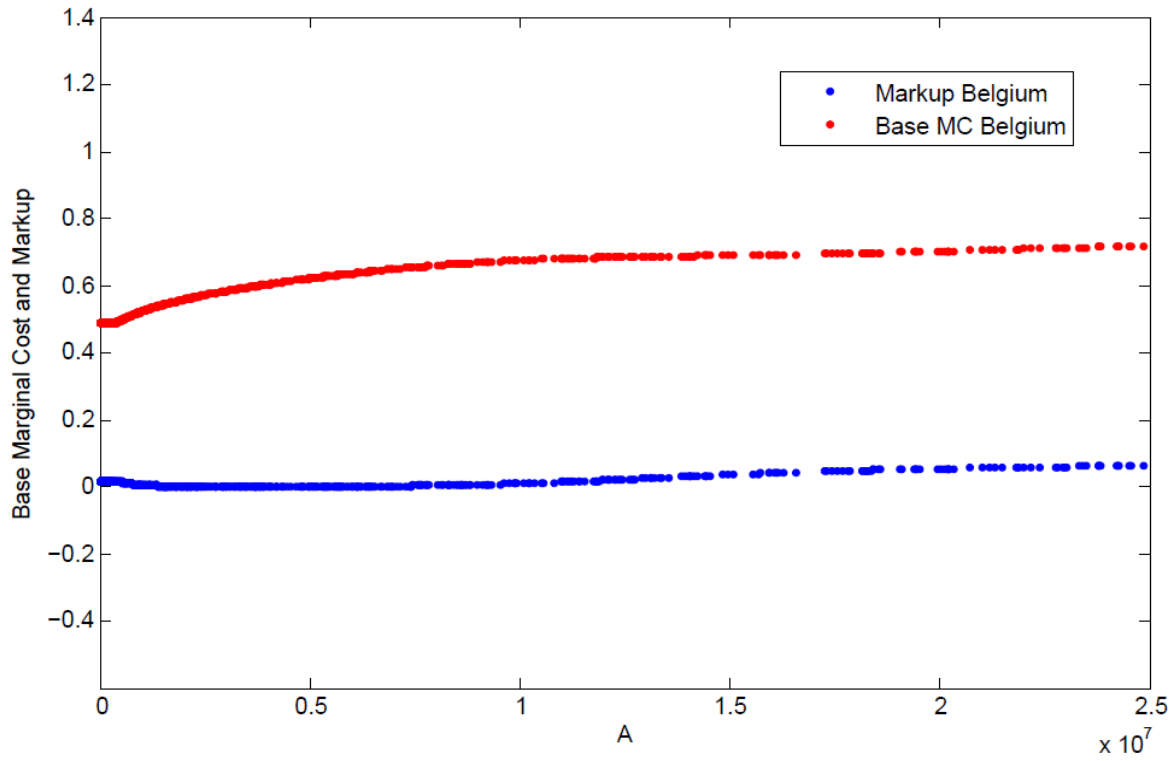
FIGURE 2: Estimates of $\widehat{c}_{ni}^{\circ,A}(\cdot)$ and Markup for Belgium
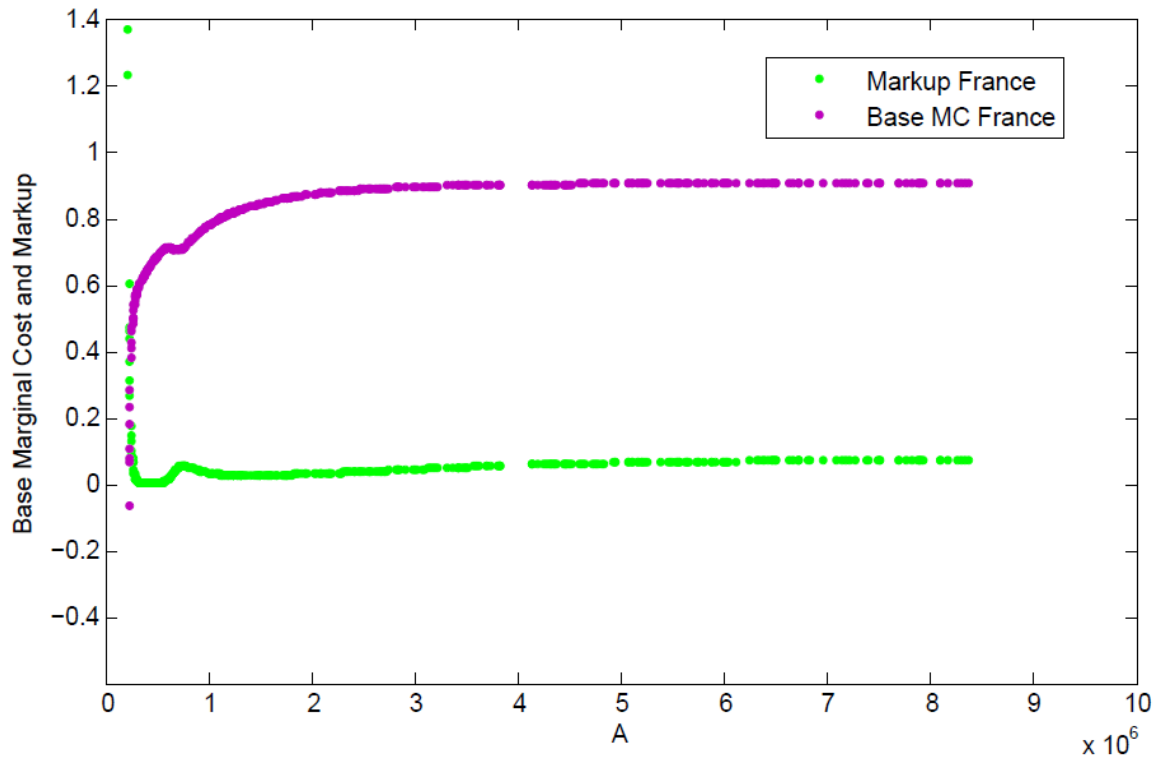
FIGURE 3: Estimates of $\widehat{c}_{ni}^{\,\circ,A}(\cdot)$ and Markup for France
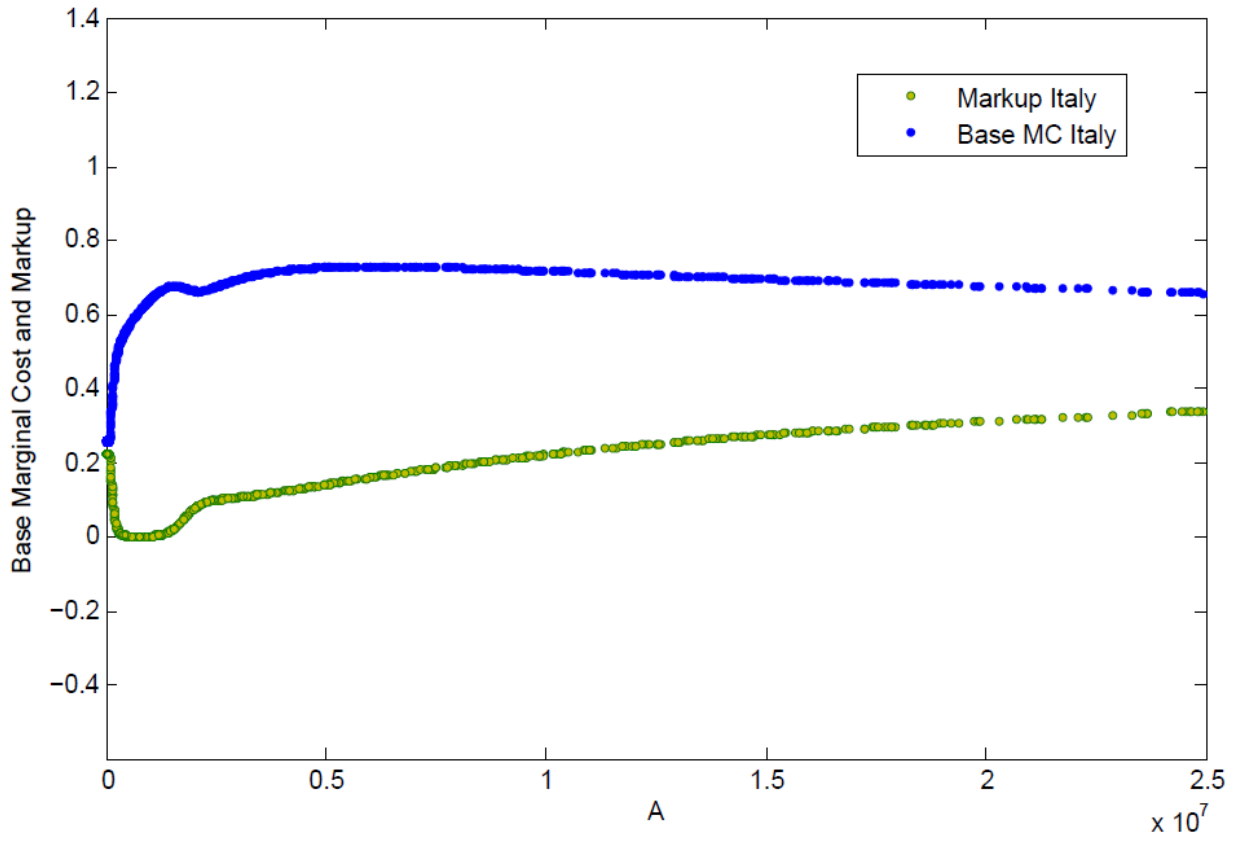
FIGURE 4: Estimates of $\widehat{c}_{ni}^{\circ,A}(\cdot)$ and Markup for Italy
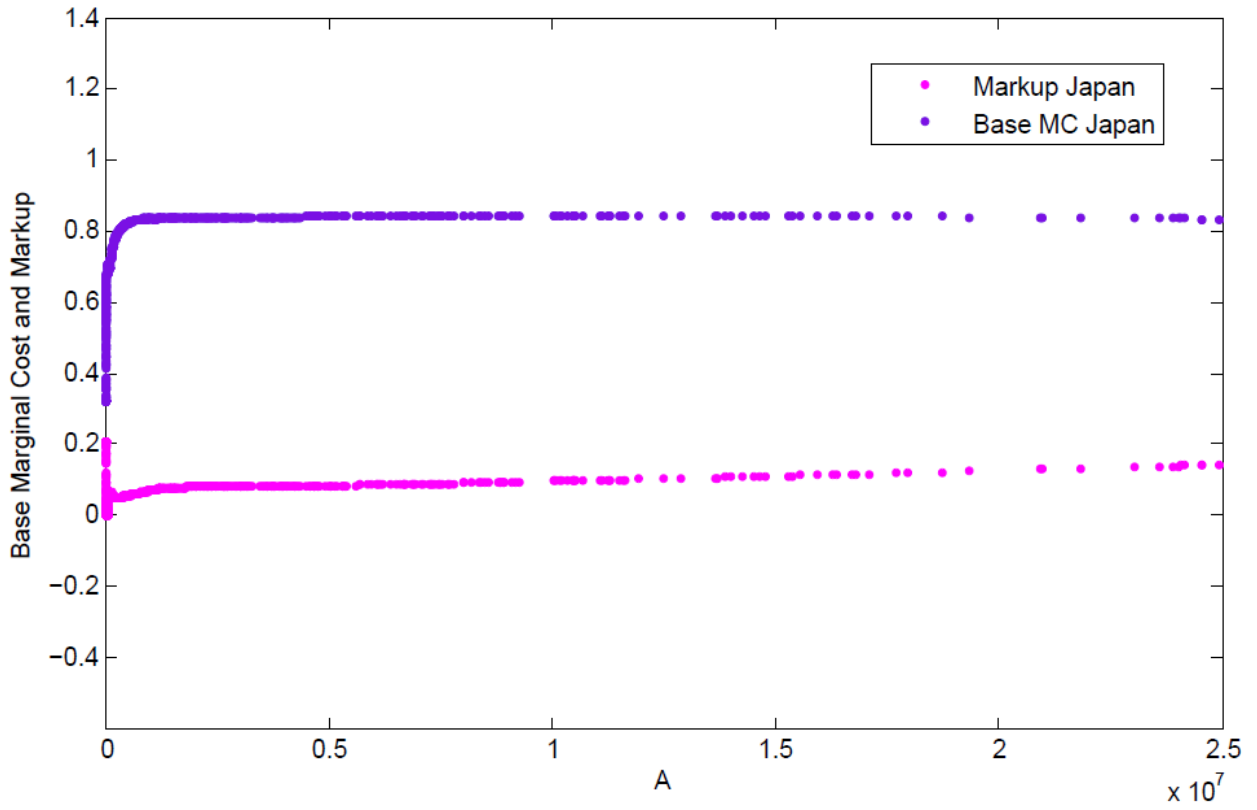
FIGURE 5: Estimates of $\widehat{c}_{ni}^{\circ,A}(\cdot)$ and Markup for Japan
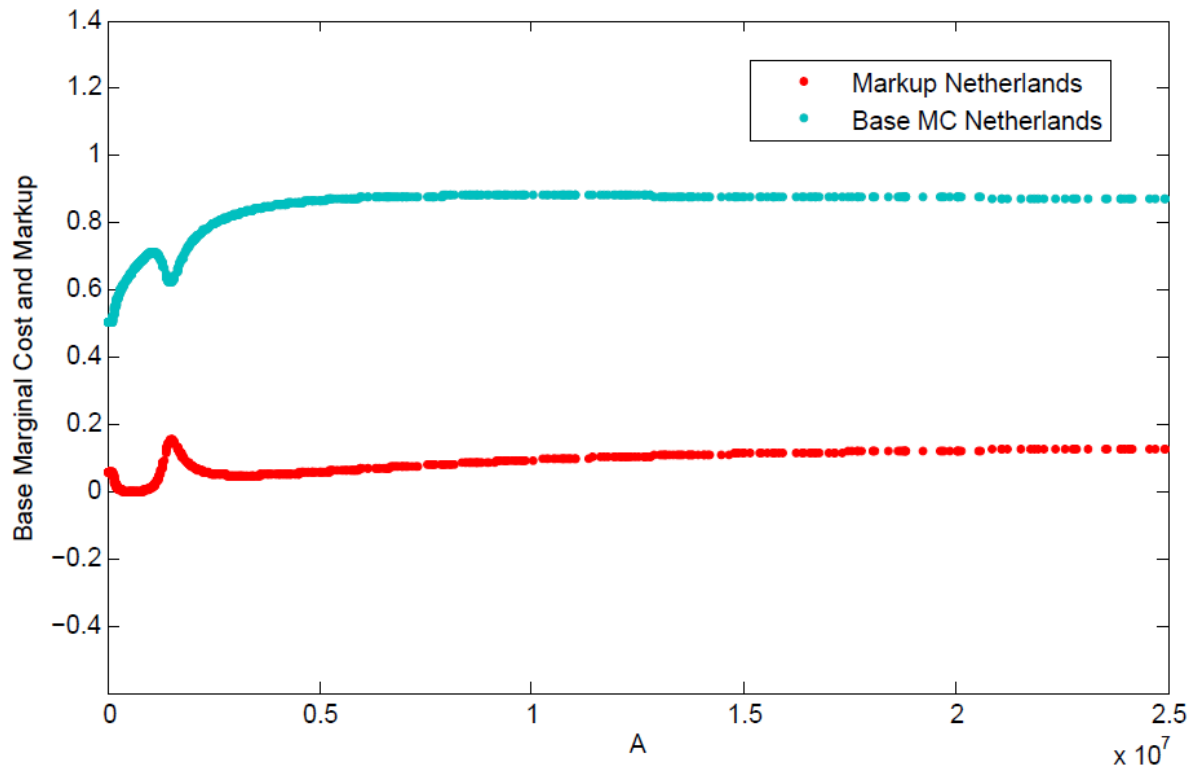
FIGURE 6: Estimates of $\widehat{c}_{ni}^{o,A}(\cdot)$ and Markup for the Netherlands
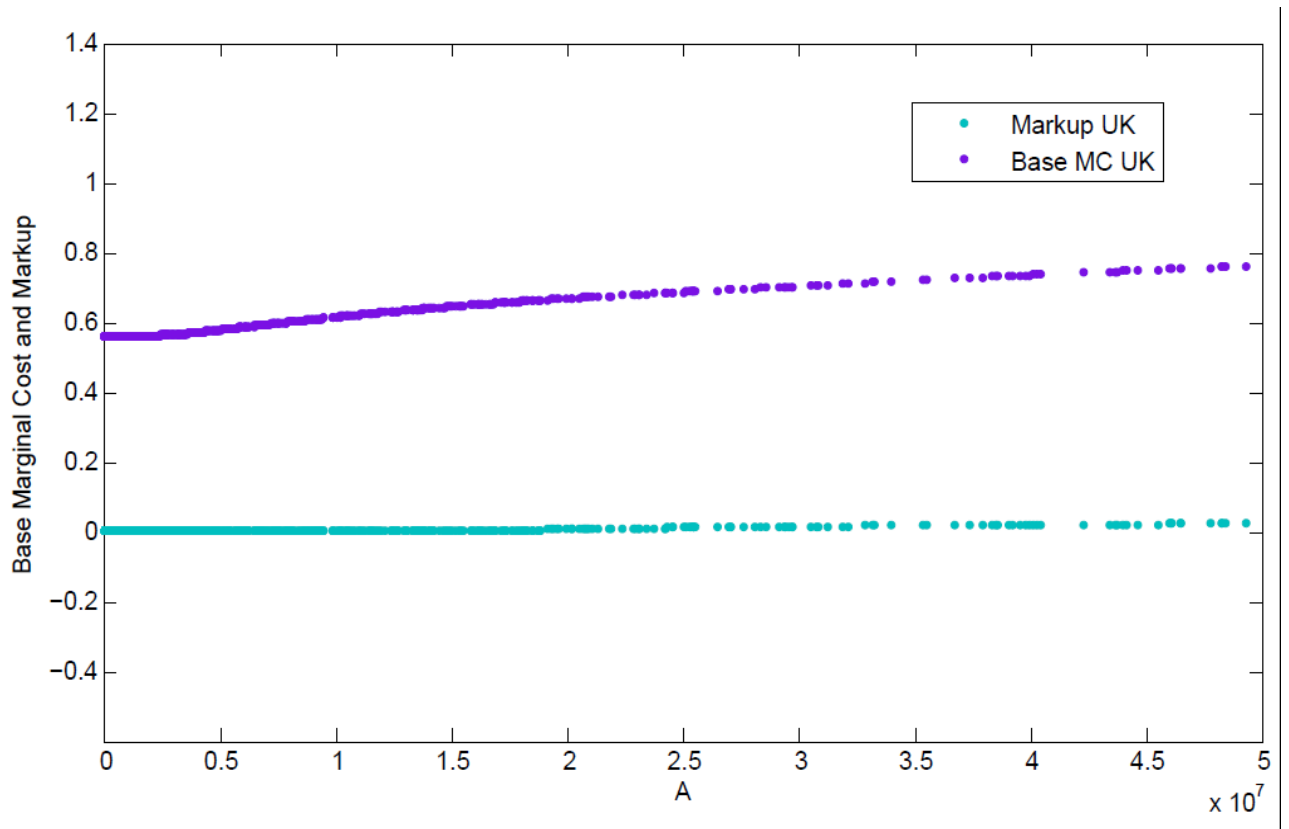
FIGURE 7: Estimates of $\widehat{c}_{ni}^{\circ,A}(\cdot)$ and Markup for UK
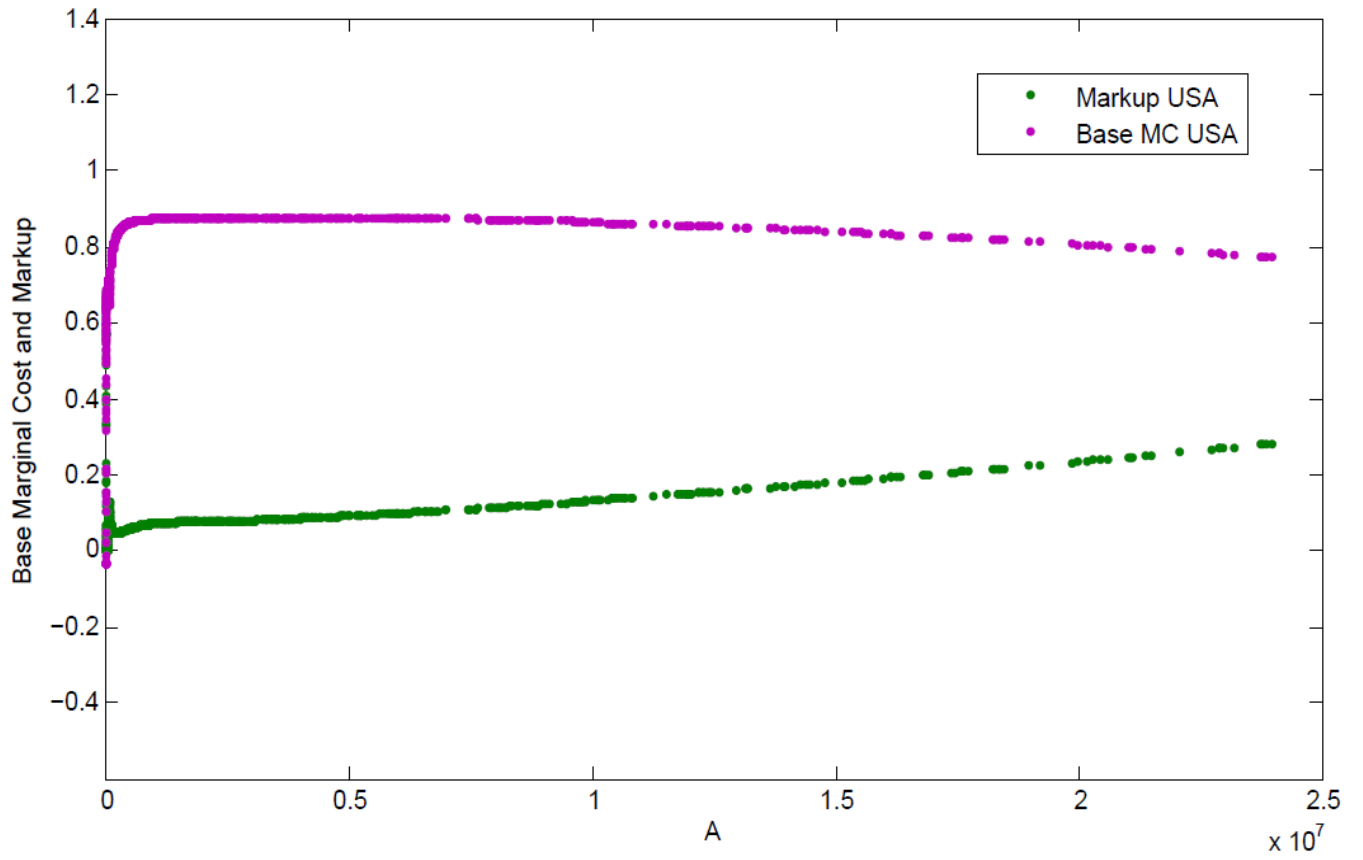
FIGURE 8: Estimates of $\widehat{c}_{ni}^{\circ,A}(\cdot)$ and Markup for US
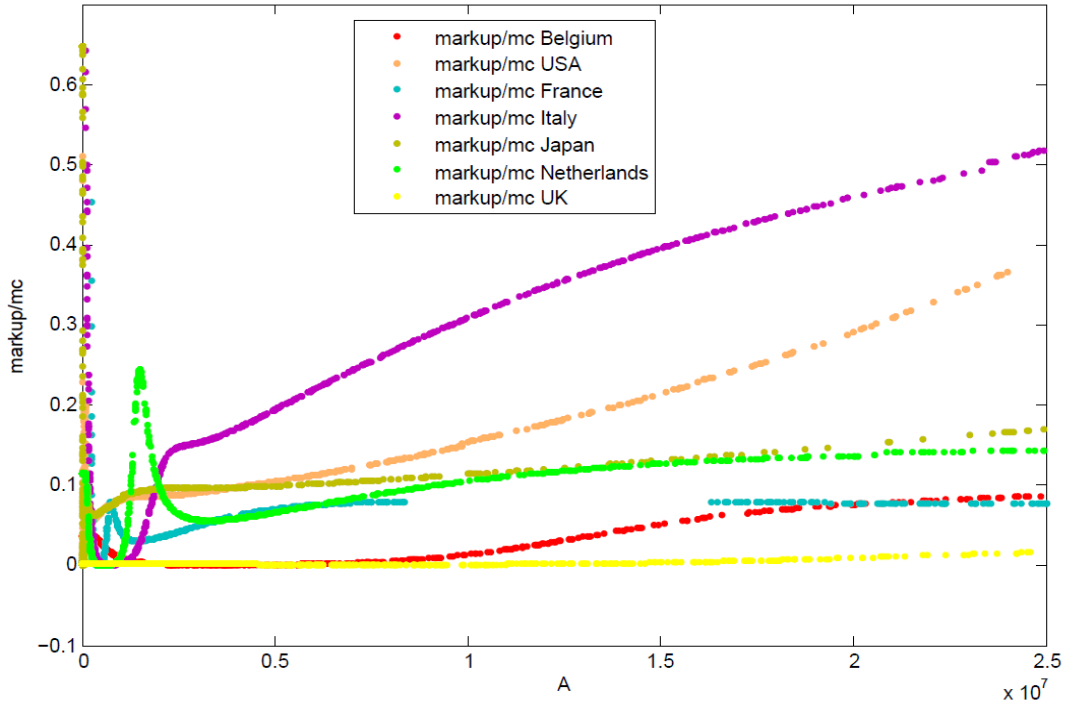
FIGURE 9: Markup to Base Marginal Cost Ratio for All Countries
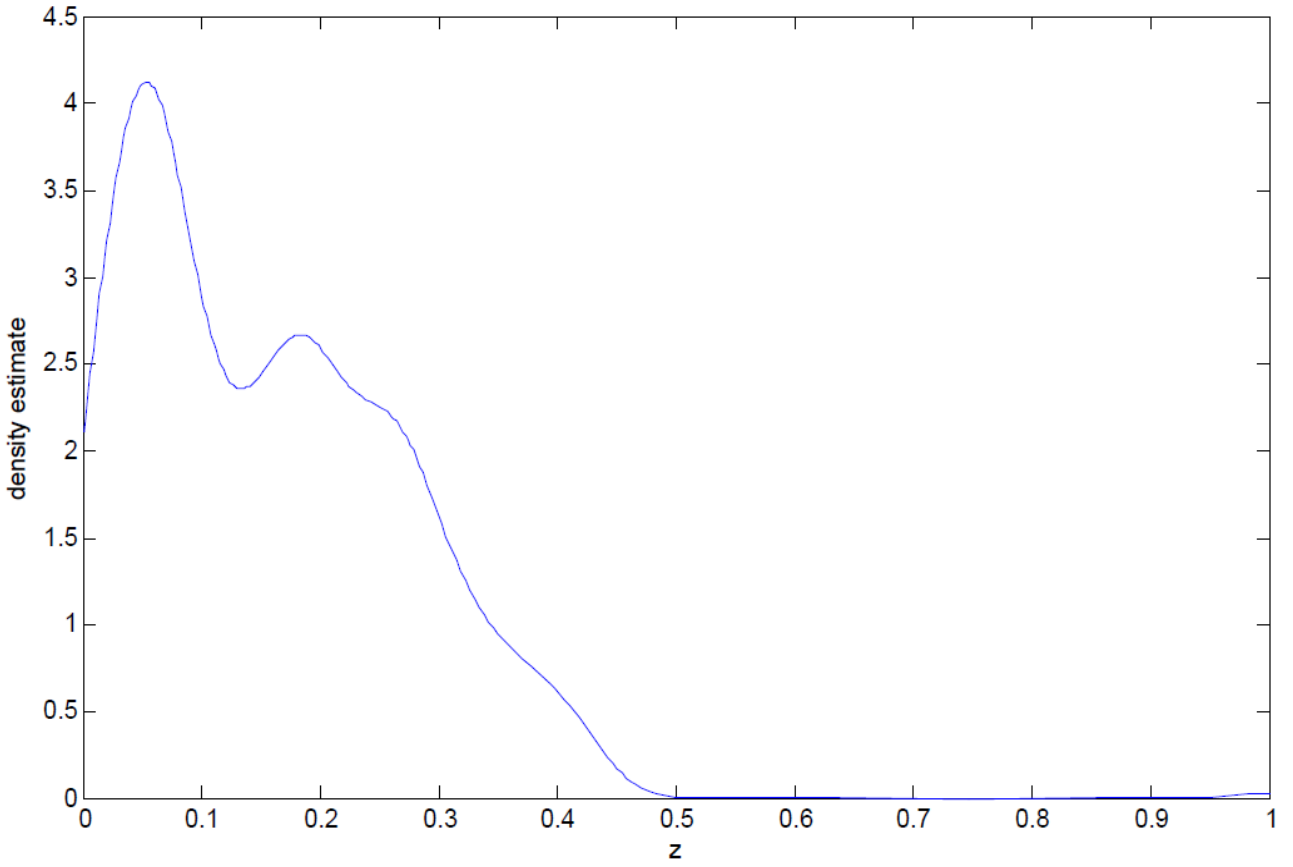
FIGURE 10: Estimated denstiy $\widehat{f}_{ni}(\cdot)$ for Belgium
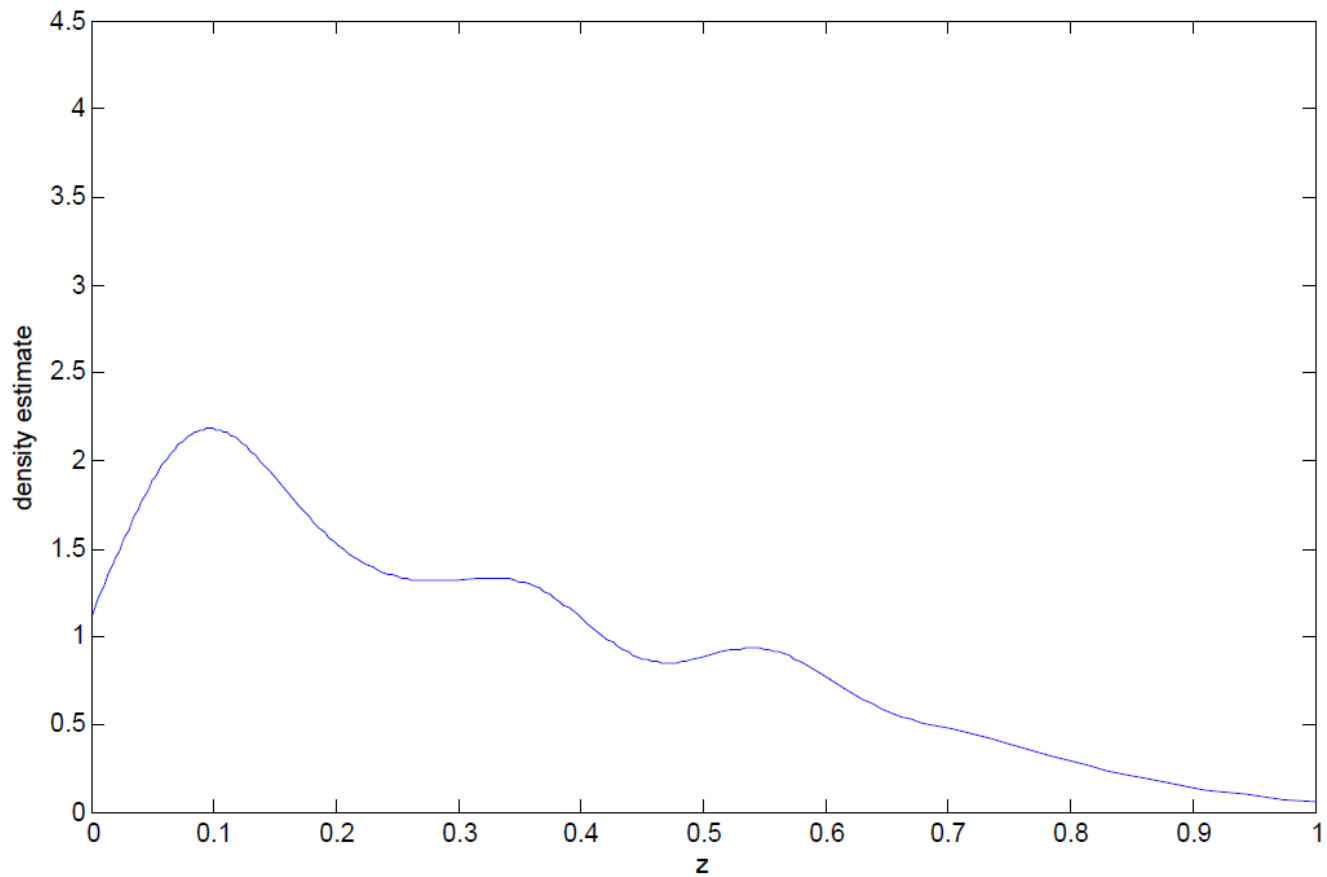
FIGURE 11: Estimated denstiy $\widehat{f}_{ni}(\cdot)$ for France
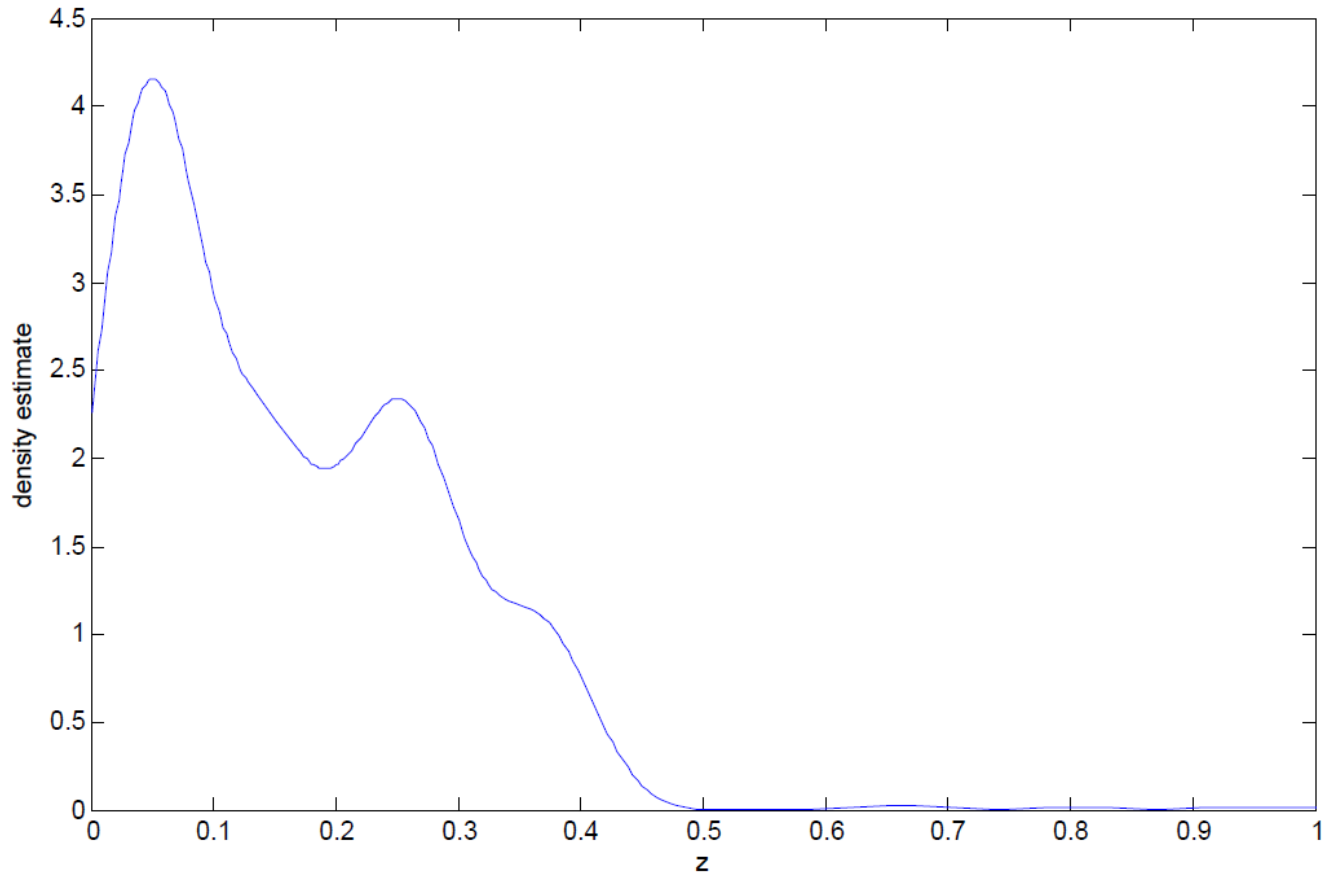
FIGURE 12: Estimated denstiy $\widehat{f}_{ni}(\cdot)$ for Italy
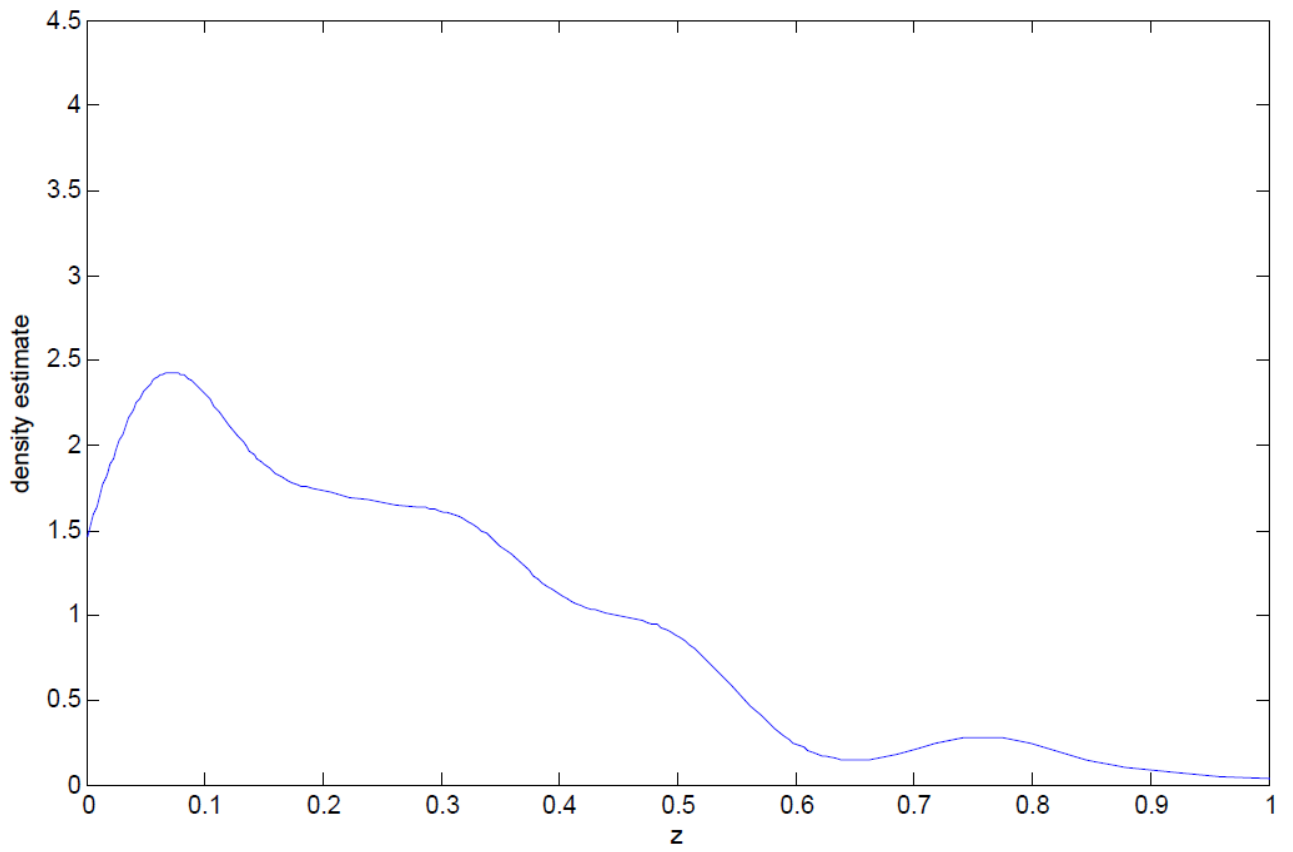
FIGURE 13: Estimated denstiy $\widehat{f}_{ni}(\cdot)$ for Japan
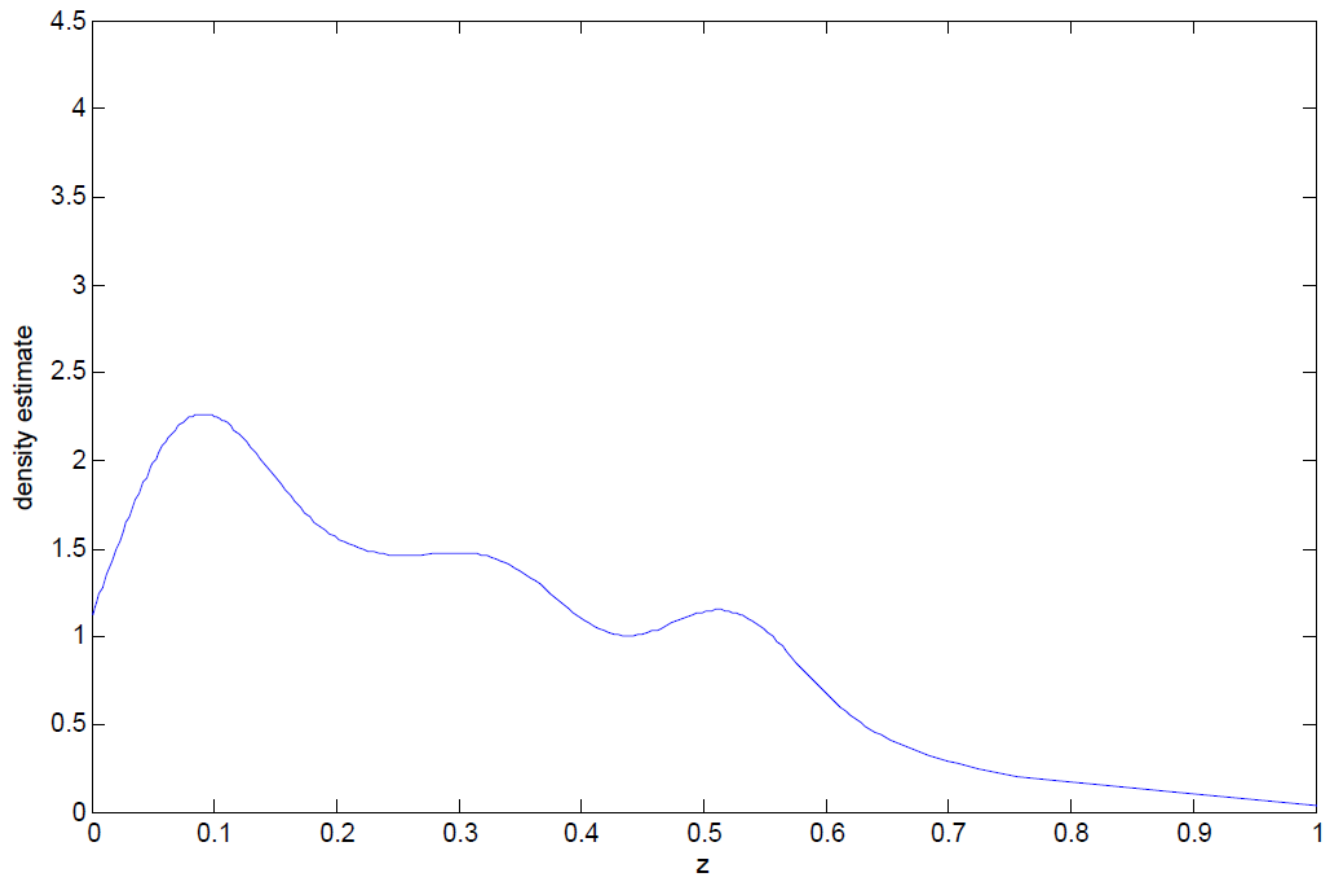
FIGURE 14: Estimated denstiy $\widehat{f}_{ni}(\cdot)$ for the Netherlands
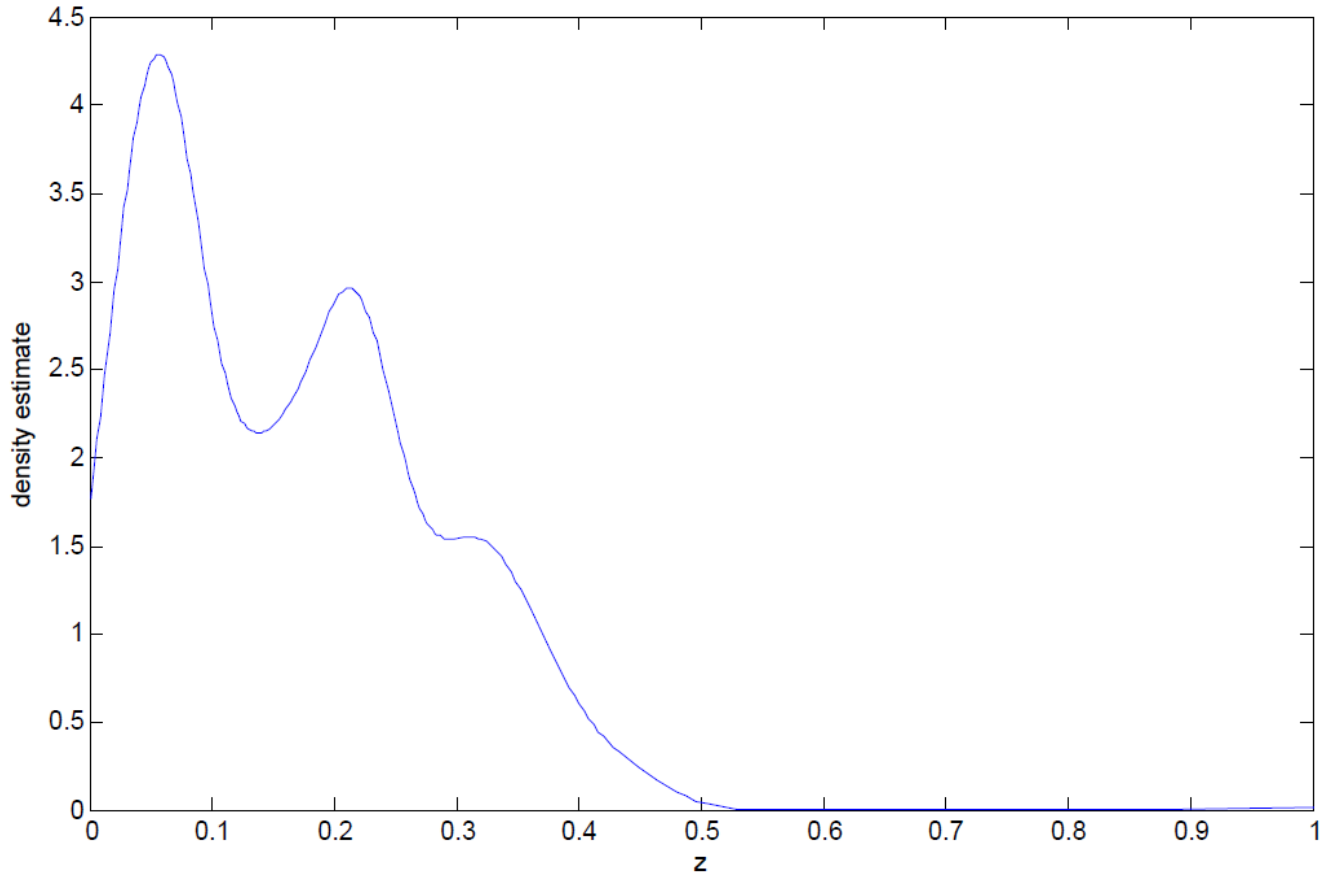
FIGURE 15: Estimated denstiy $\widehat{f}_{ni}(\cdot)$ for UK
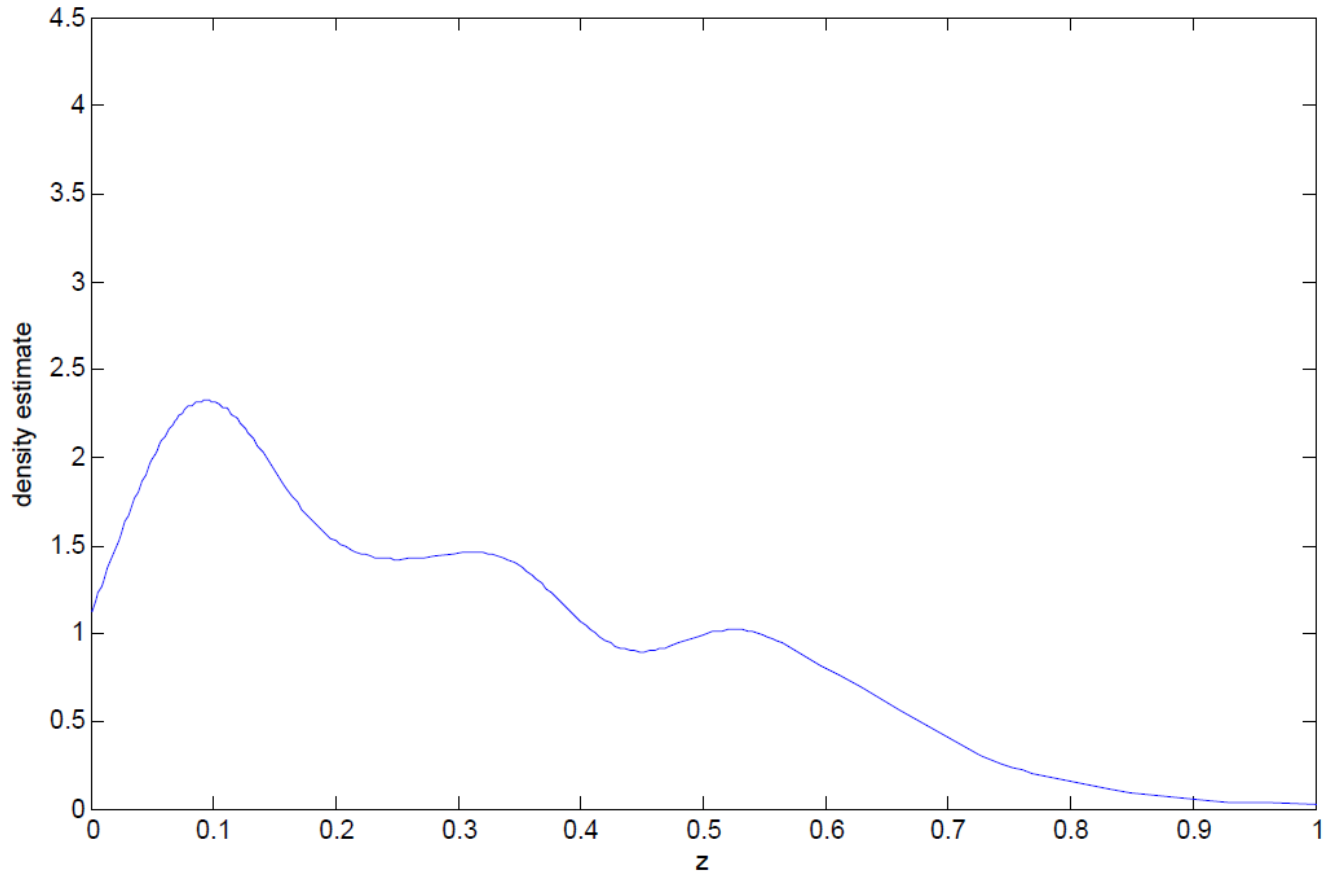
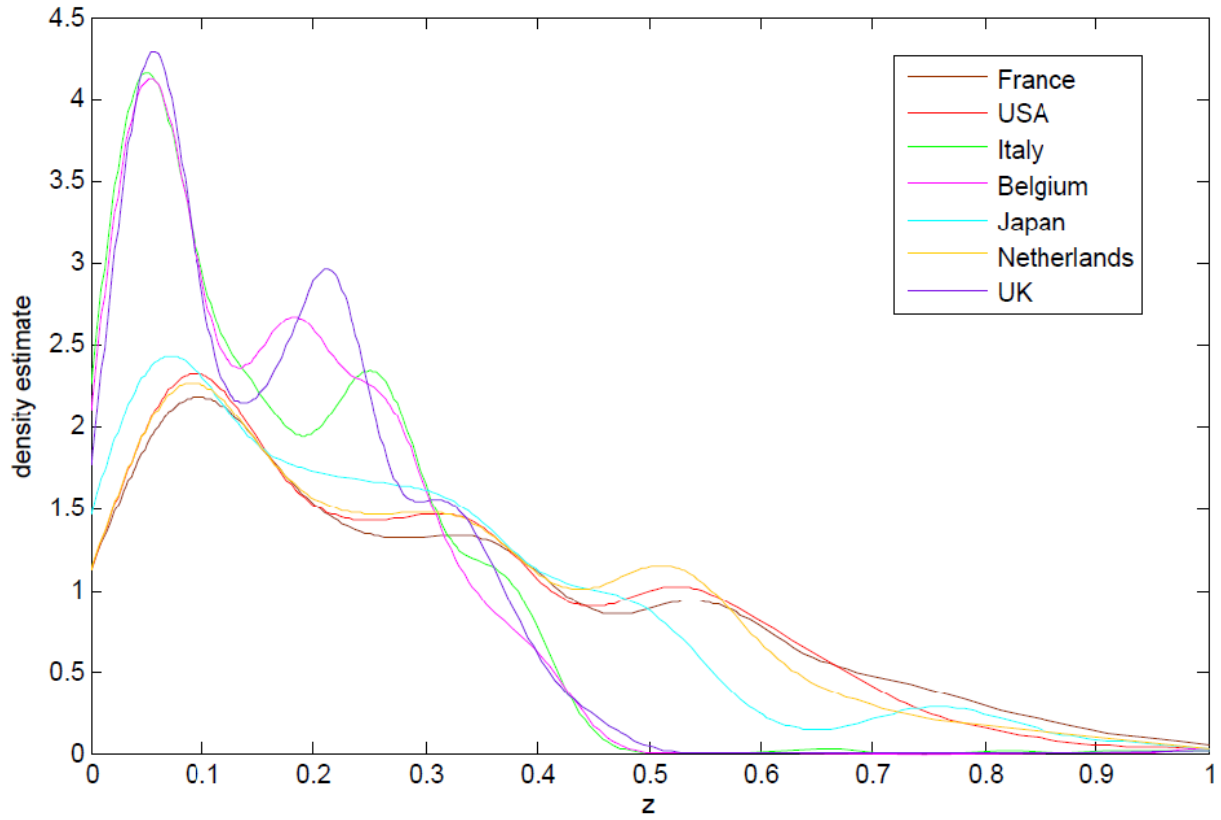**FIGURE 16: Estimated denstiy $\widehat{f}_{ni}(\cdot)$ for US**

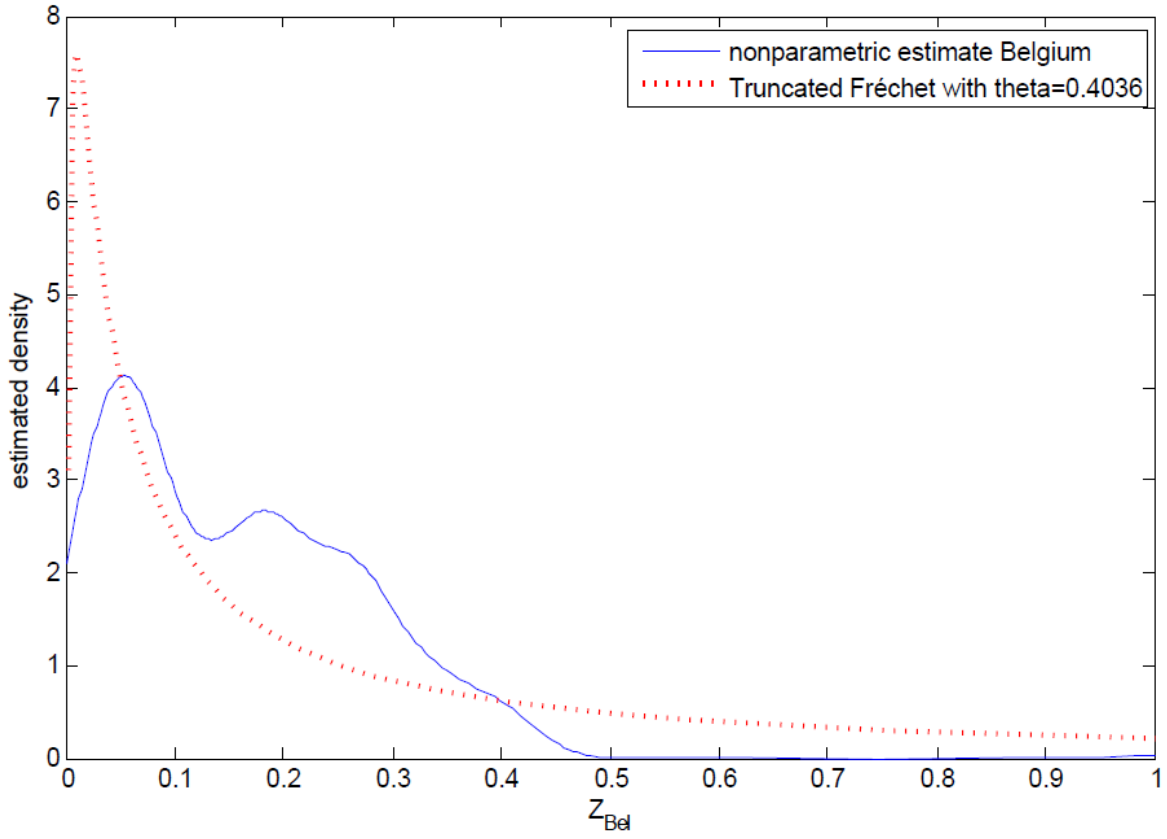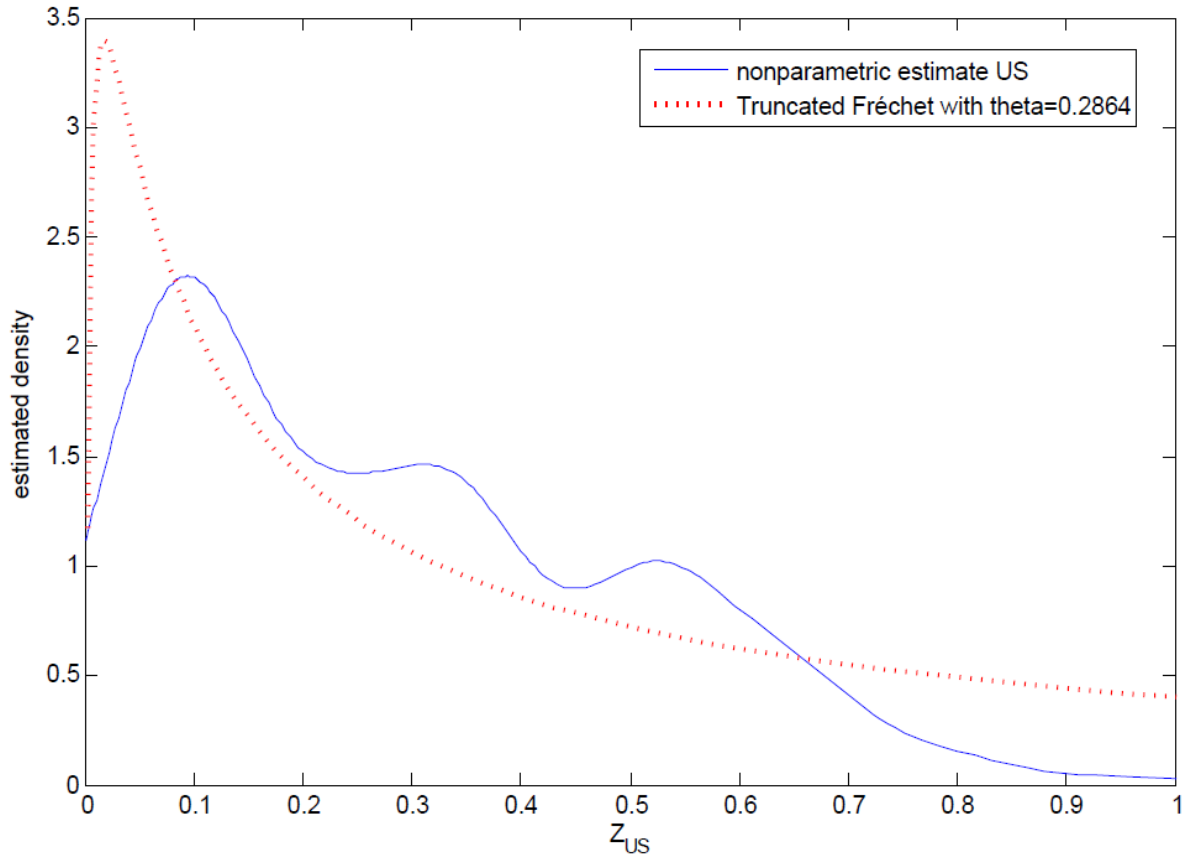**FIGURE 17: Comparison of Estimated Densities** $\widehat{f}_{ni}(\cdot)$

FIGURE 18: Nonparametric Estimate vs. Fréchet for Belgium

FIGURE 19: Nonparametric Estimate vs. Fréchet for US