88

Economie et Statistiques

Working papers du STATEC

août 2016

Productivity, Markups and International Trade:

The Case of Small Open Economy

Auteur: Umut Kilinç

Abstract

Empirical evidence suggests that exporter firms tend to charge higher markups than non-exporters, which is largely attributed to trade barriers. This study, however, finds that exporter firms have on average lower markups in Luxembourg.
According to the trade theory, trade barriers are not the only factor that can influence markups, and under certain conditions, markups can be lower for exporters.
This paper attempts to assess the patterns of micro-level markup variation due to differences in the characteristics of export destination markets. Estimating export demand functions using detailed product-level data, this study shows that markups are particularly low for exports to large, nearby, highly productive and the EU member countries. The main trade partners of Luxembourg exhibit these characteristics which explain the negative correlation of markups with firms' export intensity. The trade-driven markup variation has important implications for applied research. In a small open economy, exporters' productivity may be biased downward when measured by nominal input and outputs. Nominal productivity may also erroneously lead to a negative link between openness to trade and allocative efficiency.

Productivity, Markups and International Trade: The Case of Small Open Economy*

Umut Kılınç[†]

Abstract

Empirical evidence suggests that exporter firms tend to charge higher markups than non-exporters, which is largely attributed to trade barriers. This study, however, finds that exporter firms have on average lower markups in Luxembourg. According to the trade theory, trade barriers are not the only factor that can influence markups, and under certain conditions, markups can be lower for exporters. This paper attempts to assess the patterns of micro-level markup variation due to differences in the characteristics of export destination markets. Estimating export demand functions using detailed product-level data, this study shows that markups are particularly low for exports to large, nearby, highly productive and the EU member countries. The main trade partners of Luxembourg exhibit these characteristics which explain the negative correlation of markups with firms' export intensity. The trade-driven markup variation has important implications for applied research. In a small open economy, exporters' productivity may be biased downward when measured by nominal input and outputs. Nominal productivity may also erroneously lead to a negative link between openness to trade and allocative efficiency.

Keywords: demand estimation, export, markup, micro data, productivity, translog production function

JEL Classification: L11, L16, F14, F43, D24

1 Introduction

International trade acts as a selection mechanism that allows only the most successful producers to seek new profit opportunities in foreign markets. Once firms sell their products globally, this does not only affect their profits but also their size in the domestic economy. Establishments that enter into export markets tend to expand their input shares in the home country to meet the foreign demand. The expanding effect of exporting on firm size creates additional competitive pressure on non-exporting local producers and forces the less productive ones to shrink or exit. From a macro perspective, openness to international trade reallocates the resources of the home country towards more efficient uses so that enhances aggregate productivity growth for a given technological frontier.

The functioning of the resource allocation mechanism is critical for an economy to enjoy the gains from trade. Obstacles to factor mobility or to firm exit or entry into

*This work is done as a part of a research project co-funded by the Marie Skłodowska-Curie actions and the FNR, Luxembourg. This work is independent of the ANEC/STATEC and all errors are mine.

[†]ANEC / Institut national de la statistique et des études économiques du Grand-Duché du Luxembourg (STATEC), 13 rue Erasme, L-1468 Luxembourg, E-mail: umut.kilinc@statec.etat.lu, Phone: +352 247-88479.

domestic and foreign markets can interrupt or reverse the link between international trade and allocative efficiency. Monitoring the patterns of trade and resource allocation, therefore, is of particular importance for the economic policy. To ensure that foreign trade influences the reallocation of resources in the right direction, one needs to verify two properties by micro data. First, openness to international trade induces a selection that only allows most productive establishments to enter into export markets. Second, firms expand their input share in the domestic economy, when they enter into export markets (e.g. Melitz and Trefler, 2012). The second property is not difficult to verify using micro data, so that it would be sufficient to compare firms' input shares with their export status. Verifying the first property, however, requires computing micro-level productivity which is not straightforward in the context of international trade. The standard measures of firm-level productivity, which is based on nominal input and outputs deflated by aggregate price indices, embody price effects. These price effects are in the form of price-cost markups that are endogenous to firms' trade activities. The nominal or revenue productivity, therefore, can be a distorted measure of the technical efficiency in production and bias the analysis of the link between productivity and export status.

This study attempts to detect the patterns of markup variation due to firms' exporting activities and to understand the importance of this markup variation for the analysis of the link between productivity and trade. The first part of the study estimates markups and productivity for manufacturing firms in Luxembourg through a production function specification and finds that both are negatively correlated with the export intensity. To understand whether price effects bias the productivity measurement, a proxy for quantity productivity is retrieved from the production function estimates. The quantity productivity indicates that exporters are more productive than domestic establishments, which verifies that export market section is based on productivity. The second part of the empirical analysis introduces volume and quantity data for internationally traded products and estimates export demand functions to assess the factors driving the markup variation at the micro-level. The results provide insights into how export destination market characteristics influence the markups of exporters. The analysis detects significant markup variation for products exported to destinations with different characteristics in terms of market size, productivity advantage, distance and the EU membership status.

Besides showing that markups can be lower for exporters than for non-exporters, this study provide new empirical evidence on the role of factors other than trade barriers in shaping exporters' markups. The analysis goes beyond the comparison of exporters with non-exporters, and the markup variation within the group of exporters are analyzed using detailed micro data. The next section describes a theoretical scenario where exporters have lower markups than non-exporters based on Melitz and Ottaviano (2008). The third section recovers firm-level revenue productivity and markups from the structural estimation of a production function. The forth section estimates an export demand function and recovers the average markup gap among alternative product groups that are categorized according to the characteristics of the markets where they are sold. The fifth section interprets the empirical findings from the perspective of the trade theory.

2 Small Open Economy in the Melitz-Ottaviano Model

Empirical papers analyzing the interaction among markups, exporting and productivity at the firm-level generally focus on the role of trade barriers. Bernard et al. (2003)

suggest that trade barriers tighten the selection to export markets. Firms facing barriers in the export market raise their markups rather than producing more at a lower price. De Loecker and Warzynski (2012) provide evidence that exporting firms' price-cost markups are significantly higher than non-exporters, and firms experience an instant increase in markups upon entry into export markets. When markups are higher for exporters, the revenue productivity would overestimate exporters' actual productivity. In Luxembourg's manufacturing, however, revenue productivity is lower for exporters than for non-exporters. If this is because of the markup variation, then the markups must be not higher but lower for Luxembourg's exporters. Empirical findings on low-markup exporters are limited, if not absent, but there are theoretical models where exporters may have lower markups under certain conditions. Melitz and Ottaviano (2008), for instance, suggest that exporters of a small open economy face harsher competition in the foreign market in comparison to the local market, so that exporter' markups can be lower than their domestic counterparts. The markups of exporters can be further lower, when the small home country exporters have overall productivity disadvantage, so that the perceived competition is more intensive in the foreign markets. Conversely, in the small domestic market, profit opportunities are limited and competition is less intensive, in which case non-exporting firms find it optimal to stay small and charge higher price-cost markups. Thus, the expected positive markup difference between exporters and non-exporters may actually vanish or even be negative in a small highly open economy, which is the opposite of the trade between symmetric countries.

The theoretical model in this section considers a two-country world with symmetric trade barriers, but asymmetric country size and efficiency distributions. The theoretical setup is identical to the Melitz-Ottaviano model where the market size and productivity advantage play important roles in shaping the relationship between openness to international trade and firm dynamics. The model, for instance, predicts that the markup difference of exporting firms from non-exporters may disappear or become negative, when the home country is sufficiently small or has productivity disadvantage. In the two-country model with symmetric trade barriers ($\tau^h = \tau^f = \tau$), the markups for domestically sold and exported goods are as follows in the equilibrium.

$$\mu_D^h = \frac{1}{2}\left(c_D^h - c\right) \tag{1}$$

$$\mu_X^h = \frac{1}{2}\left[\tau c_X^h - (2-\tau)\, c\right] \tag{2}$$

In the above formulation, μ_D^h represents the markup for a domestically sold good that is produced by a home country's firm with marginal cost c, and μ_X^h is the markup for exported goods of the home country's firm. The marginal cost (c) is an inverse indicator of productivity which is exogenous and drawn from a certain distribution. c_X^h is the cut-off efficiency level to enter into the export market and c_D^h is the cut-off level for the domestic market. The cut-off levels satisfy c_X^h, $c_D^h > c$ in equilibrium for every firm with the efficiency level of c, and $\tau > 1$ is the per-unit trade cost. In this setting, markups for domestically sold goods are higher than those of exported products ($\mu_D^h > \mu_X^h$), only if the following condition is satisfied.

$$c_D^h + c > \tau\left(c_X^h + c\right) \tag{3}$$

The condition given in equation 3 is satisfied, when c_X^h is sufficiently low, and c_D^h is sufficiently high.

In the Melitz-Ottaviano model, the productivity advantage can be introduced through the upper bound of the efficiency distribution. When the home country's efficiency bound (c_M^h) is higher than that of the foreign country (c_M^f), this implies that firms in the foreign market draw from an advantageous distribution. Thus, lower efficiency bound gives the foreign country a productivity advantage over the home country. In the case of asymmetric efficiency bounds and country size, the efficiency cutoffs for market entry can be written as follows.

$$c_D^h = \left[\frac{\Psi \left[\left(c_M^h\right)^k - \left(c_M^f/\tau\right)^k \right]}{L^h \left(1 - \tau^{-2k}\right)} \right]^{1/(k+2)} \tag{4}$$

$$c_X^h = \left[\frac{\Psi \left[\left(c_M^f\right)^k - \left(c_M^h/\tau\right)^k \right]}{L^f \left(\tau^{k+2} - \tau^{2-k}\right)} \right]^{1/(k+2)} \tag{5}$$

where $\Psi = 2\gamma\,(k+1)\,(k+2)\,f_E$.

In the above formulation, L^h is the number of consumers in the home country each supplying one unit of labor. Therefore, L^h represents the home country's size, L^f is the size of the foreign trade partner. c_M^h and c_M^f are the upper bounds of the home and foreign countries' efficiency distributions from which firms draw the productivity. Ψ is a composite term that is a function of the exogenous parameters characterizing consumer preferences, productivity distribution and market structure such as the fixed-cost of entry (f_E), product differentiation (γ) and dispersion in productivity distribution (k).

In this two-country model, therefore, $\partial c_D^h/\partial L^h < 0$, $\partial c_D^h/\partial c_M^h > 0$, $\partial c_D^h/\partial c_M^f < 0$, $\partial c_X^h/\partial L^f < 0$, $\partial c_X^h/\partial c_M^h < 0$ and $\partial c_X^h/\partial c_M^f > 0$. This implies that if the home country is sufficiently smaller than its trade partner or the foreign country has a productivity advantage ($c_M^h > c_M^f$), the markups for domestically sold goods are more likely larger than markups for exported goods.

The effect of the changes in τ on the markup difference between exported and domestically sold products is not straightforward to see directly from equation 4 and 5. In the appendix part, I show that when the foreign country has a productivity advantage, the markup condition given in equation 3 is more likely satisfied for lower values of τ.

The condition given by equation 3 implies that markups tend to be smaller for exports than for domestically sold products in a special case where the home country is smaller and disadvantaged in terms of productivity, while trade barriers are symmetric and low. I refer this as the small open economy case which is particularly relevant in the context of Luxembourg. This is because the size of the domestic economy is considerably small and the local manufacturing sector is technologically less advanced relative to its main trade partners such as Germany and France. Moreover, Luxembourg's trade with the other EU countries accounted for more than 85 percent of total exports and imports during the last decade. The mutual free trade agreements among the EU member states and their geographical proximity provide some ground for the assumption of low and symmetric trade barriers. The similarities between the assumptions of the small open economy case and the observed dynamics in Luxembourg's data will be further discussed in the following sections.

3 Productivity, Markups and International Trade

This section makes use of firm-level measures of productivity and markups that are retrieved from the estimation of a translog production function. The advantage of using translog functional form is that factor elasticity parameters can be estimated for each firm and every time period, so that one can retrieve time-varying and firm specific markups. Majority of 2-digit manufacturing industries in Luxembourg is populated by only a few number of firms that is not sufficient to estimate an industry-specific production function. Thus, I first estimate the production function for the entire sample of manufacturing firms while controlling for industry fixed-effects. Alternatively, I also group the 2-digit industries into four categories according to their predefined technology level and estimate the production function separately for each group. Every production function is estimated through a control function approach that is described in the appendix along with the presentation of and a discussion on how to recover markups from production function estimates. The production function estimation results and tests on instruments are also displayed in the appendix in Table 8, 9 and 10. The conclusions derived from production function estimations do not significantly differ for alternative sample specification. Thus, I evaluate the results based on the production function estimation using the entire sample of firms. The empirical analysis in this section is replicated using the estimates from the disaggregated production functions, and the results are displayed in the appendix. Table 11 shows average factor elasticities retrieved from alternative production function estimations. Table 13 displays a correlation matrix, and Figure 7 depicts the scatter plots of markups and productivity against export intensity where the productivity and markup measures are based on the disaggregated production function estimations.

3.1 Dataset for Productivity Analysis

The main firm-level dataset used in this study is a subset of the Structural Business Survey (SBS) of Luxembourg which consists of nominal output and input expenditures of manufacturing firms for the period from 1996 to 2011[1]. The output variable is represented by the nominal value of produced goods and services for a given year deflated by the 2-digit industry-level producer price index. The intermediate inputs are the consumption of intermediate goods and services for a given year deflated by the intermediate input price index that is at the 2-digit level. The labor input is the number of full and part time employees, where the number of part time employees is re-scaled based on the ratio of total annual working hours of part to full time employees. The capital stock is constructed using investment data that is categorized into six asset groups. The investment data is deflated by the 2-digit level price index for capital goods and services. The description of the method of capital stock construction can be found in the appendix. The secondary source of firm-level data is the extended Business Register which contains firm-level volume of exports that are based on the VAT declarations and classified as intra- and extra-EU exports. In the appendix, Table 7 provides descriptive statistics on the variables used in

[1]The SBS database does not cover the entire population but a subsample of firms operating in the manufacturing sector of Luxembourg. In the appendix, Figure 4 compares the aggregates of the estimation sample with the industry-level macro indicators from the National Accounts Statistics database. The sample of the micro data covers more than 70 percent of the population, while representativeness is slightly lower before 2000. In the appendix, Figure 5 compares the degree of openness to international trade between the micro-sample and the macro indicator. The share of exports in revenues does not significantly differ between the sample and micro data aggregates.

the production function estimation.

3.2 Production Function Estimation Results

This section evaluates the production function estimation results and discusses the implications of the small open economy case for the measurement and analysis of productivity. For alternative firm groups, Table 1 presents the average TFP, markup, export intensity, labor share, firm size and price-cost margin (PCM). The PCM is introduced as a measure of profitability that is ideally positively correlated with markups, so that I can obtain some insights into the robustness of the markup measure.[2] The TFP is the revenue productivity that is based on nominal input and outputs deflated by the 2-digit price indices. The calculation of the TFP, markup and PCM are described in the appendix, and the export intensity is the ratio of nominal exports to revenues, all of which are averaged using firms' output shares as the weights. Labor share is the total number of employees in each group divided by the total number of employees in the entire manufacturing sector. Average firm size is the mean of the number of employees. Table 1 further classifies manufacturing firms as the establishments exporting within and outside of the EU. Thus, the Extra-EU exporters are the firms that export to the countries other than the EU members, regardless of whether they also export to the EU member states.

Table 1: Productivity, Markups and Export Intensity[a]

	TFP	Markup	PCM	Exp.In.	Firm Size	Share
Industry Total	1.55	1.13	1.14	0.62	145	1.00
Exporters	1.55	1.13	1.14	0.67	168	0.89
Non-Exporters	1.61	1.29	1.16	0.00	58	0.11
Intra-EU Exporters	1.55	1.13	1.14	0.68	166	0.86
Non-Intra-EU Exporters	1.60	1.25	1.16	0.03	72	0.14
Extra-EU Exporters	1.53	1.10	1.12	0.72	245	0.69
Non-Extra-EU Exporters	1.62	1.23	1.19	0.34	72	0.31

[a] *Exp. In.* is the export intensity measured by exports to revenues ratio. *Share* represents each groups' labor share in the industry total. *Firm Size* is the average number of workers employed by firms.

Table 1 shows that Luxembourg's manufacturing sector exhibits a high degree of openness to international trade with an average firm exporting 62% of its output. The annual average labor share of non-exporting firms is only 11%. Non-exporting firms have on average higher markups and PCM than exporters regardless of the type of exports considered in the comparisons. Moreover, the average TFP of non-exporters is higher than those of exporters, which contradicts with the prediction that more productive firms are more likely to export. Classifying firms as intra- and extra-EU exporters further reveals that the TFP is higher for the firm groups that have higher markups. This underlines the possibility that the TFP indicator is influenced by markups that are higher for non-exporters.

The categorization of firms as exporters and non-exporters has some shortcomings, when analyzing of the patterns of international trade with micro data. This is because

[2]The appendix contains a discussion on how to recover markups from production estimates. Table 12 and Figure 6 provide evidence to evaluate the robustness of alternative markup measures.

most firms operate simultaneously in the local and international markets. An exporting firm, for instance, may operate mainly in the domestic market and sells a larger portion of its products within the home country. While such an exporter may behave more like a domestic firm, other exporters that sell all their products to foreign countries may exhibit dynamics different than the local establishments. The classification of firms as exporting and non-exporting, however, puts these two types of firms in the same group, which makes it difficult to derive robust inferences about the impact of trade on firm behavior. This paper, therefore, makes use of a continuous variable, the export intensity, while identifying firms' export status in the empirical analysis.

Table 2: Partial Corr. Coefficients Controlled for Industry and Time Fixed-Effects[a]

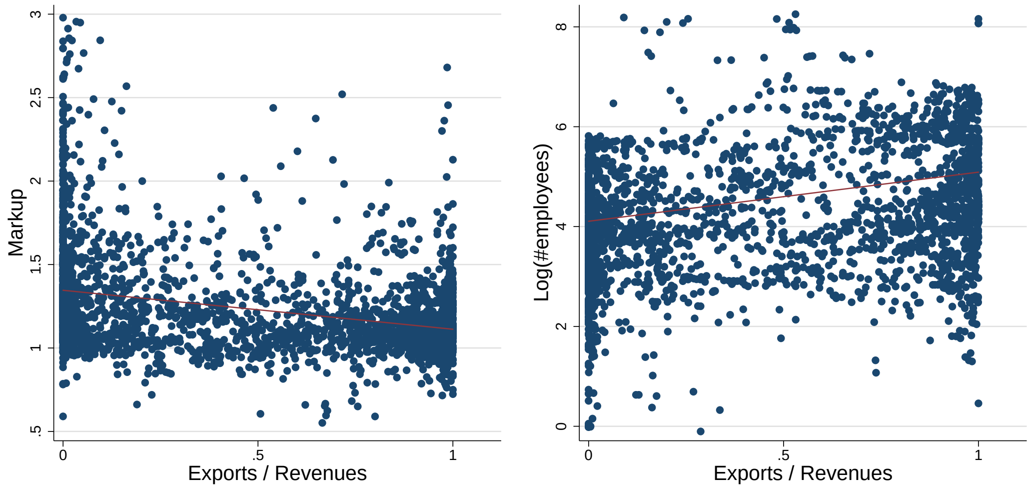
	PCM	Markup	Exp.In.	E.I. Ext-EU	Firm Size
log(TFP)	0.692	0.753	−0.229	−0.064	−0.213
PCM		0.603	−0.096	−0.012	−0.047
Markup			−0.309	−0.108	−0.139
Exp.In.				0.435	0.265
E.I. Ext-EU					0.276

[a] *Exp. In.* is the export intensity as the ratio of exports to revenues. *E.I. Ext-EU* is the intensity of the extra-EU exports which excludes the exports to the EU members. *Size* is the firm size measured by the log number of employees.

Table 2 displays the partial correlations among the markup, productivity, PCM, export intensity and firm size measured by the number of workers. The correlations of export intensity with the markups, PCM and the log of the TFP are negative. When the firm-level export intensity is based on the extra-EU exports, its correlations with the markups, PCM and the log TFP increase but are still negative. Higher correlation between markups and extra-EU export intensity is in line with the theoretical discussion, since it implies that extra-EU exporters further raise their markups as a response to trade barriers that are higher than those faced by the intra-EU exporters. Thus, the bias in the revenue productivity due to the markup variation is also smaller, and the correlation of the TFP with the export intensity is higher, when only the extra-EU exports are considered. Table 2 shows that firm size is positively correlated with both types of export intensity measures. This indicates that exporting firms' labor share in the local market is larger, which may be considered as a result of the reallocation effect of trade on the home country.

Figure 1 takes a closer look at the correlations between firm size, markups and export intensity by displaying two scatter plots; on the left markups and on the right firm size vs. export intensity. The left panel shows that there is a considerable number of high-markup firms with zero or very low export intensity, while markups are generally lower for the firms with higher export intensity. In the group of intensively exporting firms, a small number of producers have markups over 1.5, while the average markup does not significantly differ among the establishments with export intensity over 0.3. The right panel of Figure 1 shows that an important portion of the non-exporting firms are small, and there is a positive link between firm size and export intensity. Figure 1, therefore, provides some degree of evidence that local firms stay small and charge higher markups, which can be interpreted as a consequence of the lower level of competition in the domestic market relative to the international markets. Productivity, however, is lower for intensively exporting firms, which contradicts with the theory that trade-induced selection only allows high-productivity firms to enter into export markets (e.g. Bernard et al., 2003; Melitz, 2003; Melitz and Ottaviano, 2008). Whether the local firms are indeed productive or the productivity measure is biased is analyzed in the next subsection.

Figure 1: Export Intensity, Markups and Employment



3.3 Heterogeneous Markups and Productivity Measurement

One possible reason for the negative correlation between export intensity and productivity is the unobserved price effects embodied in nominal productivity measures. When prices or markups significantly differ among firms, deflating firm-level variables by industry-level price indices is not sufficient to isolate productivity from the demand side factors. As a result, the productivity performance of high-markup firms can be overestimated by productivity indices based on deflated revenues and input expenditures. To understand how price effects influence the empirical results, this section uses a proxy for quantity productivity that is isolated, to some degree, from the price effects.

Foster et al. (2008) analyze the differences between the revenue and quantity based measures of productivity and find that price effects can distort the revenue-productivity systematically for some group of firms, for instance, for entrants. Besides generating a bias in micro-level productivity indicators, price effects constitute an important issue when measuring the efficiency in the allocation of production factors using firm-level productivity indicators (Hsieh and Klenow, 2009; De Loecker et al., 2016). Assuming input prices do not significantly differ among firms, one can show that the difference between log revenue (θ_r) and quantity productivity (θ_q) is equal to the log of output prices. In the case of heterogeneous product markets, prices embody not only demand side effects but also quality differences among product varieties. Product quality should be considered as a component of productivity, since it generally reflects the quality of inputs used in production. If the true productivity that is based on quality-adjusted quantities differs from the revenue productivity due to the demand side factors, then it is more plausible to represent this difference by markups, namely that $\theta_r = \theta_q + \log(\mu)$. Price-cost markup is a better measure for demand side effects embodied in revenue productivity, since markups are somewhat adjusted for quality variation through the marginal cost in the denominator. The marginal cost can reflect quality variation because higher quality outputs are produced by higher quality inputs that are potentially more expensive. This part, therefore, uses a proxy for the quality-adjusted quantity productivity that is computed by deducting the log of the estimated markups from the log revenue productivity.

Figure 2: Quantity vs. Revenue Productivity

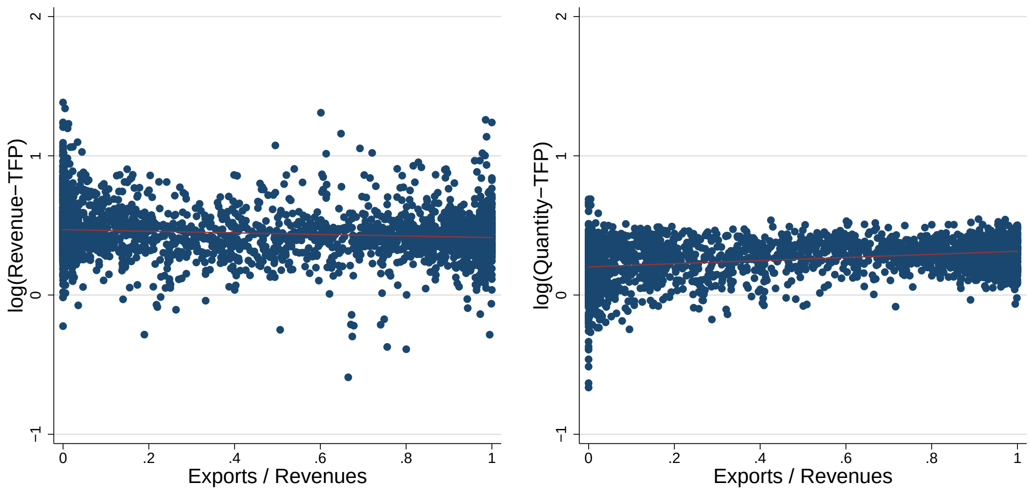


Figure 2 presents two scatter plots depicting the correlation of export intensity with the revenue and quantity productivity. The figure shows that the quantity-TFP is less dispersed than the revenue-TFP especially for the firms that have higher export intensity. The main difference between the two scatter plots, however, is in the non-exporting firms' region, where the quantity productivity is generally lower for non-exporters. This can be also seen from Table 3 that shows partial correlation coefficients among productivity measures, markups and export intensity. The partial correlation of the export intensity with the quantity productivity is significantly positive, while it is negative with the revenue productivity. The correlation of the markup is positive with quantity productivity and is negative with revenue productivity. Moreover, the weighted average (non-log) quantity productivity is 1.39 for exporting and 1.19 for non-exporting firms, while the revenue productivity averages are 1.55 for exporters and 1.64 for non-exporters.

Table 3: Partial Corr. between Markups and Productivity Measures[a]

	Log(Quantity-TFP)	Markup	Exp. In.
Log(Revenue-TFP)	0.078	0.753	-0.229
Log(Quantity-TFP)		-0.565	0.188
Markup			-0.309

[a]All correlation coefficients are significant at 1 percent level.

The proxy for quantity productivity used in the above analysis is aimed at measuring the pure technical efficiency in production that is isolated from demand side effects. The results based on this proxy tend to verify that export markets comprise a selection mechanism that only allows sufficiently productive firms to engage in international trade.[3]

[3]Allocative efficiency in a given point in time can be measured by the covariance between firms' input

The productivity indicator based on deflated nominal sales and input expenditures, however, leads to an opposite result due to the markup difference between exporting and non-exporting firms. The results of this section underline the importance of unobserved prices in the analysis of productivity. The next section introduces product-level trade data and estimates average markups for alternative product groups categorized according to the export destination characteristics. Doing so extends the analysis beyond the markup difference between exporters and non-exporters and provides insights into the determinants of markup variation.

4 Export Destination Characteristics and Markups

The measurement of quantity productivity in the previous section relies on a set of assumptions that are necessary, when quantity and prices are missing at the micro-level. Calculating the physical productivity, however, is not straightforward, even if prices and quantities are observable. Measuring the quantity productivity requires observing the quantities of outputs as well as inputs, while one also needs to separately observe the amount of inputs employed in the production of different varieties of multi-product firms. Moreover, quantity-based measures of firm-level productivity may not be directly comparable among firms due to the unobserved quality variation. The quality variation is embodied in prices which are, in most cases, not possible to be perfectly decomposed into quality effects and demand side factors by the available data. Nevertheless, estimating production functions or measuring productivity based on quantities are not the only ways to derive inferences about the markup variation at the micro-level.

This section introduces product-level price and quantity data to detect factors influencing markups for exported products. I estimate the following type of inverse export demand function and recover markups for different product groups that are later used to derive implications for the link between markups and destination country characteristics.

$$p_{it} = \rho_i + \rho_e q_{it} + \Omega X_t \tag{6}$$

In equation 6, p_{it} and q_{it} are the log of price and quantity of product i at time t. X_t is the vector of demand shifters specific to the destination market, and ρ_i represents product specific quality that is unobserved for the researcher and assumed to be fixed over time. As a solution to firms' profit maximization problem, the inverse demand elasticity satisfies $\rho_e = 1/\mu - 1$, where μ is the price-cost markup that is equivalent to the ratio of price to marginal cost.

The product-level trade data used in this section contains observations on quantities and their total nominal value for every firm and time period as well as for each product category. However, I can only observe the average unit values but not the exact price of every item sold in the export market. Using the unit values directly in the estimation would integrate any measurement error in quantities with the price variable. To avoid this shortcoming, I use the total value of exported items ($v_i = p_i q_i$) as the dependent variable in the estimation of the inverse demand function. In this alternative specification of the estimating equation, the coefficient of the quantity variable (q_{it}) on the right hand-side becomes the inverse of the price-cost markup.

share and productivity (e.g. Bartelsman et al., 2013; Maliranta and Määttänen, 2015). Thus, as long as more productive firms export and exporting has an expanding effect on firms' input share in the local market, one can conclude that there are allocative efficiency gains from trade.

The main concern of this section is to detect whether markups vary for alternative destination markets, but estimating equation 6 would only provide a single average markup estimate. To capture the destination specific markup variation, I introduce an interaction term that is the multiplication of q_{it} with the dummy variable for the destination country size. Thus, the regression equation can separately estimate markups for products that are exported to large and small countries (μ_L and μ_S). The estimated version of the inverse demand function takes the following form.

$$v_{ipct} = \rho_0 + \rho_{ipc} + \rho_t + \left(\frac{1}{\mu_S}\right) q_{ipct} + \left(\frac{1}{\mu_L} - \frac{1}{\mu_S}\right) D^L_{ct} q_{ipct} + \Omega X_{ct} + \varepsilon_{ipct} \tag{7}$$

$$X_{ct} = \left\{tariff_{ct}, exrate_{ct}, gdp_{ct}, dist_{ct}, D^{EU}_{ct}\right\} \tag{8}$$

In equation 7, there are four subscripts, i,p,c and t that stand for firm, product variety, destination country and year respectively. Thus, the unique identifier of the estimation equation has four dimensions. In equation 7, ρ_0 is the intercept, ρ_{ipc} is the firm-product-country specific fixed effects that capture the time invariant quality. ρ_t is the year fixed effects that represent the unobserved demand shocks common to all destinations. D^L_{ct} is the market size dummy that takes the value of one, if the destination is a large country, and zero otherwise. X_{ct} is the vector of destination specific demand shifters that consist of the import tariffs ($tariff_{ct}$), the exchange rates ($exrate_{ct}$), the real GDP level (gdp_{ct}), the geographical distance ($dist_{ct}$) and the dummy for the EU membership (D^{EU}_{ct}). Finally, ε_{ipct} is the error term that involves the unobserved idiosyncratic demand shocks.

To simplify the notation, the export demand specification in equation 7 contains only one interaction term that separates the markup estimates for the products exported to large countries. In the actual estimation, I use three country size groups as small, medium-sized and large. As is described in the theoretical section, markups can also depend on trade costs and the relative productivity of countries, so that I also introduce interaction terms capturing these differences.

In the estimation of the demand functions, a critical issue is the endogeneity due to unobserved demand shocks. To deal with the endogeneity, this paper uses an instrumental variable approach, where the instruments are selected among the supply side variables that are assumed to be uncorrelated with the demand shocks but are correlated with the quantities. The demand estimation employs firms' input prices for labor and imported intermediate inputs as instruments. The product-level international trade data contains the prices of firms' intermediate input imports that are used to calculate a firm specific input price variable (p^I_{it}). p^I_{it} is calculated by averaging the import prices using nominal values as the weights (z_{ipt}); namely $p^I_{it} = \sum_p p^I_{ipt} z_{ipt}$ where $z_{ipt} = p^I_{ipt} q^I_{ipt} / \sum_p p^I_{ipt} q^I_{ipt}$. Moreover, the firm-level production data includes the average wage paid by a firm (w_{it}), so that the instrument set contains p^I_{it} and w_{it} along with the previous period's demanded quantity (q_{ipct-1}) that is assumed to be independent of today's demand shock. The assumption that q_{ipct-1} and ε_{ipct} are independent is not valid, when the demand shocks are serially correlated even after controlling for time fixed-effects. Thus, I conduct a set of post-estimation tests on the validity of the exogeneity assumption.

4.1 Dataset for Demand Estimation

The product-level data used in the estimation of the export demand function is the International Trade in Goods Statistics (ITGS) for Luxembourg that covers manufacturing firms' physical imports and exports. The ITGS contains the quantity and the nominal values as well as the country of origin or destination of traded goods, where product categories correspond to the CN8 product classification. The ITGS covers the period from 2001 to 2011 and is merged with the firm-level input-output data that is described in the previous section for production function estimation. I use a set of country-level variables to characterize the export destination markets. As a proxy for destination specific tariffs, I utilize the World Integrated Trade Solutions (WITS) tariff indicator that ranges between 0 and 10 according to the strictness of the overall tariff regime in the country. The tariff indicator is set to zero for the EU member states. In addition, the nominal exchange rate as a ratio of Euro/National Currency and geographical distance in km are used to represent non-tariff barriers in the estimation. Destination specific real-GDP is used to proxy the total demand, and the country's population is taken as a benchmark for the country size classification as in the Melitz-Ottaviano model. Besides the classifications based on size, distance and EU membership, I divide the export destination countries into two categories according to their productivity advantage, so that I can estimate markups separately for the goods sold to these two country groups. The productivity classification is based on the average Competitive Industrial Performance Index (CIP) provided by the United Nations Industrial Development Organization. In the appendix, Figure 8 shows the scatter plot between the total volume of exports and the destination country size. Figure 9 and 10 display the country classifications based on the geographical distance and the CIP.

4.2 Export Demand Estimation Results

I estimate the inverse demand function in the form of equation 7 by the GMM using firm-product-destination fixed effects specification. In the appendix, Table 15 presents the estimations of the demand functions for three alternative samples and for two different explanatory variable sets. I first estimate the demand function for the entire sample of products, and then run separate regressions for the samples of plastic and metal products which are the two product categories that are exported most frequently by the manufacturing firms in Luxembourg. For each product sample, I estimate two equations. The first one provides an average markup estimate, and the second one contains two interaction terms to capture the variation of markups over the destination market size groups. The specifications (1a), (2a) and (3a) are the demand function estimations, from which an average markup is recovered for the full sample, metals and plastics respectively. The specifications (1b), (2b) and (3b) are the ones with the size-interaction terms.

In addition to the country size, I introduce interaction terms for the distance between the origin and destination markets, the EU membership status and the productivity advantage. In the appendix, Table 17 displays the demand estimation results that takes into account markup variations for alternative destination country characteristics. I estimate three equation sets, where each set contains two equations. For instance, the first equation under the title of productivity advantage introduces an interaction term for markups of goods exported to high-productivity destination countries. The second equation under the same title contains interaction terms for the productivity advantage as well as for the country size. In addition, I use cross terms to capture markup variation due to market size differences within each productivity class. The instrument sets used in the estimations and the test results on the validity of instruments are reported in the appendix in Table 16 and 18. Table 4 and 5 displays the markup estimates recovered from alternative demand function estimations.

Table 4: Markup Estimates: Export Destination Size[a]

Destination Country Size	Markup Estimates		
	All Products	Metals	Plastics
Specification:	*(1a)*	*(2a)*	*(3a)*
All Destinations	1.22	1.15	1.24
Specification:	*(1b)*	*(2b)*	*(3b)*
Small Countries	1.39	1.33	1.45
Medium-Sized	1.22	1.22	1.29
Large	1.21	1.09	1.19

[a]Small countries are classified as the ones with less than 5 million population. Medium-sized countries have a population between 5 and 40 million, and large countries have more than 40 million population.

The top row in Table 4 shows the average markup estimates for all sample, metals and plastic products. The average markup estimate is the highest for the plastic products, but overall, the markup values are close to each other for alternative sample specifications. The bottom panel presents the markup estimates for every export destination size class. Accordingly, markups are the highest for goods that are exported to small countries, while lower markups are estimated for larger destinations. This pattern is the same for the entire sample of products as well as for metals and plastics. As is described in the previous subsection, markups for alternative market size classes are estimated through a single equation using interaction terms. This implies that when the coefficient of an interaction terms is statistically significant, the difference between estimated markups for the two destination groups are also significant. The markups estimates for goods exported to medium-sized or large countries, therefore, are significantly different from those exported to small countries for all alternative product samples. The results shown in Table 4 are in line with the predictions of the Melitz-Ottaviano model, so that larger export destinations correspond to lower markups.

Table 5 shows the markup estimates for alternative destination market classifications. The first classification is based on countries' productivity advantage which corresponds to the lower-bound of the efficiency distribution in the theoretical model. On the left hand-side of the top panel, markups are separately estimated for goods exported to countries with distinctive productivity advantage and are found to be significantly lower than markups for other destinations. On the right hand-side of the top panel, the markup variation due to productivity advantage is considered together with the country size. Accordingly, the average markup estimates are the lowest for exports to large and high-productivity countries. The markups for other large countries without any distinct productivity advantage, however, are higher and not significantly different from markups for small countries. The average markups for goods exported to medium-sized countries without distinctive productivity advantage is also high and not significantly different from small country markups. The estimation results support the model prediction that the markups for goods exported to countries with distinct productivity advantage is significantly lower than those exported to other destinations. The markups, however, are lower for larger destination markets only within the group of countries with distinctive productivity advantage.

Table 5: Markup Estimates: Other Destination Characteristics[a]

Productivity Advantage (PA)

Specification (4a)	Markup	Specification (4b)	Markup
Non-PA	1.42	Small	1.40
PA	1.16	Non-PA, Medium-Sized	1.33
		PA, Medium-Sized	1.18
		Non-PA, Large	1.47
		PA, Large	1.17

Geographical Distance

Specification (5a)	Markup	Specification (5b)	Markup
Distant Countries	1.56	Small	1.56
Nearby Countries	1.14	Distant, Medium-Sized	1.50
		Nearby, Medium-Sized	1.18
		Distant, Large	1.58
		Nearby, Large	1.08

EU Membership

Specification (6a)	Markup	Specification (6b)	Markup
Non-EU Members	1.36	Small	1.44
EU Members	1.18	Non-EU, Medium-Sized	1.31
		EU, Medium-Sized	1.21
		Non-EU, Large	1.56
		EU, Large	1.07

[a]Distant countries are the ones whose capital is more than 2000 km away from the home country's capital. Countries with productivity advantage are the ones whose Competitive Industrial Performance Index is higher than 1.5.

In the middle panel of Table 5, export destination markets are classified according to their geographical distance from the home country. On the left hand-side of the panel, markups are lower for nearby countries. On the right hand-side, markups are shown to be the lowest for the goods exported to large nearby countries. The estimated markups are also high for exports to the medium-sized nearby countries. When we consider only the distant export destinations, however, markups do not differ significantly according to the country size.

In the bottom panel of Table 5, the classification is based on the EU membership status of the destination markets. The left hand-side of the bottom panel shows that markups are significantly lower for exports to the EU member countries. On the right hand-side, markups are the lowest for the products exported to the large EU-member states, and markups raise for smaller destination countries. Within the non-EU member states, markups are significantly lower for the medium-sized destinations, but markups for large destinations are not statistically different from markups for small destinations.

The results of the demand estimations show that the markups for the exports of Luxembourg's manufacturers are lower for geographically close-by countries as well as for the EU member destinations. Moreover, the estimated markup differences from the benchmark groups are statistically significant at 1 percent level. This can be interpreted as a result of relatively low tariff and non-tariff barriers for exports to EU member countries. The markups can be particularly low for goods sold to the EU countries also because of the distinct productivity advantage or geographical proximity of some countries in this group. In other words, the interaction term for the EU countries captures a markup gap not only due to tariff barriers, but also due to other factors such as productivity and distance.

When we consider markups for exports to distant or non-EU member countries or to destinations without any distinct productivity advantage over Luxembourg's manufacturing, the significant link between destination size and markups disappear. This implies that the markup rising effect of trade barriers or productivity disadvantage of the home country outpaces the markup effect of destination market size. This result does not contradict with the earlier findings based on the production function estimates, because the majority of Luxembourg's trade activities are with the other EU member states. As is shown in Figure, the first six main trade partners of Luxembourg's manufacturing sector are Germany, France, Belgium, the United Kingdom, the Netherlands and Italy all of which are classified as nearby, EU member states that have productivity advantage over Luxembourg in manufacturing according to the CIP. This implies that for the majority of the trade activities observed in the data, the destination market size is a statistically significant determinant of markups for exported goods.

5 Conclusions

International trade theory suggests that only the most productive firms are able to seek new profit opportunities and compete in foreign markets. Once start exporting, establishments tend to expand their input shares in the home country. This moves domestic resources toward more efficient uses, which in turn increases aggregate productivity growth. The well-functioning of the resource allocation mechanism is necessary to realize economic gains from trade, but how to monitor the functioning of this mechanism empirically is not straightforward. In particular, whether the export market selection is based on firms' productivity performance may not be possible to answer using standard productivity measures. This is because productivity measures based on nominal input and outputs involve price-cost markups that are endogenous to firms' export activities. Thus, nominal productivity may be systematically biased for the group of exporting firms.

This paper investigates how openness to international trade influences markups at the micro-level and discusses the implications of the trade-driven markup variation for the productivity measurement. The empirical analysis is structured based on the Melitz-Ottaviano model, and the focus is put on the case of the small open home country having a large and overall more productive trade partner. The model predicts that the small home country's markups for exported goods can be lower than those for the domestically sold products, which is the opposite of the trade between symmetric countries. This study, therefore, considers the trade-driven markup variation as a potential source of bias that cause exporting firms' to be measured less productive than non-exporters.

The empirical analysis consists of two steps. In the first step, markups and revenue productivity are estimated through a production function specification. The results show that the estimated markups as well as revenue productivity are lower for exporters. Conversely, the proxy for quantity productivity, which is isolated from demand side factors, verifies the theory that exporters tend to be more productive. The first step, therefore, compares markups between exporters and non-exporters and discuss the implications of the markup variation for the productivity measurement.

Besides investigating the markup difference between exporters and non-exporters, this study attempts to empirically assess the factors driving the micro-level markup variation. The Melitz-Ottaviano model, for instance, puts a particular emphasis on the role of export destination market characteristics in shaping the markups for exported goods. If market characteristics influence markups, then one should also observe certain degree of markup variation for goods exported to different countries. In the second step of the empirical analysis, therefore, I estimate an export demand function and assess the patterns of markup variation using detailed price-quantity data.

Overall, the small open economy case in the Melitz-Ottaviano model provides good predictions for the dynamics observed in Luxembourg's manufacturing. The markups of Luxembourg's exports are significantly lower, when they are exported to nearby, EU-member, highly productive and large countries. The main trade partners of Luxembourg accommodate these four characteristics, which explains the overall negative markup gap between exporters and non-exporters. For the products exported to non-EU member and distant countries as well as to the destinations with no distinct productivity advantage, the link between markups and destination market size disappears. This is does not contradict with the theory, since distant markets imply higher trade barriers that are known to have markup raising effect for exported products. Moreover, when an exporter firm has a productivity advantage over its competitors in the export destination market, the exporter can gain some monopolistic power and charge higher price-cost markups. Thus, the markup raising effect of having productivity advantage or facing large trade barriers may outpace the markup lowering effect of exporting to larger destination markets.

The results on the link between markups and firms' trading activities can be used to derive direct welfare implications for the home country. The welfare consequences of the impact of trade on markups are analyzed for alternative scenarios, for instance, by Melitz and Ottaviano (2008), Corcos et al.(2012), Demidova and Rodriguez-Clare (2009, 2013) and Behrens et al. (2014). Alternatively, this paper evaluates the importance of the results from the perspective of growth accounting and underlines the issues in assessing the link between openness to trade and allocative efficiency. The unobserved price effects, therefore, may distort the indicative quality of standard productivity measures and lead to the incorrect conclusion that non-exporting local establishments exhibit better productivity performance in small open economies. While this implies negative allocative efficiency or productivity gains from trade, controlling for the unobserved price variation removes the bias, and the results tend to verify that openness to trade accelerates productivity growth.

References

Daniel Ackerberg, Kevin Caves, and Garth Frazer. Structural identification of production functions. MPRA Paper 38349, University Library of Munich, Germany, 2006.

Eric Bartelsman, John Haltiwanger, and Stefano Scarpetta. Cross-Country Differences in Productivity: The Role of Allocation and Selection. *American Economic Review*, 103(1):305–34, 2013.

Kristian Behrens, Giordano Mion, Yasusada Murata, and Jens Sdekum. Trade, Wages, and Productivity. *International Economic Review*, 55:1305–1348, 2014.

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

Gregory Corcos, Massimo Del Gatto, Giordano Mion, and Gianmarco I.P. Ottaviano. Productivity and Firm Selection: Quantifying the New Gains from Trade. *Economic Journal*, 122(561):754–798, 2012.

Chiara Criscuolo and Ralf Martin. Multinationals and U.S. Productivity Leadership: Evidence from Great Britain. *The Review of Economics and Statistics*, 91(2):263–281, 2009.

Jan De Loecker and Frederic Warzynski. Markups and Firm-Level Export Status. *American Economic Review*, 102(6):2437–71, 2012.

Jan De Loecker, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik. Prices, Markups and Trade Reform. *Econometrica*, 84(2):445–510, 2016.

Svetlana Demidova and Andres Rodriguez-Clare. Trade policy under firm-level heterogeneity in a small economy. *Journal of International Economics*, 78(1):100–112, 2009.

Svetlana Demidova and Andres Rodriguez-Clare. The simple analytics of the Melitz model in a small economy. *Journal of International Economics*, 90(2):266–272, 2013.

Sabien Dobbelaere and Jacques Mairesse. Panel data estimates of the production function and product and labor market imperfections. *Journal of Applied Econometrics*, 28(1): 1–46, 01 2013.

Lucia Foster, John Haltiwanger, and Chad Syverson. Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? *American Economic Review*, 98 (1):394–425, 2008.

Zvi Griliches and Tor Jakob Klette. The Inconsistency of Common Scale Estimators When Output Prices Are Unobserved and Endogenous. *Journal of Applied Econometrics*, 11 (4):343–61, 1996.

Zvi Griliches and Jacques Mairesse. Production Functions: The Search for Identification. NBER Working Papers 5067, National Bureau of Economic Research, Inc, 1995.

Robert E Hall. The Relation between Price and Marginal Cost in U.S. Industry. *Journal of Political Economy*, 96(5):921–47, 1988.

Lars Peter Hansen. Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*, 50(4):1029–54, 1982.

Chang-Tai Hsieh and Peter J. Klenow. Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics*, 124(4):1403–1448, 2009.

Umut Kilinc. Estimating entrants' productivity when prices are unobserved. *Economic Modelling*, 38(C):640–647, 2014.

Frank Kleibergen and Richard Paap. Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133(1):97–126, 2006.

Ulrich Kohli. Production theory, technological change, and the demand for imports. *European Economic Review*, 18(2):369–386, 1982.

James Levinsohn and Amil Petrin. Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies*, 70(2):317–341, 2003.

Mika Maliranta and Niku Määttänen. An Augmented Static OlleyPakes Productivity Decomposition with Entry and Exit: Measurement and Interpretation. *Economica*, 82: 1372–1416, 2015.

Ralf Martin. Building the capital stock. Ceriba working papers, Mimeo, 2002.

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

Marc J. Melitz and Gianmarco I. P. Ottaviano. Market Size, Trade, and Productivity. *Review of Economic Studies*, 75(1):295–316, 2008.

Marc J. Melitz and Daniel Trefler. Gains from Trade When Firms Matter. *Journal of Economic Perspectives*, 26(2):91–118, 2012.

OECD. *Measuring Capital - OECD Manual 2009: Second edition*. OECD Publishing, 2009. ISBN 9789264025639.

G. Steven Olley and Ariel Pakes. The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64(6):1263–1297, 1996.

Amil Petrin, Brian P. Poi, and James Levinsohn. Production function estimation in Stata using inputs to control for unobservables. *Stata Journal*, 4(2):113–123, 2004.

James H. Stock and Motohiro Yogo. Testing for Weak Instruments in Linear IV Regression. In *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, page 80108. Cambridge: Cambridge University Press, d. w. k. andrews and j. h. stock edition, enero-mar 2005.

Jeffrey M. Wooldridge. On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, 104(3):112–114, 2009.

6 Appendix

6.1 Markups and Trade Barriers

This part is intended to show that when foreign country has productivity advantage $(c_M^h > c_M^f)$, markups are more likely lower for exporters than for non- exporters for lower values of τ.

In order to ensure positive numbers of domestic and exporting firms, the efficiency cutoffs for the foreign and home markets (c_D^h, c_X^h) have to be larger than 0. From equation 4 and 5, this implies that the following conditions hold in equilibrium.

$$\left(c_M^h\right)^k - \left(c_M^f/\tau\right)^k > 0 \tag{9}$$

$$\left(c_M^f\right)^k - \left(c_M^h/\tau\right)^k > 0 \tag{10}$$

In the Melitz-Ottaviano model, the efficiency cutoff for exporters satisfies $c_X^h = c_D^f/\tau$. Thus, the condition given in equation 3 can be rewritten in the following form.

$$c_D^h - c_D^f > (\tau - 1)\, c \tag{11}$$

Thus, I need to show whether the inequality given by equation 11 is more likely satisfied for lower values of τ. The righthand side of equation 11 is positive and decreasing as τ decreases for every $\tau > 1$. The lefthand side is also positive, as long as the home country is sufficiently small or the foreign country has a considerable productivity advantage. If the foreign country has a productivity advantage, so that $c_M^h > c_M^f > 0$, and $c_M^h - c_M^f$ is sufficiently large, $c_D^h - c_D^f$ is a negative function of τ. This can be shown in the following way.

$$\frac{\partial c_D^f}{\partial \tau} = A\left[\left(\left(c_M^h\right)^k - \left(c_M^f/\tau\right)^k\right) - \tau^{-k}\left(\left(c_M^f\right)^k - \left(c_M^h/\tau\right)^k\right)\right] \tag{12}$$

where $A = k\Psi/\left[(k+2)\, c_D^f L^f \left(1 - \tau^{-2k}\right)^2 \tau^{k+1}\right] > 0$.

According to the derivative given by equation 12, c_D^f is an increasing function of τ, as long as $c_M^h > c_M^f$. $\partial c_D^h/\partial \tau$ is symmetric to $\partial c_D^f/\partial \tau$. Thus, $\partial c_D^h/\partial \tau$ is negative, when c_M^h is sufficiently larger than c_M^f, which ensures the negative link between $c_D^h - c_D^f$ and τ.

The relationship between $c_D^h - c_D^f$ and τ can be positive or negative depending on the country characteristics. If the foreign country has a sufficiently large productivity advantage over the home country, the cutoff-gap $(c_D^h - c_D^f)$ increases with the bilateral trade liberalization. In this case, the markup inequality given by the equation 3 is more likely to hold, namely that the markups for exported goods are higher than the domestic markups. From equation 12, one can see that for some values $c_M^h > c_M^f$, $\partial c_D^h/\partial \tau$ is not negative. However, even if $\partial c_D^h/\partial \tau > 0$, the cutoff-gap $(c_D^h - c_D^f)$ is still a decreasing function of τ, as long as $c_M^h > c_M^f$.

$$\frac{\partial\left(c_D^h/c_D^f\right)}{\partial \tau} = \frac{kL^f}{\tau^{k+1}L^h}\left[\frac{\left(c_M^f\right)^{2k} - \left(c_M^h\right)^{2k}}{\left(c_M^f\right)^k - \left(c_M^h/\tau\right)^k}\right] \tag{13}$$

On the righthand side of equation 13, the denominator in the square brackets is positive from the condition given by equation 10. Thus, for any $c_M^h > c_M^f > 0$, the nominator so the first derivative given in equation 13 is negative. Given that c_D^h, $c_D^f > 0$ and $\partial c_D^h/\partial \tau$, $\partial c_D^h/\partial \tau > 0$, equation 13 implies $\partial\left(c_D^h - c_D^f\right)/\partial \tau < 0$ for $c_M^h > c_M^f$.

6.2 Construction of Capital Stock at the Firm-Level

The firm-level capital stock used in this paper is computed based on a modified version of the perpetual inventory method (PIM). The PIM method adds real investments and subtracts depreciation and retirement from an unknown initial stock of capital to calculate the next year's capital. To approximate each firm's initial capital stock, I first estimate total initial capital stock at the industry-level. In the next step, I disaggregate the initial capital among firms using some weights (e.g. Martin, 2002). Approximating the initial capital at the industry-level has the advantage of having longer time series with positive investments, since there are gaps in the firm-level data due to entry and exits or mismeasurement. In this paper, I modify the PIM method to be more consistent with the micro data. At the industry-level, the evolution of capital stock is given by the following identity.

$$K_t = K_{t-1}(1 - \delta - ret_t - ex_t + en_t) + I_t \tag{14}$$

In equation 14, δ is the depreciation rate, ret_t is the retirement probability of capital assets, and I_t is the total investments of firms operating at the industry. Unlike in the firm-level data, in the industry-level data, retirement and depreciation are not the only ways of obsolescence of capital stock, neither investment is the only way of acquisition. When the data is aggregated over firms, new capital stock coming from entrant firms raises the total capital. Similarly, exiting establishments constitute a component of capital obsolescence. In addition to firm entry and exit, establishments may appear in or disappear from the sample of a specific industry for reasons such as the change of the type of main activity, which also alters the aggregate capital stock. Thus, in equation 14, entry (en_t) and exit (ex_t) rates are defined to cover all types of gaps in the micro data, so that I can fully account for acquisition and obsolescence of capital stock in the aggregated data. Entry and exit rates are calculated based on the firms' employment share in the industry. Equation 14 can be simplified in the following way.

$$K_{t-1} = \frac{I_t}{gr_t + \phi_t} \tag{15}$$

In equation 15, $\phi_t = \delta + ret_t + ex_t - en_t$, and gr_t is the growth rate of capital. Equation 15 can be used to calculate an approximation of aggregate capital stock by assuming numerical values for δ and ret_t, and gr_t (e.g. Kohli, 1982). Alternatively, one can derive a general rule for the initial capital K_0 by iterating equation 15 over time as follows.

$$K_0 = \frac{I_t}{(gr_t + \phi_t)\prod_{z=1}^{t-1}(1-\phi_z)} - \sum_{i=1}^{t-1} \frac{I_i}{\prod_{j=1}^{i}(1-\phi_j)} \tag{16}$$

Equation 16 is the rule for the initial capital that is generalized for every year in the sample period, so that one can obtain several approximations of the initial capital and compare the results. Selecting the benchmark year (t) far away from the initial point (0), however, would cause less reliable estimates of initial capital, since higher t would magnify the errors introduced by the guesses of δ and ret_t. In this paper, therefore, I compute the initial capital approximations by evaluating equation 16 for the first three years of the sample period. Namely, three different initial capital approximations are computed by setting $t \in \{1, 2, 3\}$, and the final value is computed by averaging the three approximations.

In the approximation of the aggregate initial capital stock, I use the industry-level investments that are the aggregation of firm-level investments net of capital sales. In the analysis at the firm-level, I utilize the data for different investment types for which I assume individual depreciation rates, life times and retirement profiles. The asset composition of the initial capital stock, however, is unknown but not necessary to compute to estimate the capital stock at the firm-level. Therefore, I assume a constant depreciation rate, life time and retirement profile for every firm's initial capital stock.

The retirement patterns of capital assets are modeled by assuming that the retirement probability of an asset has a Weibull distribution (e.g. OECD, 2009).

$$F_T = \alpha\lambda \left(\lambda T\right)^{\alpha-1} e^{-(\lambda T)^{\alpha}} \tag{17}$$

Equation 17 represents the Weibull distribution where T is the time index, α and λ are the parameters of the density function. Figure 3 displays the density functions for each asset class where the "unknown" asset class type represents the initial capital.

Figure 3: Retirement Probabilities

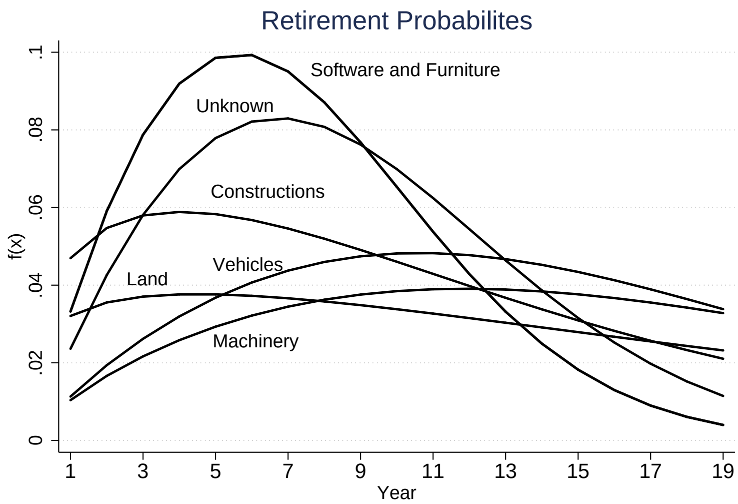


Table 6 shows the parameter assumptions for the retirement profile together with asset specific service life times and constant depreciation rates.

Table 6: Parameter Setup for Capital Stock Measurement

Asset Type	δ	life (years)	α	λ
Unconstructed Land	0.00	≥ 16	1.2	0.05
Constructions and Arrangement of Grounds	0.07	≥ 16	1.3	0.08
Machinery and Equipment	0.09	11	1.7	0.05
Furnitures	0.05	11	1.9	0.12
Vehicles and Other Transportations	0.09	11	1.8	0.06
Software	0.05	3	1.9	0.13
Unknown Type	0.05	≥ 16	1.9	0.10

In Table 6, the life times of unconstructed land, constructions and the unknown type of capital are assumed to be longer than 16 years that is the span of the data used in this study. This is because, the initial capital generally contains mostly the capital goods with long service lives like buildings, land and other constructions for infrastructure.

The approximation of the initial capital is not feasible for every 2-digit industry, because some of the industries contain few numbers of firms or observations. Thus, I approximate the initial capital separately for six firm groups, where each group consists of multiple 2-digit manufacturing industries. Once the initial capital is computed, it is disaggregated over firms using the net book values of capital assets (NBV) as the weights.[4]

Table 7: Description of Production Function Variables[a]

	#obs.		Output	Int.Inputs	Labor	Capital
Industry Total	2823	mean	33.60	24.43	145.01	17.84
		std	76.61	59.37	280.58	85.13
Exporters	2231	mean	40.88	29.93	168.15	21.52
		std	84.63	65.65	309.87	95.20
Non-Exporters	592	mean	6.16	3.70	57.81	3.96
		std	6.92	4.73	63.08	12.73
Intra-EU Exporters	2203	mean	39.98	29.25	165.55	20.32
		std	77.24	60.19	290.85	87.79
Non-Intra-EU Exporters	620	mean	10.94	7.30	72.03	9.04
		std	69.84	52.97	226.14	74.33
Extra-EU Exporters	1193	mean	61.37	45.35	245.20	33.76
		std	108.96	84.98	398.71	128.06
Non-Extra-EU Exporters	1630	mean	13.28	9.12	71.68	6.18
		std	22.42	16.33	85.60	15.28

[a]Output, intermediate inputs and capital are in terms of million Euros deflated by 2-digit (NACE) price indices specific to each variable with the base year of 2000. Labor is the number of full and part time employees where the number of part time employees is adjusted by work hours ratio of the part time to the average full time employee.

[4]The NBV is retrieved from accounting data which contains amortization as the proxy for depreciation. The amortization, however, is based on predetermined constant obsolescence rates for each capital asset class, while these rates are generally not aimed at representing the actual rates of depreciation. The computation of NBV does not take into account time variation in retirement probabilities and incorporates unrealistically short service lives. For these reasons, the NBV is a less reliable measure of capital, which can fluctuate sharply or become negative throughout the life time of a production unit. To minimize possible errors, I use the time averaged NBV in the construction of firm-level weights. Once the total initial capital is disaggregated among firms, the firm-level capital stock is computed by $k_{it} = k_{it-1}(1 - \delta - ret_{it}) + I_{it}$.

Figure 4: Representativeness of the Micro Sample

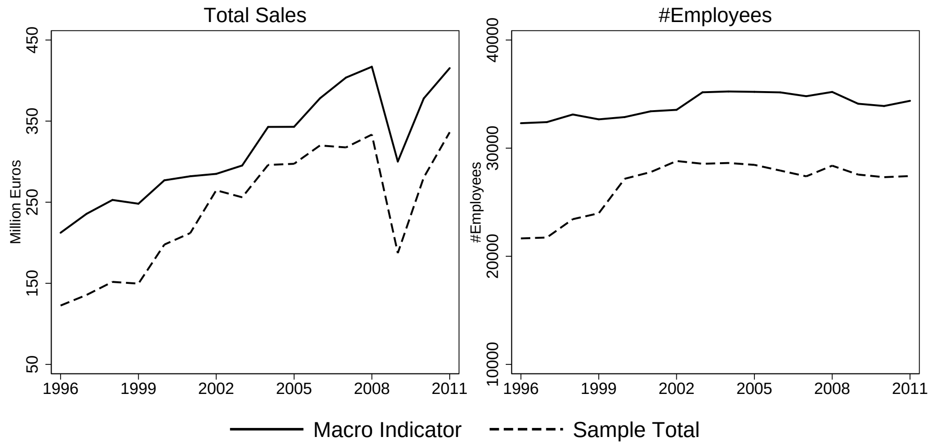
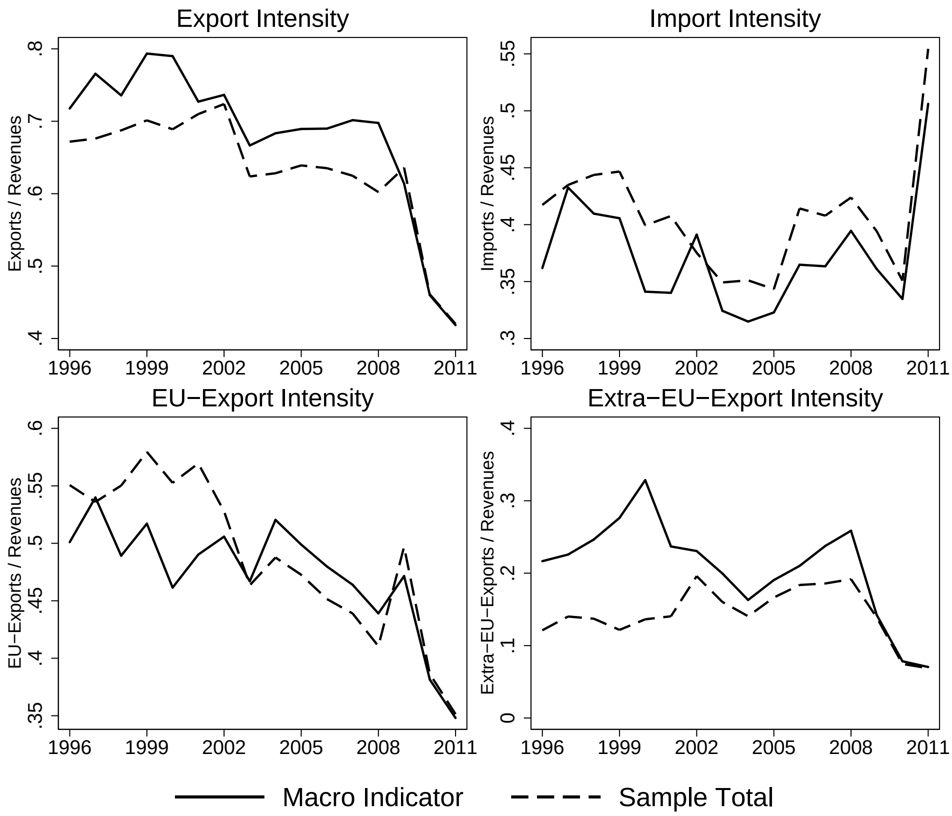


Figure 5: Trade Intensity: Micro Sample vs. Macro Sample



6.3 Estimation of Production Functions

The estimation of production function relies on Wooldrige (2009) that is an extension of Levinsohn and Petrin (2003) (LP). The Wooldridge method relaxes a critical identifying restriction in the LP that is the assumption of predetermined labor input. Assuming that a firm's manager hires labor before realizing the firm's productivity, the LP algorithm identifies factor elasticity of labor by the OLS in the first stage of a two-stage control function approach. The identification assumption, however, ignores any degree of correlation between labor and productivity shock, which may cause downwards biased labor elasticity estimates (e.g. Ackerberg et al., 2006). Wooldrige (2009) reduces the two step control function approach into a single step, and identifies all parameters of production function simultaneously.

$$\begin{aligned} q_{it} &= \alpha_0 + \alpha_L l_{it} + \alpha_M m_{it} + \alpha_K k_{it} + \alpha_{LM} l_{it} m_{it} + \alpha_{KM} k_{it} m_{it} \\ & \quad + \alpha_{LK} l_{it} k_{it} + \alpha_{L2} l_{it}^2 + \alpha_{M2} m_{it}^2 + \alpha_{K2} k_{it}^2 + \theta_{it} + \epsilon_{it} \end{aligned} \tag{18}$$

Equation 18 is the translog production function, where all the variables are in logarithms. The production function is in terms of three factors that are labor (l), intermediate inputs (m) and capital (k). q stands for the output, i and t are the firm and time subscripts. The TFP consists of two components where θ_{it} is the systematic component based on which the manager develops her expectations, and ϵ_{it} is the i.i.d component. The production function parameters are represented by the α's. To simplify the notation, the translog production function is presented by $q_{it} = \alpha_0 + X_{it}\beta + \theta_{it} + \epsilon_{it}$ where X_{it} is the variable and β is the parameter vector.

The first stage equation in the LP introduces a control function to proxy for the unobserved productivity that is a function of m_{it} and k_{it}.

$$q_{it} = \alpha_0 + X_{it}\beta + g\left(m_{it}, k_{it}\right) + \epsilon_{it} \tag{19}$$

In the first stage, the LP only identifies the coefficients of variables that are sole functions of l_{it}. The two production factors, m_{it} and k_{it}, appear both in the production and control functions, so that the identification of their coefficients is not feasible in the first stage. For the variables that cannot be identified in the first stage, the LP defines a non-parametric function $g\left(m_{it}, k_{it}\right)$ that is in the form of a third order polynomial.

The second stage in the LP a non-parametric function $g\left(m_{it}, k_{it}\right)$ that is in the form of a third order polynomial. The evolution of the unobserved productivity over time is represented by an unknown Markov process. At this stage, I assume that productivity follows a random walk with a drift, so that $g\left(m_{it}, k_{it}\right) = \beta_0 + g\left(m_{it-1}, k_{it-1}\right) + \omega_{it}$. The fitted values of the productivity regression serve as an estimate for the conditional expectation of systematic component in productivity which is used to control for the endogeneity of inputs. The second stage of the LP, therefore, is written in the following form.

$$q_{it} = \gamma_0 + X_{it}\beta + g\left(m_{it-1}, k_{it-1}\right) + \nu_{it} \tag{20}$$

The LP minimizes the joint error term, $\nu_{it} = \epsilon_{it} + \omega_{it}$ using a set of moment conditions that contains previous periods' capital, labor and intermediate inputs. Moreover, k_{it} is included into the set of instruments, since it is a function of previous periods investments that are independent of current productivity shock. The moment conditions of the second stage in the LP, therefore, are different from the first stage where the current period's labor and intermediate inputs are assumed exogenous.

The Wooldridge method adopts the semi-parametric approach in the first stage of the LP algorithm, but estimates equation 19 jointly with the second stage equation by the GMM using a set of moment conditions. The joint estimation of equation 19 and 20 turns out to be a linear GMM minimization problem under the assumption that productivity follows a random walk with drift.

$$\begin{pmatrix} q_{it} \\ q_{it} \end{pmatrix} = \begin{pmatrix} 1 & 0 & X_{it} & g_{it} \\ 0 & 1 & X_{it} & g_{it-1} \end{pmatrix} \times \begin{pmatrix} \alpha_0 & \gamma_0 & \beta & \phi \end{pmatrix}' + \begin{pmatrix} \epsilon_{it} \\ \nu_{it} \end{pmatrix} \tag{21}$$

The original Wooldridge method uses the moment conditions based on the LP. Thus for the second stage equation, $E(\nu_{it} \mid k_{it}, l_{it-1}, m_{it-1}, k_{it-1}, g^n_{it-1}, ..., l_{i1}, m_{i1}, k_{i1}, g^n_{i1} = 0)$, where g^n, represents the variables in the third order polynomial $g(.)$ excluding the linear terms m and k. In the original Wooldridge approach, the instrument set in the first stage contains g^n_{it}, m_{it} and l_{it} in addition to the instruments in the second stage.

In the application of the Wooldridge method, I slightly deviate from the original setup, so that I include g^n_{it}, m_{it} and k_{it} in the set of endogenous variables also in the first stage. In both stages, the instrument matrix (Z_{it}), therefore, consists of certain functions k_{it}, k_{it-1}, m_{it-1}, l_{it-1}. The moment conditions for the translog production function estimation by the modified Wooldridge method are given as follows.

$$E\left[\begin{pmatrix} 1 & 0 & Z_{it} \\ 0 & 1 & Z_{it} \end{pmatrix}' \times \begin{pmatrix} \epsilon_{it} \\ \nu_{it} \end{pmatrix}\right] = 0 \tag{22}$$

In the estimation of equation 21 by the GMM, which functions of k_{it}, k_{it-1}, m_{it-1}, l_{it-1} are included in the instrument matrix Z_{it} is decided based on a set of specification tests on the redundancy and validity of instruments. Table 8 presents the estimation results and Table 9 lists the instruments contained in Z_{it} together with the test results.

In addition to the estimations for the entire sample of firms, I divide the sample into four, where the grouping is based on the predefined technology levels of the 2-digit industries. Table 10 displays the included industries, the estimation results and the tests on instruments for each group. Table 11 compares the results in alternative production function estimations by displaying the factor elasticities evaluated at the sample means.

Table 8: Estimation of Production Functions[a]

Translog - Wooldridge			Cobb - Douglas		
	Coef.	Std.	Wooldridge		
l	0.321***	0.057		Coef.	Std.
m	0.671***	0.187	l	0.211***	0.015
k	0.125**	0.063	m	0.681***	0.079
ml	-0.110^{***}	0.019	k	0.060**	0.026
mk	-0.012	0.016	Levinsohn - Petrin		
lk	-0.013^{***}	0.008		Coef.	Std.
l^2	0.072***	0.009	l	0.194***	0.019
m^2	0.053**	0.022	m	0.769***	0.037
k^2	0.005	0.007	k	0.110***	0.038

[a]2-digit industry and time dummies are included in all equations. *** significant at 1%. ** significant at 5%. * significant at 10%. In the Levinsohn-Petrin approach, standard errors are computed by block bootstrapping following the *levpet* routine by Petrin et al. (2004). In the estimations by the Woodridge method, the clustered robust standard errors are reported.

Table 9: Production Function Estimation: Tests on Instruments[a]

Instruments in Translog Production Function Estimation			
$Z_{it} = \{l_{it-1}, m_{it-1}, k^2_{it-1}, m^2_{it-1}, m_{it-1}l_{it-1}, m_{it-1}k_{it-1}, l_{it-1}k_{it-1}, m^2_{it-1}k_{it-1}, m_{it-1}k_{it}, l_{it-1}k_{it}, m^2_{it-1}k_{it}, l^2_{it-1}k_{it}, l^3_{it-1}, m^3_{it-1}, k^3_{it}\}$			
Endogenous Variables in the Production Function			
$\{l, m, ml, mk, lk, l^2, m^2\}$			
Underidentification Test			
Kleibergen-Paap rk LM Stat.	22.157	χ^2 p-value	0.008
Overidentification Test of All Instruments			
Hansen J Stat.	7.408	χ^2 p-value	0.493

[a]The null hypothesis of the under-identification test is that the system is under-identified, while the null for the over-identification test is that the over-identifying restriction are valid (Hansen, 1982).

Table 10: Production Function Estimates at a Disaggregated-Level[a]

	Food, Textile, Leather Wood and Paper		Chemicals, Rubber Plastics and Furniture		Basic and Fabricated Metal Products		Computer, Electronics Mach. and Vehicles	
	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
l	-0.062	0.131	0.086	0.111	0.383***	0.036	0.427***	0.067
m	0.431	0.494	1.305***	0.200	0.539*	0.313	0.545*	0.304
k	0.519***	0.172	-0.175	0.111	0.094	0.103	0.058	0.172
ml	0.034	0.045	-0.055*	0.031	-0.144***	0.019	-0.107***	0.022
mk	-0.121**	0.050	0.047	0.032	0.035	0.054	-0.020	0.033
lk	-0.068*	0.036	-0.023	0.026	-0.007	0.011	-0.004	0.019
l^2	0.051**	0.021	0.061***	0.012	0.088***	0.012	0.059***	0.012
m^2	0.084*	0.045	-0.063	0.048	0.053*	0.030	0.073**	0.043
k^2	0.053**	0.025	0.004	0.018	-0.017	0.031	0.009	0.009
	Underid.	Overid.	Underid.	Overid.	Underid.	Overid.	Underid.	Overid.
test stat.	12.712	9.168	12.359	3.251	15.451	6.977	17.954	8.541
p-value	0.079	0.164	0.089	0.777	0.031	0.323	0.056	0.481
#firms&obs.	170	1734	98	1196	102	1198	112	1162

[a]Underid. and Overind. represent instrument test results for underidentification and overidentification that are described in Table 9.

Table 11: Factor Elasticities Evaluated at the Sample Means[a]

	m	l	k
All Sector	0.744	0.244	0.056
Food, Textile, Leather, Wood and Paper	0.910	0.221	0.084
Chemicals, Rubber, Plastics and Furniture	0.572	0.148	0.045
Basic and Fabricated Metal Products	0.697	0.289	0.092
Computer, Electronics, Mach. and Vehicles	0.817	0.305	0.013

[a]Factor elasticities the derivatives of the production functions evaluated at the sample means.

6.4 Recovering Markups from Production Function Estimates

Equation 23 is the Hall's (1988) optimality condition that equates the production elasticity of intermediate inputs to the multiplication of markups (μ_{it}) and the input's expenditure share in revenues (s_{it}^M).

$$\frac{\partial Q_{it}}{\partial M_{it}} \frac{M_{it}}{Q_{it}} = \alpha_{it}^M = \mu_{it} s_{it}^M \tag{23}$$

Equation 23 can be derived as a first order condition to firms' per-period profit maximization (e.g. Criscuolo and Martin, 2009) or cost minimization problem (e.g. De Loecker and Warzynski, 2012), and is widely used in applied research to retrieve an empirical measure of markups from estimated factor elasticities (e.g. Griliches and Mairesse, 1995; Griliches and Klette, 1996; Dobbelaere and Mairesse, 2013; Kilinc, 2014). The condition, however, requires the production factor to be perfectly variable, otherwise the objective function of the maximization problem cannot be represented by per-period profits. In other words, the optimality condition may not hold when defined in terms of quasi-fixed factors of production such as labor and capital.

To compute the markups for each firm and every time period through Hall's optimality condition, I use factor elasticity parameters recovered from the translog production function estimation. Two different markup measures are computed by evaluating the optimality condition using labor (Markup-L) and intermediate inputs (Markup-M). I compare the markup measures based on a set of criteria, one of which is the expected positive and high correlation between the price-cost margin (PCM) and the markup. To understand the link between the PCM and markups, one may rely upon a simplified relationship based on the optimality condition. Assuming all production factors are perfectly variable and the total returns to scale ($RTS_{it} = \alpha_{it}^L + \alpha_{it}^M + \alpha_{it}^K$) does not significantly vary among firms, the following condition entails positive relation between the PCM ($PCM_{it} = 1/\left[s_{it}^L + s_{it}^M + s_{it}^K\right]$) and markups.

$$\mu_{it} = RTS_{it} PCM_{it} \tag{24}$$

In the approximation of the firm-level PCM, I utilize the flexible part of the expenditures and calculate the PCM by the ratio of the total expenditures on labor and intermediate inputs to revenues. Table 12 presents the partial correlation matrix between the firm-level PCM and the markup measures. In addition to the PCM, I introduce the RTS into the analysis to be consistent with the condition given by equation 24. The time specific RTS is recovered at the firm-level from the translog production function estimation.

Table 12: Partial Correlation Matrix for Markups and PCM

	Markup-L	PCM	PCM*RTS
Markup-M	−0.140	0.603	0.671
Markup-L		0.376	0.344
PCM			0.985
	Markup-L	PCM	Markup-M
Wght. Average	0.772	1.137	1.135
Std.	0.297	0.192	0.311

The upper panel of Table 12 displays the partial correlation coefficients that are controlled for industry and year fixed-effects. The correlation between the Markup-M and Markup-L is negative emphasizing the importance of the selection of the right markup measure. The correlation of the PCM with the Markup-M is higher than its correlation with the Markup-L. The correlation coefficient decreases for Markup-L but raises for Markup-M, when the PCM is replaced by PCM*RTS.

In the firm-level data, one can observe markups lower than 1 for some particular firms and possibly for a temporary period, after which the firm is expected to raise its markup or exit the market. In most cases, firms' markups exceed 1 indicating positive profit opportunities. The below panel of Table 12 shows that the weighted average of the firm-level Markup-L is lower than 1, while the weighted average PCM and Markup-M are slightly above 1.

Figure 6: Measures of Markup vs. TFP

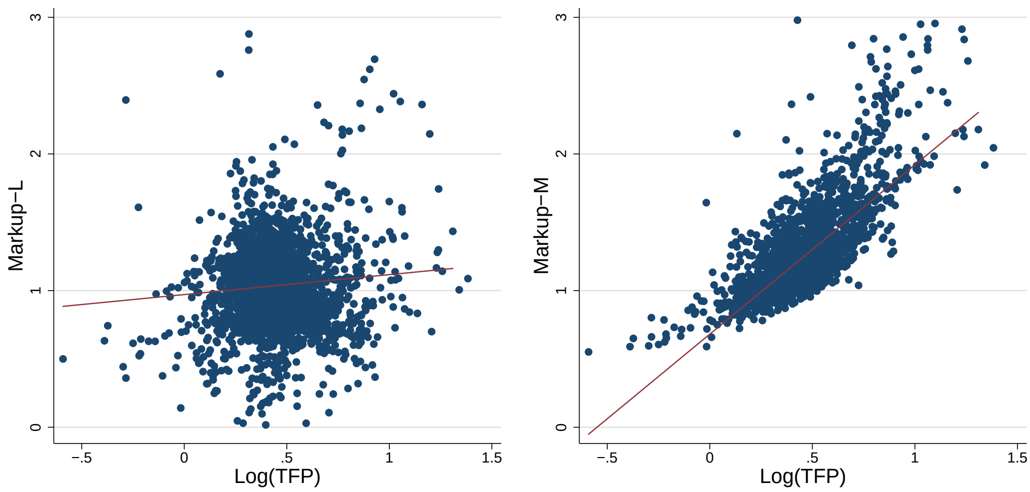


Figure 6 displays two scatter plots for the measures of markup against the log of the TFP that is retrieved from the translog production function estimation. In the scatter plots, each point represents a markup-productivity combination of a firm in a year. The left panel displays that the Markup-L is below 1 for a large portion of firms in the sample, while on the right panel, the Markup-M mostly lies between 1 and 2.

The correlation of markups with actual productivity can be positive or negative depending on various factors such as the market structure and the level of competition. When productivity is measured by deflated nominal sales and input expenditures, however, the productivity index (revenue productivity) embodies markups, so that the correlation between markups and the revenue productivity is more likely positive.[5] Figure 6 shows that the correlation of the log TFP with the Markup-L is weak, while its correlation with the Markup-M is strongly positive.

Overall, Figure 6 also provides, to some degree, evidence that the Markup-M is more robust, so that it is chosen as the right markup measure to be used in the analysis.

[5]The expected positive correlation between markups and standard measures of revenue productivity is supported theoretically and empirically, for instance, by the studies of Bernard et al.(2003), Melitz and Ottaviano (2008), De Loecker and Warzynski (2012) and De Loecker et al. (2012).

Figure 7: Productivity, Export Intensity and Markups for Each Industry Group

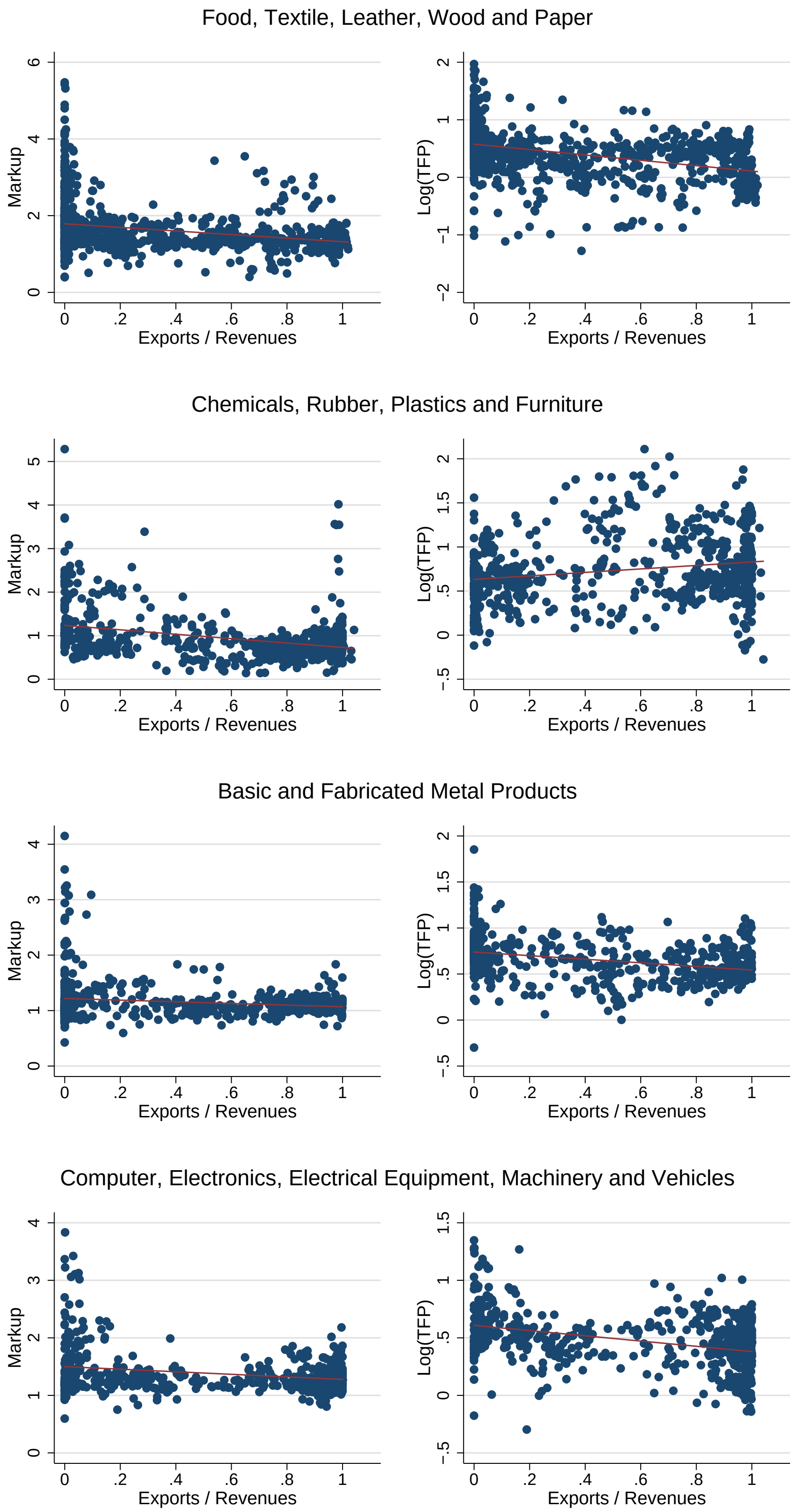


Table 13: Correlation Matrix Based on Disaggregated Prod. Function Estimates[a]

	log(R. TFP)	Markup-M	Markup-L	Exp. Int.	PCM	PCM*RTS	Size
log(Q. TFP)	0.698	-0.494	0.065	0.002	-0.053	-0.366	-0.069
log(R. TFP)		0.233	-0.140	-0.203	0.379	0.143	-0.216
Markup-M			-0.227	-0.249	0.486	0.636	-0.058
Markup-L				0.178	0.181	0.264	0.256
Exp. Int.					-0.072	-0.047	0.280
PCM						0.891	-0.017
PCM*RTS							0.040

[a]Correlation coefficients are controlled for industry and time fixed-effects. R. and Q. TFP represent revenue and quantity productivity, Exp. Int. is the export intensity based on the sum of intra and extra-EU exports.

6.5 Analysis of Export Demand Functions

Table 14: Descriptives on Demand Function Variables[a]

Export Destination Country Size ⇒		**Small**	**Medium**	**Large**
Sector Totals				
Number of Exporting Firms		93	145	142
Value of Exp. Goods (million Euro)	Annual Avg.	115.1	1451.9	3868.5
Number of Quantities (million)	Annual Avg.	89.1	1335.6	3853.0
Description of Destination or Firm Specific Variables				
EU Member Dummy	mean	0.24	0.61	0.64
	std	0.43	0.49	0.48
Tariff Indicator (1 to 10)	mean	3.26	2.87	3.36
	std	3.45	3.46	3.55
Wage per Employee (firm-level)	mean	1.72	1.67	1.67
	std	0.51	0.50	0.50
Imported Goods' Price (firm-level)	mean	2.08	2.24	1.67
	std	36.85	64.62	56.33
Exchange Rate	mean	110	92	275
(Euro/National Currency)	std	387	886	1846
Distance (km)	mean	3547	1828	2649
	std	3623	2892	3202

[a]Small countries are classified as the ones with less than 5 million population. Medium-sized countries have a population between 5 and 40 million, and large countries are the ones with more than 40 million population.

Figure 8: Total Volume of Exports vs. Destination Country Size

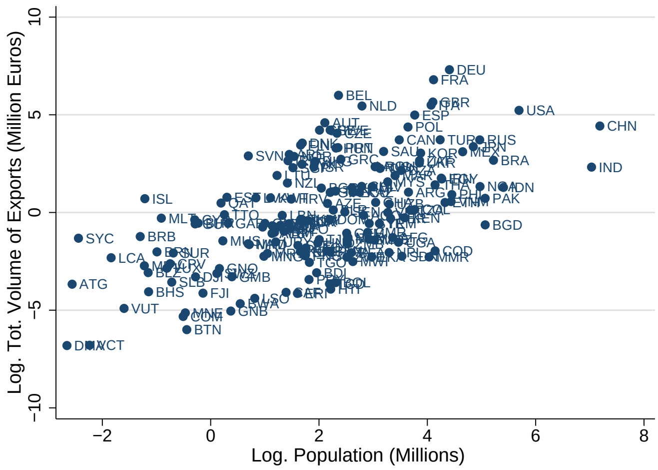


Figure 9: Distance vs. Destination Country Size

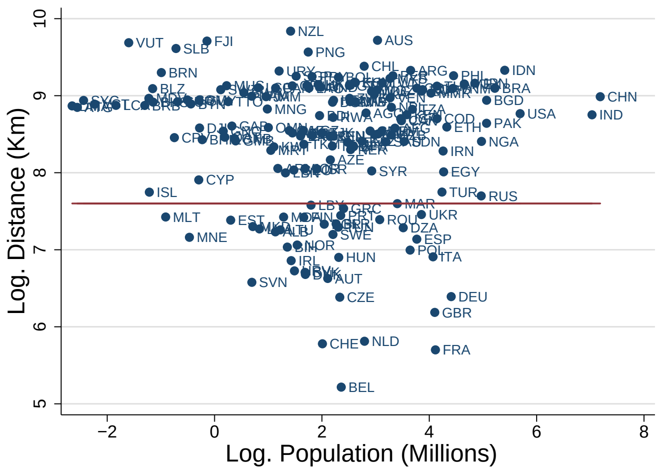


Figure 10: CIP vs. Destination Country Size

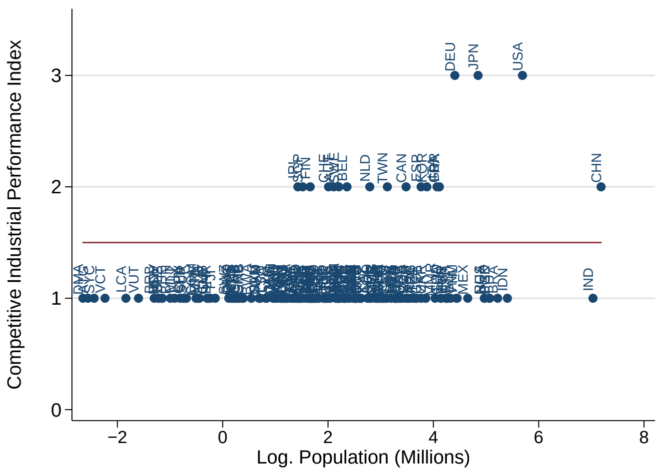


Table 15: Demand Estimation for Alternative Product Categories[a]

	Full Sample		Metals		Plastics	
	(1a)	(1b)	(2a)	(2b)	(3a)	(4b)
q_{ipct}	0.816***	0.720***	0.869***	0.753***	0.803***	0.690***
	(0.012)	(0.034)	(0.031)	(0.094)	(0.028)	(0.046)
$D^M_{ct}q_{ipct}$		0.098***		0.067		0.086***
		(0.031)		(0.097)		(0.032)
$D^L_{ct}q_{ipct}$		0.107***		0.164*		0.151**
		(0.038)		(0.099)		(0.062)
D^M_{ct}		-0.935***		-0.645		-0.851***
		(0.191)		(0.687)		(0.310)
D^L_{ct}		-1.248***		-1.622**		-2.031***
		(0.267)		(0.779)		(0.599)
gdp_{ct}	-0.007	0.029	-0.362*	-0.268	0.290*	0.334**
	(0.057)	(0.058)	(0.189)	(0.198)	(0.163)	(0.162)
$tariff_{ct}$	0.170***	0.171***	0.135***	0.130***	0.098**	0.094**
	(0.017)	(0.017)	(0.050)	(0.051)	(0.040)	(0.040)
$exrate_{ct}$	0.011	0.013	-0.009	-0.018	-0.003	0.005
	(0.009)	(0.010)	(0.015)	(0.018)	(0.020)	(0.022)
D_{EU}	-0.458***	-0.462***	-0.472***	-0.427***	-0.517***	-0.515***
	(0.044)	(0.045)	(0.124)	(0.128)	(0.102)	(0.103)
$\#obs$	95360	95360	11838	11838	18866	18866

[a]For explanations see Table 17.

Table 16: Demand Estimation for Alternative Product Categories: Instrument Tests[a]

Instrument Sets in Demand Function Specifications						
(1a) (2a) (3a) $\{q_{ipct-1}, p^I_{it}, w_{it}\}$						
(1b) (2b) (3b) $\{q_{ipct-1}, D^L_{ct-1}q_{ipct-1}, D^M_{ct-1}q_{ipct-1}, p^I_{it}, w_{it}\}$						
Endogenous Variables						
(1a) (2a) (3a) $\{q_{ipct}\}$						
(1b) (2b) (3b) $\{q_{ipct}, D^L_{ct}q_{ipct}, D^M_{ct}q_{ipct}\}$						
Underidentification Test	**(1a)**	**(1b)**	**(2a)**	**(2b)**	**(3a)**	**(3b)**
Kleibergen-Paap rk LM Stat.	1294.5	386.3	187.8	69.9	331.3	172.4
χ^2 p-value	0.000	0.000	0.000	0.000	0.000	0.000
Weak Identification Test						
Kleibergen-Paap rk Wald Stat.	485.7	87.4	68.6	14.2	118.1	36.6
Overidentification Test of All Instruments						
Hansen J Stat.	1.380	1.445	3.065	3.367	1.818	1.636
χ^2 p-value	0.502	0.486	0.216	0.186	0.403	0.441
LM test for Instrument Redundancy						
$H_0 : q_{ipct-1}$ is redundant (LM)	1290.8	134.7	320.2	48.6	180.0	17.8
χ^2 p-value	0.000	0.000	0.000	0.000	0.000	0.001

[a]For explanations see Table 18.

Table 17: Demand Estimation for Alternative Destination Characteristics[a]

$z \Rightarrow$	R. Productivity		Distance		EU Membership	
	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
q_{ipct}	0.703***	0.717***	0.632***	0.643***	0.735***	0.693***
	(0.024)	(0.035)	(0.027)	(0.045)	(0.016)	(0.036)
$D^z_{ct} q_{ipct}$	0.156***		0.244***		0.115***	
	(0.028)		(0.030)		(0.014)	
$D^M_{ct} q_{ipct}$		0.036		0.025		0.073**
		(0.037)		(0.035)		(0.032)
$D^z_{ct} D^M_{ct} q_{ipct}$		0.098***		0.177***		0.061***
		(0.027)		(0.044)		(0.015)
$D^L_{ct} q_{ipct}$		-0.037		-0.009		-0.051
		(0.058)		(0.054)		(0.046)
$D^z_{ct} D^L_{ct} q_{ipct}$		0.174***		0.296***		0.290***
		(0.050)		(0.040)		(0.037)
D^M_{ct}		-0.805***		-0.520**		-0.806***
		(0.201)		(0.210)		(0.194)
D^L_{ct}		-0.683*		-0.664**		-0.440
		(0.359)		(0.331)		(0.308)
$D^z_{ct} D^M_{ct}$						-0.495***
						(0.111)
$D^z_{ct} D^L_{ct}$						0.949*
						(0.571)
gdp_{ct}	0.014	0.028	0.250***	0.324***	0.027	0.150**
	(0.058)	(0.059)	(0.072)	(0.078)	(0.059)	(0.061)
$tariff_{ct}$	0.163***	0.172***	0.127***	0.124***	0.150***	0.147***
	(0.017)	(0.017)	(0.018)	(0.019)	(0.017)	(0.018)
$exrate_{ct}$	0.014	0.017*	0.007	0.011	0.020**	0.017*
	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
D^{EU}_{ct}	-0.438***	-0.462***	-0.382***	-0.383***	-1.128***	-0.327***
	(0.045)	(0.045)	(0.046)	(0.047)	(0.096)	(0.062)

[a]Every equation is estimated by the GMM IV for which product-firm-destination specific fixed-effects model is used. Time dummies are included in all equations. *** significant at 1%. ** significant at 5%. * significant at 10%. Robust standard errors are in parentheses.

Table 18: Demand Estimation for Alt. Destination Characteristics: Instrument Tests[a]

Instrument Sets in Demand Function Specifications						
(4a) (5a) (6a) $\{q_{ipct-1}, p^I_{it}, w_{it}\}$						
(4b) (5b) (6b) $\{q_{ipct-1}, D^L_{ct-1}q_{ipct-1}, D^M_{ct-1}q_{ipct-1}, D^L_{ct-1}D^z_{ct-1}q_{ipct-1},$ $D^M_{ct-1}D^z_{ct-1}q_{ipct-1}, p^I_{it}, w_{it}\}$						
Endogenous Variables						
(4a) (5a) (6a) $\{q_{ipct}\}$						
(4b) (5b) (6b) $\{q_{ipct}, D^L_{ct}q_{ipct}, D^M_{ct}q_{ipct}, D^L_{ct}D^z_{ct}q_{ipct}, D^M_{ct}D^z_{ct}q_{ipct}\}$						
Underidentification Test	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Kleibergen-Paap rk LM Stat.	346.0	101.9	316.7	143.8	1039.4	361.8
χ^2 p-value	0.000	0.000	0.000	0.000	0.000	0.000
Weak Identification Test						
Kleibergen-Paap rk Wald-F Stat.	95.5	16.0	88.1	22.6	293.0	57.4
Overidentification test						
Hansen J Stat.	2.519	2.175	1.010	1.421	1.387	1.414
χ^2 p-value	0.284	0.337	0.604	0.492	0.500	0.493

[a]Kleibergen-Paap rk Wald statistics (Kleibergen and Paap, 2006) can be used for two different weak identification tests. In the first test, the null hypothesis is that the bias in the IV coefficient estimates on the endogenous variables is greater than 5 percent of the OLS bias. The null of the second type of weak identification test is that the actual size of the t-test for the significance of the IV coefficient estimate of the endogenous variable at 5 percent significance level is greater than that at 10 percent. Stock and Yogo (2005) reports the critical values at 5 percent significance level. The reported Wald statistics, which reduces to F statistics in the case of single exogenous variable, are large enough to reject the null. The null hypothesis of the under-identification test is that the system is under-identified, while the null for the over-identification test is that the over-identifying restriction are valid.