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

(Preliminary and Incomplete. Please do not Distribute or Cite.)

Umut Kılınç*

April 25, 2014

Abstract

Empirical evidence suggests that openness to international trade influences firms’ price-setting behavior, so that exporting firms tend to charge higher price-cost markups than domestically operating establishments. This well-known effect of trade on markups alters in a special case, namely when trade barriers are relatively low and the market size of the home country is smaller than its trade partner. This paper provides evidence on the validity of the small country case by estimating firm-level markups and productivity through a production function specification using firm-level data for Luxembourg. The empirical results show that non-exporting producers tend to be small and charge higher markups than exporters, because competition is less intensive in the domestic markets. The trade-driven markup variation has important implications for the measurement of productivity. In a small highly open economy, exporting firms’ relative productivity may be underestimated by productivity indicators that are calculated by deflated revenues and input expenditures.

Keywords: export, translog production function, productivity, price-cost markup, firm-level data

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

1 Introduction

International trade acts as a selection mechanism that allows only most successful producers to seek new profit opportunities in foreign markets. Once firms are able to sell their products internationally, this does not only affect their profits but also their size in the domestic economy. Establishments that enter into export markets tend to grow to meet the foreign demand and to expand their input shares in the local market. This positive effect of international trade on exporting firms’ size constitutes a competitive pressure that forces non-exporting local producers to shrink or exit. From a macro perspective, openness to international trade stimulates creative destruction that leads the resources of the home country to be reallocated towards more efficient producers and

*Institut national de la statistique et des etudes economiques du Grand-Duche du Luxembourg (STATEC), 13 rue Erasme, L-1468 Luxembourg, E-mail: umut.kilinc@statec.etat.lu (https://sites.google.com/site/kilincumut/).
enhances aggregate productivity growth for a given technological frontier (i.e. Melitz, 2003).

Barriers to international trade play a crucial role in the mechanism that links openness to international trade to productivity growth. Firms facing additional fixed costs in the export market raise their markups rather than producing more at a lower price. Higher magnitudes of trade costs, therefore, restrict growth opportunities of exporters and suppress allocative efficiency gains from trade. De Loecker and Warzynski (2012), for instance, show 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.

In an open economy, trade barriers are not the only source of the markup variation of exporters from non-exporters. Bernard et al. (2003) suggest that the selection into international markets only allow highly productive firms to export, and more productive firms tend to charge higher markups. As the starting point of this study, Melitz and Ottaviano (2008) find that relative market size is an important factor shaping the interaction between trade patterns, markups and allocative efficiency gains from trade. For instance, when the home country is sufficiently small relative to its trading partner, non-exporting firms’ markups may exceed those of exporters under certain conditions. This paper studies the relationship between international trade and firm dynamics in Luxembourg and finds that observed patterns considerably fit the small open economy case depicted in the Melitz-Ottaviano model.

This study attempts to test some micro foundations of international trade theory in a small open economy by estimating firm-level markups and total factor productivity through a production function specification. The results show that exporting firms have on average lower markups than non-exporters. This is somewhat contradictory with the case of trade between symmetric countries where exporters raise their markups as a response to increased fixed costs due to trade barriers. The Melitz-Ottaviano model, however, shows that in the case of small highly open economy with a large trading partner, exporter firms face lower trade barriers but harsher competition in the foreign market, so that their markups are lower. In the 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. The observed markup variation between exporting and non-exporting firms has important implications for empirical research. In the calculation of productivity, deflating nominal input and outputs by aggregate price indices would not isolate micro-level price variation, which causes to underestimate exporting or to overestimate non-exporting firms’ productivity in a small highly open economy. This paper provides empirical evidence on distorting effects of unobserved prices embodied in standard productivity measures simply by running a probit on export status while controlling for unobserved markup variation.

This study makes use of firm-level data for manufacturing firms operated in Luxembourg over the period from 1996 to 2011. Productivity and markups are recovered at the firm-level from the estimation of a translog production function by imposing Hall’s (1988) optimality condition. The production function is estimated by taking into account the endogeneity due to unobserved productivity using the control function approach suggested by Wooldridge (2009). The next section describes the small country case in the Melitz-Ottaviano model. The third section presents the estimation methodology and retrieves the estimates of productivity and markups. The third section also develops a discussion over how to implement Hall’s optimality condition to recover markups from
estimated factor elasticities. The forth section interprets the results in the context of the theoretical framework and discusses the importance of the distorting effects of the unobserved markup variation in the analysis of productivity. The fifth section summarizes conclusions and interprets the relevance of the empirical findings for the industrial policy aiming to accelerate productivity growth.

2 Small Open Economy Case in the Melitz-Ottaviano Model

This section develops a discussion over Melitz and Ottaviano’s (2008) trade model by elaborating a special case that is the international trade between two countries, where the home country is small and the foreign country is large with symmetric and low trade barriers. The case of asymmetric country size with high degrees of openness to international trade is particularly relevant in the context of Luxembourg, first because the size of the home country is significantly small relative to its main trading partners Germany and France. Second, Luxembourg’s trade with the EU countries accounted for more than 85 percent of total exports and imports during the last decade. The presence of mutual free trade agreements among the EU member states provide some ground for the assumption of low and symmetric trade barriers.

The Melitz-Ottaviano model provides a rich set of predictions on the role of market size in shaping the relationship between international trade and market dynamics. In particular, when the country of origin is very small relative to its trading partner and trade barriers are low some empirically well-supported effects of foreign trade on the markup gap between trading and non-trading firms in the home country alter. In the Melitz-Ottaviano model with two countries having symmetric trade barriers ($\tau^h = \tau^f = \tau$), the markups on domestically sold and exported goods are as follows in the equilibrium.

$$\mu^h_D = \frac{1}{2} \left( c_h^D - c \right)$$

$$\mu^h_X = \frac{1}{2} \left[ \tau c_h^X - (2 - \tau) c \right]$$

In the above formulation, $\mu^h_D$ represents the markup on domestically sold goods of a firm of the home country with marginal cost $c$ and $\mu^h_X$ is the markup on exported goods of the home country’s firm. The marginal cost parameter ($c$) is exogenous and an inverse indicator of productivity, so that lower $c$ corresponds to higher productivity. Thus, $c_h^X$ is the cut-off efficiency or productivity level to enter into the export market and $c_h^D$ is the cut-off level for the domestic market. $c_h^X$ and $c_h^D > c$ in equilibrium for every operating firm with efficiency draw of $c$, and $\tau > 1$ is the per unit trade cost. According to this setting, markups on exported goods are higher than those of domestically sold goods ($\mu^h_X > \mu^h_D$), only if the following condition is satisfied.

$$c_h^D - c > \tau \left( c_h^X + c \right)$$

The condition given in equation 3 is satisfied when trade barriers ($\tau$) are sufficiently low, and $c_h^D$ is sufficiently higher than $c_h^X$.

In the Melitz-Ottaviano model the threshold level of efficiency to enter into domestic and export markets are given by the following identities in the equilibrium.

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

where \( \Psi = \left[ 2\gamma (k + 1) (k + 2) \left( 1 - \tau^{-k} \right)c_M^k f_E \right]^{1/(k+2)}. \)

In equations 4 and 5, \( L_h \) represents the number of consumers in the home country each supplying one unit of labor. Therefore, \( L_h \) represents the country size in home country and \( L_f \) is the size of the foreign trade partner. \( \Psi \) is a composite term that consists of exogenous parameters of the model including fixed-cost of entry \( (f_E) \), upper bound of productivity distribution \( (c_M) \), dispersion \( (k) \) and product differentiation \( (\gamma) \) parameters which characterize consumer preferences, productivity distribution and market structure.

Equation 4 shows that as the home country size is smaller, the threshold level of efficiency is higher. This indicates that for firms in the small home country, staying in the market is easier and the competition is less intensive, so that the threshold efficiency as well as markups are higher. Equation 5 shows that as the trade partner’s size is larger, the threshold to export is larger and markups on exported goods are lower due to more intense competition in the foreign market.

The Melitz-Ottaviano model suggests that when the home country size \( (L_h) \) is sufficiently small, the foreign country size \( (L_f) \) is sufficiently large and trade barriers \( (\tau) \) are low, the exporting firms’ markups are higher than non-exporting firms. This result is opposite of what one would find in a model of trade between two symmetric countries, so that any positive trade barrier raises exporters’ markups relative to non-exporters. Melitz and Ottaviano (2008) interpret the results for the asymmetric country size case by comparing the differences in the intensity of competition in domestic and foreign markets. “On the export side, a larger trading partner represents increased export market opportunities. However, this increased export market size is offset by its increased “competitiveness” (a greater number of more productive firms are competing in that market, driving down mark-ups). On the import side, a larger trading partner represents an increased level of import competition. In the long run, this is offset by a smaller proportion of entrants, and hence less competition in the smaller market.”

In the abovementioned scenario, trade partnership with a large country does not only cause less competition but also lower average productivity for non-exporting firms in the small home country. Holding the home country size \( (L_h) \) and upper bound of productivity distribution (which is the lower bound of the cost-efficiency distribution that is 0) constant, higher cut-off level of cost-efficiency in the domestic market \( (c_D^h) \) means higher average cost-efficiency or lower aggregate productivity. In other words, lowering \( c_D^h \) reallocates a portion of the fixed amount of resources \( (L_h) \) toward less efficient firms holding the technological frontier constant. As the home country size is smaller, the threshold to stay in the home country is lower and the efficiency in the allocation of resources is deteriorated, so that smaller country size corresponds to lower aggregate productivity in the long-run.

3 Estimation of Firm-Level Productivity and Markups

In the estimation of productivity and markups, I utilize a translog production function specification that allows for variation in factor elasticity parameters over time and among firms. The production function is defined at the firm-level and markups are recovered through Hall’s (1988) optimality condition using the factor elasticity estimates and the
observed factor expenditure shares in firms’ revenues. Estimating the production function in this way, therefore, enables a micro-level analysis of the interaction between international trade and firm dynamics by also taking into account the variation over time.

\[ Q_{it} = \Theta_{it} F (L_{it}, M_{it}, K_{it}) \] (6)

Equation 6 represents the production function in terms of three production factors that are labor \( L \), intermediate inputs \( M \) and capital \( K \). \( Q \) stands for the output, \( \Theta \) is the total factor productivity, \( i \) and \( t \) are the firm and time subscripts.

\[ \frac{\partial Q_{it}}{\partial M_{it}} M_{it} Q_{it} = \alpha_{it} M_{it} = \mu_{it} s_{it} M \] (7)

Equation 7 is the Hall’s optimality condition that equates the production elasticity of a variable factor to the multiplication of markups \( \mu_{it} \) and the input’s expenditure share in revenues \( s_{it} M \). Equation 7 can be derived as a first order condition of a firm’s per-period profit maximization (e.g. Criscuolo and Martin, 2009) or cost minimization problem (e.g. De Loecker and Warzynski, 2012), and is extensively 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; Dobbelare 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. Thus, the optimality condition may not hold when defined in terms of quasi-fixed factors of production such as labor and capital.

The next part presents the estimation methodology and results of alternative production function specifications. While calculating markups, I consider two different measures that are based on the empirical evaluation of the optimality condition using intermediate inputs and labor. In the following step, I develop a discussion over how to select the right measure of markups among the two alternatives. To choose the more robust proxy for markups, I rely upon a simplified measure of the optimality condition, which suggests a high degree of correlation between price-cost margin (PCM) and markups. Assuming all production factors are perfectly variable and the total returns to scale \( \lambda_{it} = \alpha_{it}^L + \alpha_{it}^M + \alpha_{it}^K \) does not significantly vary among firms, the following condition indicates a positive relation between the PCM \( (PCM_{it} = 1 / [s_{it}^L + s_{it}^M + s_{it}^K]) \) and markups.

\[ \mu_{it} = \lambda_{it} PCM_{it} \] (8)

In the approximation of the firm-level PCM, I utilize a relatively more flexible part of total expenditures due to the problem of unobserved user cost of capital. Thus, the PCM is calculated by the ratio of the total expenditures on labor and intermediate inputs to revenues.

### 3.1 Estimation Methodology

In the estimation of the production function, I utilize Wooldrige’s (2009) method that is an extension of Levinsohn and Petrin (2003) (LP). The Wooldridge method abandons one of the identifying restrictions of the LP that is the assumption of predetermined labor input. Assuming that a firm’s manager hires labor before the realization of productivity shock, 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). Wooldridge (2009) reduces the two step control function approach into a single step, and identifies all parameters of production function simultaneously. This paper estimates production functions by both the LP and the Wooldrige approaches, so that the below lines describe the two econometric frameworks comparatively.

\[ q_{it} = \alpha_0 + \alpha_L l_{it} + \alpha_M m_{it} + \alpha_K k_{it} + \alpha_{LM} l_{it} m_{it} + \alpha_{KM} k_{it} m_{it} + \alpha_{LK} l_{it} k_{it} + \alpha_{LM} l_{it}^2 + \alpha_{M2} m_{it}^2 + \alpha_{K2} k_{it}^2 + \theta_{it} + \epsilon_{it} \]  

(9)

In equation 9, all the variables are in logarithms. \( \theta_{it} \) and \( \epsilon_{it} \) represent the log of the systematic component in the TFP that affects the managerial decisions and the i.i.d component of productivity respectively. \( \alpha \)'s are the production function parameters. To simplify the notation, the translog production function will be represented by \( q_{it} = \alpha_0 + X_{it} \beta + \epsilon_{it} \) where \( X_{it} \) is the variable and \( \beta \) 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 \( k_{it} \).

\[ q_{it} = \alpha_0 + X_{it} \beta + g (m_{it}, k_{it}) + \epsilon_{it} \]  

(10)

In the first stage, the LP only identifies the coefficient 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 a separate identification of their coefficients is not feasible. For the variables that cannot be identified in the first stage, the LP defines a non-parametric function \( g(m_{it}, k_{it}) \) that is in the form of a third order polynomial. The Wooldridge method adopts the semi-parametric approach of the first stage of the LP algorithm, but estimates equation 10 jointly with the estimating equation of the second stage by the GMM using a set of moment conditions as will be discussed below.

The second stage in the LP defines an unknown Markov process that represents the evolution of the unobserved productivity over time. At this stage, I assume that productivity follows a random walk with a drift, so that \( g(m_{it}, k_{it}) = \beta_0 + g(m_{it-1}, k_{it-1}) + \omega_{it} \). The fitted values of the productivity regression serves as an estimate for the conditional expectation of productivity that is used to control for the endogeneity of the amount of inputs used in production to the unobserved productivity that is partially observed by the manager. The second stage of the LP, therefore, is written in the following way.

\[ q_{it} = \gamma_0 + X_{it} \beta + g (m_{it-1}, k_{it-1}) + \nu_{it} \]  

(11)

The LP minimizes the joint error term, \( \nu_{it} = \epsilon_{it} + \omega_{it} \) using a set of moment conditions that contains current and previous periods’ capital, previous periods’ labor and intermediate inputs. The moment conditions of the first and second stages in the LP, therefore, is given by the two identities below respectively.

\[ E (\epsilon_{it} \mid l_{it}, m_{it}, k_{it}, g^n_{it}, l_{it-1}, m_{it-1}, k_{it-1}, g^n_{it-1}, \ldots, l_{i1}, m_{i1}, k_{i1}, g^n_{i1}) = 0 \]  

(12)

\[ E (\nu_{it} \mid k_{it}, l_{it-1}, m_{it-1}, k_{it-1}, g^n_{it-1}, \ldots, l_{i1}, m_{i1}, k_{i1}, g^n_{i1}) = 0 \]  

(13)

In equation 12 and 13, \( g^n \) represents the variables in the third order polynomial excluding the linear terms \( m \) and \( k \).
The Wooldridge method estimates equation 10 and 11 simultaneously by GMM, which turns out to be a linear GMM minimization problem under the assumption that productivity follows a random walk.

\[
\begin{pmatrix}
 q_{it} \\
 g_{it}
\end{pmatrix} =
\begin{pmatrix}
 1 & 0 & X_{it} & g_{it} \\
 0 & 1 & X_{it} & g_{it-1}
\end{pmatrix}
\times
\begin{pmatrix}
 a_0 & \gamma_0 & \beta & \phi
\end{pmatrix} +
\begin{pmatrix}
 \epsilon_{it} \\
 \nu_{it}
\end{pmatrix}
\]

(14)

In addition to the non-parametric control function, the variables containing sole functions of \( k_{it} \) in the explanatory variables’ vector \( X_{it} \) are assumed to be exogenous, since \( k_{it} \) is a function of previous periods investments. The explanatory variables of the translog production function that contain at least one of the endogenous inputs, \( m_{it} \) and \( l_{it} \), are instrumented. Excluding the exogenous variables, the instruments consist of certain functions of \( k_{it} \), \( k_{it-1} \), \( m_{it-1} \) and \( l_{it-1} \), so that \( Z_{it} = (l_{it-1}, k_{it-1}, m_{it-1}, l_{it-1}^2, k_{it-1}m_{it-1}, k_{it-1}l_{it-1}, m_{it-1}l_{it-1}, k_{it}l_{it}^2, l_{it-1}^2, m_{it-1}^2l_{it-1}, m_{it-1}l_{it-1}^2, k_{it}^2m_{it-1}, k_{it}m_{it-1}^2). \) In the estimation of translog production function with the Wooldridge method, the moment conditions are defined as follows.

\[
E\left[
\begin{pmatrix}
 1 & 0 & k_{it} & k_{it}^2 & g_{it} & Z_{it} \\
 0 & 1 & k_{it} & k_{it}^2 & g_{it-1} & Z_{it}
\end{pmatrix}
\times
\begin{pmatrix}
 \epsilon_{it} \\
 \nu_{it}
\end{pmatrix}
\right] = 0
\]

(15)

### 3.2 Dataset

The primary firm-level dataset used in this study is the Structural Business Survey (SBS) of Luxembourg that consists of nominal output and input expenditures. The output variable is 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 represented by the consumption of intermediate goods and services for a given year deflated by the intermediate input price index that is reported at the 2-digit level. The labor input is the number of full and part time employees, where the number of part time employees are 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 that is grouped into alternative capital assets. The investment data is deflated by the 2-digit price index that is for capital goods and services. The description of the method of capital construction and descriptive statistics can be found in the appendix. The final unbalanced sample based on the SBS consists of 228 firms and 2734 firm*time observations for the entire manufacturing sector and for the period between 1996 and 2011. The secondary source of micro data is the Business Register which is used to assess information on firm demographics such as age, entry and exit status, as well as nominal import and exports that are classified based on the trading partners proximity as intra- and extra-EU trade.

### 3.3 Estimation Results

Table 1 presents the estimation results of translog and Cobb-Douglas form production functions by the Wooldridge and LP methods. On the right handside, Cobb-Douglas production function estimates by the two methods are displayed. The coefficient of labor is slightly higher in the Wooldridge case which is in line with our previous discussion. Namely, the Wooldridge method revises the LP to account for the endogeneity of labor to the unobserved productivity shock which otherwise causes a downward biased elasticity estimate on labor. The factor elasticity estimates for the other inputs and the estimate of
total returns to scale is lower in the Wooldridge case. On the contrary, the LP indicates an increasing returns to scale in production.

<table>
<thead>
<tr>
<th>Translog - Wooldridge</th>
<th>Cobb-Douglas</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef.</td>
<td>Std.</td>
</tr>
<tr>
<td>$l$</td>
<td>0.314**</td>
</tr>
<tr>
<td>$m$</td>
<td>0.619**</td>
</tr>
<tr>
<td>$k$</td>
<td>0.237*</td>
</tr>
<tr>
<td>$ml$</td>
<td>-0.115**</td>
</tr>
<tr>
<td>$mk$</td>
<td>-0.056</td>
</tr>
<tr>
<td>$lk$</td>
<td>-0.011</td>
</tr>
<tr>
<td>$l^2$</td>
<td>0.076**</td>
</tr>
<tr>
<td>$k^2$</td>
<td>0.021</td>
</tr>
</tbody>
</table>

Avg. Factor Elasticity in Translog Specification

$\partial q/\partial l = 0.260 \quad \partial q/\partial m = 0.745 \quad \partial q/\partial k = 0.078$

2-digit industry and time dummies are included in all equations. ** significant at 1%. * significant at 10%.

The left handside of Table 1 displays the results of the translog production function estimation by the Wooldridge method. In the Wooldridge method, the production elasticity of inputs are not fixed among firms and over time, namely that $\partial q/\partial m = \alpha_M + \alpha_{LM}l_{it} + \alpha_{KM}k_{it} + 2\alpha_{M2}m_{it}$. The bottom row of the table displays average factor elasticity estimates based on the translog production function specification. The elasticity estimate for labor is the highest in the translog case, and the results indicate on average increasing returns to scale in production in manufacturing industries of Luxembourg.

To compute the markups for each firm and time period, I need firm-level estimates of factor elasticity parameters. Thus, the below analysis takes the translog production function estimation results as the benchmark. Two different markup measures are computed through the optimality condition given by equation 7 using labor (Markup-L) and intermediate inputs (Markup-M). The two markup measures are evaluated, first, by comparing their correlation with the PCM that is expected to be significantly positive and high. Second, when the productivity is measured by deflated nominal sales and input expenditures, micro-level price-cost markup variation is embodied in the productivity measure. Standard measures of productivity, therefore, is expected to be positively and highly correlated with markups, which can be considered as a criterion to test the robustness of the markup measure. 2 I calculate the total factor productivity (TFP) using

\[ TFP = \text{productivity} \times \text{TFP} \]

1In the LP, standard errors are computed by block bootstrapping, while the robust standard errors are reported in the Wooldridge case. The standard errors of the coefficients of capital containing variables are relatively large in comparison to those of other variables. One possible reason is that $k_{it}$ is not directly observed but is approximated by a version of perpetual inventory method. The approximation requires a set of assumptions on the retirement and depreciation profiles of capital assets which introduce further errors in the measurement and raise the standard errors of the elasticity estimates. Nevertheless, the elasticity estimate of the capital stock is around 0.1 in alternative specifications, and the estimation results are significant at 1% level for the coefficients of the variables that are linear in $k_{it}$.

2The expected positive correlation between markups and standard measures of nominal productivity
the deflated nominal input-output data and based on the translog production function estimation results that corresponds to \( \log(TFP_{it}) = q_{it} - X_{it} \beta \) in the structural model. The PCM is the ratio of revenues to total expenditures on labor and intermediate inputs. Table 2 provides a descriptive analysis of the calculated indices of productivity and markups.

Table 2: Retrieving Markups from Factor Elasticities

<table>
<thead>
<tr>
<th></th>
<th>Markup-M</th>
<th>Markup-L</th>
<th>PCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \log(TFP) )</td>
<td>0.75</td>
<td>-0.06</td>
<td>0.44</td>
</tr>
<tr>
<td>Markup-M</td>
<td>-0.14</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>Markup-L</td>
<td>0.29</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

P. Correlations Controlled for Industry Fixed-Effects

<table>
<thead>
<tr>
<th></th>
<th>( \log(Markup-L) )</th>
<th>( \log(PCM) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \log(Markup-M) )</td>
<td>-0.08</td>
<td>0.76</td>
</tr>
<tr>
<td>( \log(Markup-L) )</td>
<td></td>
<td>0.24</td>
</tr>
</tbody>
</table>

The upper panel of Table 2 displays the partial correlation matrix among the two markup measures, the TFP and PCM, where the correlation coefficients are controlled for industry fixed-effects. The correlation between the two markup measures are negative and low emphasizing the importance of the selection of the markup measure. The correlation of the PCM with the Markup-M is higher than the correlation with the Markup-L. Moreover, the Markup-M exhibit strong positive correlation with the estimated productivity index with a correlation coefficient of 0.74, while the correlation of the TFP with the Markup-L is negative and weak.

The correlation between the PCM and a robust measure of firm markups is expected to be positive as is shown in the reduced form optimality condition given by equation 7. To be more precise with the structural setup, I introduce the return to scale parameter (\( \lambda_{it} \)) into the set of control variables, take the log of every variable and recalculate the partial correlation coefficients. \( \lambda_{it} \) is retrieved from the estimation of the translog production function for each firm and year. The lower panel of Table 2 presents the partial correlations between the two markup measures and the PCM while controlling for industry fixed-effects and \( \lambda_{it} \). The correlation between the Markup-M and the PCM considerably rises, when \( \lambda_{it} \) is added into the set of control variables. Conversely, the correlation of the PCM with the Markup-L is slightly diminished by controlling for the variation in the total returns to scale.

is supported both 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 1 provides more detailed information on the correlation between the measures of markups and the log of the TFP. The left panel displays that there is no seemingly significant correlation between the TFP and Markup-L. Conversely, the Markup-M exhibits a strong positive correlation with the TFP, where there is some evidence that the relationship is non-linear with a stronger correlation for high-productivity and high-markup firms.

In addition to the correlation of markups with the PCM, the mean and the distribution of markups can be used to intuitively evaluate the soundness of the markup measures. In a real market economy, price-cost markups can be different than one due to various reasons such as imperfect competition, fixed costs, uncertainty and the dynamic nature of firm decisions. In most cases, however, firm markups can be expected to be over 1 indicating positive profits or the presence of significant fixed cost. In firm-level data, markups lower than 1 also can be observed commonly but possibly for a temporary period of time after which the firm is expected to make positive profits or exit the market. Figure 1 shows that according to the Markup-M, majority of firms have markups between 1 and 1.5. When markups are calculated based on the optimality condition for labor input, a large portion of firms have markups significantly lower than 1 irrespective of their productivity level.

The comparisons between the two markup measures were based on three criteria that are the correlation of markups with the PCM, the correlation of markups with the TFP and the distribution of markups for which one would expect the majority of the estimated markups to lie above one, so that firms are able to make positive profits. The Markup-M provides more robust results according to these selection criteria, so that it is selected as the true markup measure to be used for the rest of this paper. The discussion on the price effects embodied in standard measures of productivity and its implications for productivity analysis will be revisited in the latter parts of this study.

4 Productivity, Markups and International Trade

This section adds the international trade dimension into the empirical analysis and tests the validity of the small open economy case in the manufacturing sector of Luxembourg.
In addition to the interaction between markups and openness to international trade, this section discusses the implications of the small open economy case for the measurement and analysis of firm-level productivity. For this purpose, I attempt to understand the sensitivity of the empirical results to the unobserved price effects embodied in the productivity measures based on deflated sales and input expenditures. The discussions on the productivity measurement are developed and the results are interpreted in the context of Foster et al. (2008).

Table 3 presents the average TFP, markup, PCM, labor share, average firm size, import and export intensities for alternative firm groups. The TFP, markup and PCM are calculated in the same way as described in the previous part. Import and export intensities are the ratios of nominal imports and exports to revenues. Labor share is the total number of employees in each group divided by total number of employees in the entire manufacturing sector. Average firm size is also based on the number of employees. Every variable except labor shares and size is first calculated at the firm-level, and then averaged over individual units using firms’ revenue shares as the weights. Firms are grouped based on their entry, exit, import and export status. While selecting entrant and exiter firms, I utilize an indicator variable for firms’ entry-exit status in the business register of Luxembourg. When calculating the statistics for entrants and exiters, however, I do not only consider the entry or exit year, but the entire time series of a firm that is marked as an entrant or exiter in any year in the sample. The entrants or exiters in Table 3, therefore, represent the firms that are in the start-up or liquidation period. Firms are also grouped based on their export status in a given year. I further classified firms in Luxembourg’s manufacturing sector as the establishments exporting and not exporting outside of the EU. One reason for this is that trade barriers in the form of, for instance, transportation costs, taxes and tariffs may significantly differ when exporting to distant destinations. The impact of trade costs on firm markups over exported goods may differ for exports to the non-EU countries.

Table 3: Productivity, Markups and International Trade Intensity

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry Total</td>
<td>1.151</td>
<td>1.128</td>
<td>1.122</td>
<td>0.610</td>
<td>0.415</td>
<td>1.000</td>
<td>162</td>
</tr>
<tr>
<td>Entrants</td>
<td>1.340</td>
<td>1.281</td>
<td>1.238</td>
<td>0.462</td>
<td>0.304</td>
<td>0.101</td>
<td>97</td>
</tr>
<tr>
<td>Exiters</td>
<td>1.158</td>
<td>1.101</td>
<td>1.185</td>
<td>0.800</td>
<td>0.325</td>
<td>0.005</td>
<td>109</td>
</tr>
<tr>
<td>Exporters</td>
<td>1.148</td>
<td>1.123</td>
<td>1.121</td>
<td>0.625</td>
<td>0.421</td>
<td>0.938</td>
<td>176</td>
</tr>
<tr>
<td>Non-Exporters</td>
<td>1.274</td>
<td>1.324</td>
<td>1.143</td>
<td>—</td>
<td>0.192</td>
<td>0.062</td>
<td>71</td>
</tr>
<tr>
<td>Exporter Extra-EU</td>
<td>1.133</td>
<td>1.115</td>
<td>1.116</td>
<td>0.669</td>
<td>0.397</td>
<td>0.795</td>
<td>243</td>
</tr>
<tr>
<td>N.-Exporter Extra-EU</td>
<td>1.250</td>
<td>1.204</td>
<td>1.155</td>
<td>0.276</td>
<td>0.533</td>
<td>0.205</td>
<td>70</td>
</tr>
<tr>
<td>Importers</td>
<td>1.151</td>
<td>1.127</td>
<td>1.122</td>
<td>0.611</td>
<td>0.416</td>
<td>0.993</td>
<td>162</td>
</tr>
<tr>
<td>Non-Importers</td>
<td>1.297</td>
<td>1.796</td>
<td>1.024</td>
<td>0.006</td>
<td>—</td>
<td>0.007</td>
<td>151</td>
</tr>
</tbody>
</table>

*Exp. In.* is the export intensity measured by exports to revenues ratio. *Imp. In.* is the import intensity. *Share* represents each groups’ labor share in the industry total. *Av. Size* is the average of the number of workers employed by a firm.

According to Table 3, non-exporting firms have on average higher markups and productivity than exporters. The markup difference between the exporting and non-exporting establishments can be considered as evidence to the small open economy case, so that the lack of competition in the domestic market may be responsible for domestic
producers’ decisions to set higher markups. The PCM as an alternative imperfect indicator of markups also indicates that non-exporting firms have higher markups. The average TFP of exporters is low relative to non-exporters, which contradicts with the predictions of standard trade theory such that highly productive firms are more likely to export. This may be because of the distorting impact of unobserved price effects contained in standard productivity measures that are calculated by nominal input and outputs. Thus, high-markup firms’ productivity would be overestimated relative to low-markup producers, when the productivity index embodies micro-level price variation.

Luxembourg’s economy exhibits a high degree of openness to international trade and integration with international economic institutions. An average firm sells 60% of its output to abroad and the share of non-exporter (6%) and non-importers (0.7%) are very small in the economy. The country’s main trade partners are the other EU members, trading with which is subject to lower tariff and non-tariff barriers in comparison to trade with oversea countries. Since the impact of openness to trade on firm markups occurs as a consequence of the trade barriers, reclassifying firms as exporters to outside of the EU (extra-EU) and non-extra-EU exporters would be meaningful in this context. Table 3 shows that when only extra-EU exports are considered, the labor share of non-exporters rises from 6 to 21%. The non-extra-EU exporters, however, have higher markups than the extra-EU exporters, although non-exporters’ average markups diminishes in this alternative classification. The average TFP of non-extra-EU exporters are also higher than the extra-EU exporters indicating that taking into account export destination does not significantly alter the previous findings.

The rightmost column of Table 3 displays firms’ average number of employees in each group and shows that exporting firms are significantly larger than non-exporting firms. The size difference between the two firm groups expands, when the classification is based on extra-EU exports. Assuming that the TFP index is a distorted measure of productivity due to the unobserved prices, the difference in the amount of labor employed by exporting and non-exporting establishments provides some degree of evidence to the presence of allocative efficiency gains from trade. This is because more productive firms tend to expand and exploit their productivity advantage, when they enter into export markets. Openness to international trade, therefore, induces the resources of the home country to be reallocated towards more productive exporting producers.

In addition to openness to international trade, entry and exit status may influence the distribution of firm-level markups and productivity. According to Table 3, entrant firms have higher productivity than the industry average. Moreover, the PCM and markups are higher for entrant firms. Having highly productive entrants are not contradictory with previous findings, especially if one considers a new firm as an entrant throughout its entire life within the sample period. The results are somewhat contradictory with the findings of Foster et al. (2008) who suggest that entrants set on average lower markups due to adverse demand shocks faced in the start-up phase. Entrants’ export intensity is lower than the industry average, which may indicate that engaging into international trade has a greater influence on markups than the entry status. Exiting firms’ average productivity is not significantly different from incumbents, while their average markup and PCM are slightly lower than those of the overall industry. This may be because the market selection process is mainly based on profitability rather than productivity.

3 Olley and Pakes (1996) and Bartelsman and Doms (2000) provide evidence that entrants initially have poor productivity performance, but the ones survive the start-up phase often exhibits higher productivity growth rates and become more productive than incumbents.
in Luxembourg. Although being out of the scope of this paper, exporter firms’ average import intensity is higher than that of the non-exporters. This, however, is reversed when export status is determined by the extra-EU exports. Thus, firms that only export to the EU countries heavily rely on imported intermediate inputs in production in Luxembourg’s manufacturing sector.

Table 4: Partial Correlation Coefficients Controlled for Industry Fixed-Effects

<table>
<thead>
<tr>
<th></th>
<th>PCM</th>
<th>Markup</th>
<th>Exp. In.</th>
<th>E.I. Ext-EU</th>
<th>Imp. In.</th>
<th>Size</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(TFP)</td>
<td>0.443</td>
<td>0.745</td>
<td>-0.210</td>
<td>-0.135</td>
<td>-0.008</td>
<td>-0.391</td>
<td>-0.062</td>
</tr>
<tr>
<td>PCM</td>
<td>0.557</td>
<td>-0.095</td>
<td>-0.020</td>
<td>-0.010</td>
<td>-0.080</td>
<td>-0.057</td>
<td></td>
</tr>
<tr>
<td>Markup</td>
<td>-0.250</td>
<td>0.423</td>
<td>-0.067</td>
<td>-0.003</td>
<td>-0.101</td>
<td>0.027</td>
<td>0.082</td>
</tr>
<tr>
<td>Exp. In.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.247</td>
<td>0.088</td>
</tr>
<tr>
<td>E.I. Ext-EU</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.011</td>
<td>0.283</td>
<td>0.088</td>
</tr>
<tr>
<td>Imp. In.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.023</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>Labor</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.183</td>
</tr>
</tbody>
</table>

Exp. In. is the export intensity as a ratio of exports to revenues. E.I. Ext-EU is the intensity of exports outside the EU. Imp. In. is the import intensity. Size is the firm size measured by the log number of employees.

Table 4 extends the partial correlation matrix in Table 2 by introducing import and export intensities, firm age and size measured by the number of workers employed by firms. In line with the previous discussions, the partial correlations of export intensity with the markups, PCM and the log of the TFP are negative. When the firm-level export intensity is calculated by the ratio of extra-EU exports to revenues, its correlations with the markups, PCM and the log of the TFP rise but are still negative. This is somewhat consistent with the standard trade theory in the sense that when trade barriers are larger, as in the case of exporting to the outside of the EU, the trade driven selection mechanism is stricter and allows only very high-productivity firms to export. Thus, extra-EU exporters tend to be more productive and have higher markups as a response to larger trade costs. The case of small open economy, however, is more likely to be still valid and restricting the competition in the domestic markets, so that the partial correlations of the export intensity with the TFP and markups are negative, even when the export intensity is measured by the extra-EU exports.

Table 4 shows that firm age is not significantly correlated with either markups, trade intensity or productivity. The relationship between firm age and other variables are possibly nonlinear as it is supported in Table 3 that entrants have significantly higher productivity and markups than the industry average. Firm size measured by the log of labor input is positively correlated with export intensity in terms of both the overall and the extra-EU exports. This further provides evidence, to some degree, to the allocative efficiency effects of international trade. In addition to motivating the reallocation of resources among incumbent establishments, the size expanding effect of international trade on more productive exporters is expected to generate a competitive pressure on inefficient businesses. In the long term, openness to international trade is expected to positively contribute into the functioning of creative destruction and to play important role in the microeconomic restructuring of economies.
Figure 2: Export Intensity, Markups and Employment

Figure 2 takes a closer look to the interaction between firm size, markups and export intensity by displaying two scatter plots; on the left markups vs. export intensity and on the right firm size vs. export intensity. In the scatter plots, each point represents the x-y combination of a firm in a year. The left panel shows that there are a large number of high-markup firms with zero or very low export intensity. The markups rapidly drop down for the firms with positive but low export intensity. A small number of producers in the intensively exporting firms’ group have markups over 1.5, while the average markup does not significantly differ for establishments whose export intensity is over 0.3. The right panel of Figure 2 shows that an important portion of non-exporting firms are small. Excluding few very large manufacturing establishments that have export intensity around or lower than 0.5, the average firm size increases almost linearly within the group of exporting firms.

4.1 Heterogeneous Markups and Implications for Productivity Measurement

Theoretical models of international trade with heterogeneous agents indicate that trade induces a selection mechanism, so that only sufficiently high productivity firms can enter into export markets (e.g. Bernard et al., 2003; Melitz, 2003; Melitz and Ottaviano, 2008). The results of the previous part, however, show that non-exporters’ average productivity is higher than that of exporters. One reason for this can be the unobserved price effects embodied in the nominal sales and input expenditures based productivity measures such as the one used in this study. When prices or markups significantly differ among firms, deflating firm-level variables by industry-level price indices may not be sufficient to isolate nominal productivity measures from demand side factors. As a result, the productivity performance of some particular firms that have higher markups than the industry average will be overestimated by deflated revenue and input expenditures based productivity indices.

Foster et al. (2008) analyze the differences between revenue and quantity based measures of productivity and find that price effects may distort the revenue-productivity systematically for some group of firms, for instance, for entrants. This study also provides some evidence that the price effects influence the productivity comparison between
exporters and non-exporters, for which using a measure of quantity-productivity would yield some insights on the robustness of the productivity comparisons. Calculating physical productivity, however, is not straightforward and requires observing quantities of outputs as well as inputs, where one also needs to separately observe the amount of inputs employed in the production of different varieties for multi-product firms. In addition to data limitations, quantity based measures of firm-level productivity may not be directly comparable among firms due to unobserved quality variation. Moreover, the quality variation is embodied in the price-cost markup variation which is, in most cases, not possible to be decomposed into quality effects and demand side factors by the available data. Thus, in heterogeneous product markets, the analysis of productivity based on quantities without quality adjustment may provide biased results even for a set of similar products or for firms within narrowly defined industries.

A growing body of empirical research has been devoted to the structural estimation of production functions with the aim of controlling for certain types of price variations using theoretical foundations (for instance, see Griliches and Klette, 1996; Levinsohn and Melitz, 2004; De Loecker, 2011). This part keeps the discussion simple, since the aim is not to retrieve a consistent measure of physical productivity, but to understand whether non-exporter firms are found to be more productive, because they have higher markups. Assuming revenue productivity is a function of physical productivity and price-cost markups, the high-productivity non-exporters puzzle can be investigated by running a probit on export status.

Table 5 presents the results of the estimation of three probit specifications. Every equation contains time and industry dummies at the 2-digit level. Dependent variable is the export dummy that takes the value of one, when a firm has positive exports for a given year. In the first specification, the firm-level TFP in logarithms is solely used as the explanatory variable that is retrieved through the translog production function estimation in the previous parts. The second specification extends the explanatory variables’ set that contains the log of TFP and the markups retrieved through the Hall’s (1988) condition that is described in the previous sections. The third specification adds the square root of markups to take into account nonlinearities in the relationship between revenue productivity and markups in the quadratic form.

| Table 5: Probit on Export Status$^a$ |
|----------------------------------|--------|--------|--------|
| #obs = 2608                      | (1)    | (2)    | (3)    |
| log(TFP) ($\theta_{it}$)        | -0.604* | 0.248  | 0.290  |
|                                  | (0.351) | (0.346)| (0.341) |
| markup ($\mu_{it}$)             | -1.032**| -1.244*|        |
|                                  | (0.208) | (0.533)|        |
| $\mu_{it}^2$                    | -      | -      | 0.053  |
|                                  |        |        | (0.138) |
| Pseudo R$^2$                     | 0.167  | 0.196  | 0.196  |

$^a$Dependent variable takes the value of 1 when exports are positive and 0 otherwise. Std. errors are in parenthesis. ** significant at 1%. * significant at 10%. 2-digit industry and time dummies are included in all equations.

Table 5 shows that the estimation of the first specification replicates the result given in Table 3, so that non-exporting firms have, on average, higher TFP. In the second spec-
ification that introduces firm-level markups as a control variable, the average marginal effect of the log TFP turns out to be positive but insignificant, while the marginal effect of markup is significantly negative. The third specification introduces markups in the form of a second order polynomial, but the estimated average marginal effect on the quadratic term is very close to zero and the estimates of other coefficients are not significantly different from the estimates obtained in the second specification. Introducing higher order polynomials of markups do not alter the results significantly.

The probit analysis provides some degree of evidence that when the estimation is controlled for firm-level markup variation, higher productivity firms are found to be more likely to export. The estimated average marginal effect of the log TFP is insignificant in the second and third probit specifications. This is probably because previously mentioned reasons that price-cost markup variation among firms is not only due to demand side factors or trade barriers. Markups also can be functions of output and input quality and managerial skills that are components of productivity. Using productivity and markups jointly as explanatory variables would cause a collinearity issue that is possibly responsible for the insignificant coefficient estimates on the TFP.

5 Conclusions and Implications for Policy

This paper investigates the impact of openness to international trade on markups and productivity performance of firms in a small highly open economy. The empirical framework and interpretations of the results are based on the theoretical model of international trade by Melitz and Ottaviano (2008) who emphasize the importance of country size while explaining trade outcomes. This study utilizes firm-level data from the manufacturing sector of Luxembourg for the period from 1996 to 2011. The empirical results show that some well-known effects of openness to international trade alter, when the domestic country size is sufficiently small. The findings also have important implications for economic policy aiming to accelerate productivity growth.

Openness to international trade motivates more productive firms to seek new profit opportunities in the export markets. In the case of small domestic and large foreign economy, exporting firms of the small economy face higher demand and more intense competition in the foreign markets. Firms that are not productive enough to export stay in the small home country and are exposed to lower level of competition. Openness to trade, therefore, influences the competition faced by firms in the local and international markets and alters the distribution of markups of the home country’s producers. The markup estimates of manufacturing firms in Luxembourg supports the predictions of the Melitz-Ottaviano model for the small open economy case, so that exporting firms have lower markups than non-exporters. The analysis of firms’ productivity performance, however, contradicts with the trade theory such that exporters are estimated to have low productivity relative to non-exporters. This paper provides evidence that the estimated productivity index embodies price effects that distort the measurement of firms’ productivity performance. Thus, when productivity is measured by deflated nominal sales and input expenditures, the productivity index is downward (upward) biased for (high-) low-markup firms, so that the low-markup exporters are found to be less productive than domestically operating high-markup establishments.

This study does not attempt to assess welfare effects of openness to international trade but stresses the importance of the trade-induced duality between non-exporting and ex-
porting firms in policy-relevant empirical research. Theoretical models of international trade provide ample evidence that openness to trade generate welfare gains regardless of the country size of trade partners. In the Meltiz-Ottaviano model, international trade enhances welfare also in the small economy, because the impact of trade on domestically operating establishments is offset by the welfare gains generated by exporting firms. Although country size is not a tool or target of economic policy, the observed differences in markups and productivity performance of exporting producers from non-exporters requires particular attention while designing industry policies. For instance, subsidizing small establishments is often expected to enhance productivity growth, since small firms have higher potential to innovate and grow. In the small open economy case, this study shows that export status is an important determinant of firm size. Thus, policies facilitating domestic firms to engage into international trade may help small establishments to go beyond the export threshold and exploit their productivity advantage.

This paper highlights the fact that standard productivity measures based on deflated revenues and input expenditures are not solely reliable benchmarks in the formulation of industry policy. The unobserved price effects may distort the indicative quality of standard productivity measures and cause to find that non-exporting local establishments exhibit better productivity performance in small open economies. Such a conclusion would wrongly justify policy actions toward rewarding local producers and induce the production factors to be retained by inefficient units which would impede the expected productivity gains from international trade through factor reallocation and creative destruction.

References


Appendix

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 requires an initial point in time over which an iteration is conducted by adding real investments in and subtracting
depreciation and retirement from the stock of capital. To calculate each firm’s initial capital stock, I first approximate total capital stock at the industry level. In the next step, I use firm-level weights to disaggregate the initial capital among firms (e.g. Martin, 2002). Approximating the initial capital at the aggregate-level has the advantage of having longer time series with positive investments. Firm-level data, however, is unbalanced due to the natural process of entry and exits as well as due to omissions in data collection all of which cause a number of production units to have very few time observations that can be non-positive. In this paper, I modify the PIM method to be applicable to industry-level data that is constructed by an aggregation over firms. At the industry-level, the evolution of capital stock can be represented by the following identity.

\[ K_t = K_{t-1}(1 - \delta - ret_t - ex_t + en_t) + I_t \]  \hspace{1cm} (16)

In equation 16, \( \delta \) is the constant 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 case of firm-level data, in the industry-level data that is aggregated over firm-level observations, 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 at the industry-level. These entry and exits do not only consist of real entrants and exiters, but firms changing their main industry of operation should also be considered as entrant or exiters to fully account for acquisition and obsolescence of capital stock in the analysis of industry-level data that is aggregated over firms. In equation 16, entry \( (en_t) \) and exit rates \( (ex_t) \) are introduced to take into account changes in the capital stock due to firm entry and exit. Entry and exit rates that are calculated based on firms’ employment share in the industry, because the number of employees is the most complete part of the dataset and can be used to calculate shares of almost all firms in the industry. Equation 16 can be simplified in the following way.

\[ K_{t-1} = \frac{I_t}{gr_t + \phi_t} \]  \hspace{1cm} (17)

In equation 17, \( \phi_t = \delta + ret_t + ex_t - en_t \) and \( gr_t \) is the growth rate of capital. Assuming values for \( \delta \) and \( ret_t \), and approximating \( gr_t \), one can calculate an approximation of aggregate capital stock (e.g. Kohli, 1982). Alternatively, one can find a general rule for the initial capital \( K_0 \) by iterating equation 17 over time as follows.

\[ K_0 = \frac{I_t}{(gr_t + \phi_t) \prod_{z=1}^{t-1} (1 - \phi_z)} - \sum_{i=1}^{t-1} \frac{I_i}{\prod_{j=1}^{i} (1 - \phi_j)} \]  \hspace{1cm} (18)

Equation 17 is the formula for the initial capital that is generalized for every period in the sample, so that one can obtain several approximations of the initial capital and compare the results. The values of \( \delta \) and \( ret_t \), however, are rough approximations that are subject to errors. Thus, selecting the benchmark year (which is \( t \) in equation 17) far away from the initial point (0) would cause the procedure to be subject to higher degree of error due to rough approximations of \( \delta \) and \( ret_t \). In this paper, therefore, I select the first three years of the sample period as the benchmark and compute three different
initial capital approximations for each industry. The final value of the initial aggregate capital stock is computed by averaging the three approximations.

In the approximation of the industry-level initial capital stock, I aggregate firm-level investments that are the investments net of capital sales. At the firm-level, I have information on the type of investment for which I assume individual depreciation rates, life times and retirement profiles. The asset composition of the initial capital stock, however, is unknown and unnecessary to approximate in this context. Therefore, I assume a single constant depreciation rate, life time and retirement profile for initial capital.

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

\[ F_T = \alpha \lambda (\lambda T)^{\alpha - 1} e^{-(\lambda T)^{\alpha}} \]  

Equation 19 represents the Weibull distribution where \( T \) is the time index, \( \alpha \) and \( \lambda \) are the parameters of the density function. Figure 3 displays the density functions for each asset class where the asset class that is labeled as "unknown" represents the initial capital.

![Figure 3: Retirement Probabilities](image)

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

<table>
<thead>
<tr>
<th>Asset Type</th>
<th>( \delta )</th>
<th>life (years)</th>
<th>( \alpha )</th>
<th>( \lambda )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unconstructed Land</td>
<td>0.00</td>
<td>( \geq 16 )</td>
<td>1.2</td>
<td>0.01</td>
</tr>
<tr>
<td>Constructions and Arrangement of Grounds</td>
<td>0.02</td>
<td>( \geq 16 )</td>
<td>1.5</td>
<td>0.03</td>
</tr>
<tr>
<td>Machinery and Equipment</td>
<td>0.06</td>
<td>10</td>
<td>1.6</td>
<td>0.10</td>
</tr>
<tr>
<td>Furnitures</td>
<td>0.07</td>
<td>10</td>
<td>1.6</td>
<td>0.08</td>
</tr>
<tr>
<td>Vehicles and Other Transportations</td>
<td>0.09</td>
<td>13</td>
<td>3.0</td>
<td>0.09</td>
</tr>
<tr>
<td>Software</td>
<td>0.05</td>
<td>5</td>
<td>1.9</td>
<td>0.15</td>
</tr>
<tr>
<td>Unknown Type</td>
<td>0.05</td>
<td>( \geq 16 )</td>
<td>1.6</td>
<td>0.08</td>
</tr>
</tbody>
</table>
In Table 6, the life time of unconstructed land, constructions and the unknown type of capital are assumed to be longer than 16 years that is the span of data used in this study. The unknown type capital represents the initial capital that is roughly approximated and consists of an unknown combination of capital assets. The initial capital, therefore, is assumed to contain mostly the assets with long service lives like buildings, land and other constructions for establishing the material infrastructure.

I approximate the initial capital separately for six firm groups by the above-mentioned routine. Each group consists of multiple 2-digit (based on Nace rev.2) manufacturing industries, because some of the 2-digit industries contain single or very few firms. Once the initial capital is computed, it is disaggregated over firms using weights that are calculated based on net book values of capital assets (NBV). The NBV is retrieved from accounting data which accommodates any type of capital obsolescence within the amortization. In the calculation of amortization, however, predetermined constant obsolescence rates are used for each capital asset class, while these rates are higher than actual or estimated rates of depreciation, do not take into account time variation in retirement probabilities and incorporate unrealistically short service lives. For this reason, the NBV is a more flexible and often biased measure of capital, which can fluctuate sharply throughout the life time of a production unit. To avoid the firm-level weights to suffer from biases due to temporary fluctuations in the NBV, 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

$$k_{it} = k_{it-1}(1 - \delta - ret_{it}) + I_{it}.$$