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Multi Product Firms, Import Competition, and the Evolution of Firm-product Technical Efficiencies
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ABSTRACT

We study how increased import competition affects the evolution of firm-product technical efficiencies in the small open economy of Belgium. We use a production survey where we observe quarterly firm-product data at the 8-digit level on quantities sold and firm-level labor, capital, and intermediate inputs from 1997 to 2007, a period marked by stark declines in tariffs applied to Chinese goods. We extend the methodology developed in Dhyne et al. (2020) to estimate firm-product measures of productivity. We find that a 1% increase in the import share leads to a 1.05% gain in technical efficiency. This elasticity translates into gains from competition over the sample period exceeding 1.2 billion euros, which is over 2.5% of the average annual value of manufacturing output in Belgium. Firms appear to be less technically efficient at producing goods the further they get from their "core" competency product and firms respond to competition by focusing more on their core products. Instrumenting import share - while not important for the signs of the coefficients - is very important for the magnitudes as the effect of competition increases tenfold when one moves from OLS to IV.

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1 Introduction

Economists have shown in a variety of theoretical settings that product-market competition can provide firms with strong incentives to adopt cost-lowering production processes in order to remain profitable (see e.g. Aghion and Howitt, 1996 and Holmes and Schmitz, 2010 for discussion). Several important contributions in the empirical productivity literature have established a strong positive relationship between firm-level total factor productivity growth and increased competition, where the former is given by total firm-level deflated revenue less its predicted value given input use (see e.g. Olley and Pakes, 1996; Pavcnik, 2002; Bloom, Draca and Van Reenen, 2016).

A well-known feature of micro-level production data is that most firms produce multiple products, which suggests the possibility that within-a-firm different products may be produced with different levels of technical efficiency.[1] In this paper, we adapt the framework developed in Dhyne et al. (2020) to estimate firm-product measures of productivity for all firms in Belgian manufacturing. They extend the seminal contributions of Diewert (1973) and Lau (1974) and implement it in the modern control function approach first introduced by Olley and Pakes (1996) and later extended by e.g. Levinsohn and Petrin (2003), Ackerberg, Caves and Frazer (2015) and Wooldridge (2009). The intuition is the following. The standard single product production function gives the maximal output for any tuple of inputs (e.g. labor, capital, and intermediate inputs). A multi-product production function extends the single product setting by giving the maximal amount of output achievable of one of the goods the firm produces holding inputs *and* the levels of other goods produced constant. A major strength of the theory is that it neither requires us to assume that multi-product production is a collection of single-product production functions nor does it require us allocate aggregate firm-level input measures across them.

The practical problem that researchers face when considering such an estimation is that very few firms will produce the same subset of products, especially in a small open economy like Belgium. We therefore suggest a way to generalize the method suggested by Dhyne et al. (2020) by aggregating the vector of "all other goods produced" aside from the referenced product, as first suggested by Roberts and Supina (2000). This aggregation approach relies on the strong assumption that all firms producing a specific product within a given economic environment face the same coefficient for this aggregate. The approach further generalizes what researchers have been doing with inputs for decades. We discuss alternative modeling strategies that relax this assumption, and this is also discussed in more details in our companion paper.

[1]See e.g. Eckel and Neary (2010), Bernard, Redding and Schott (2010, 2011) and Mayer, Melitz and Ottaviano (2014).

Firm-product technical efficiencies allow for more direct identification of the impact of competition as changes in firm-product technical efficiencies can be directly related to changes in competitive conditions for that particular 8-digit product category. They also allow us to explore implications of various theoretical models of multi product firms, in particular Eckel and Neary (2010), Bernard, Redding and Schott (2010, 2011), and Mayer, Melitz and Ottaviano (2014). All of these models have - in equilibrium - higher revenue "core" products being produced more efficiently within multi-product firms.[2]

We explore all of these margins using our Belgian dataset from 1997 to 2007, a period of increased competition with China's 2001 entry into the World Trade Organization (WTO). We estimate multi-product production function for 12 industries separately. Consistent with the production theory of Diewert (1973), the estimated coefficient on the other-goods-produced quantity index is the correct sign - negative - and significant for all 12 industries, implying that holding all input levels constant an increase in the firm's output index of other-goods-produced leads to a fall in the output of the good under consideration.

We calculate the implied estimates of quarterly firm-product technical efficiency and regress them on last period's import share while controlling for last period's technical efficiency, the product's "rank" in terms of revenue generated at the firm, interactions between the lagged import shares and product rankings, and 8-digit product- and quarter-specific fixed effects, We instrument for the share using European tariffs on Chinese imports and an estimate of world export supply (excluding Belgium), as suggested by Hummels et al. (2014). Consistent with the theory models we find that product rankings on average lines up one-to-one with the level of technical efficiency with which a good is produced, with the highest revenue good being produced most efficiently. We find that a 1% increase in the lagged import share is associated with a 1.05% percent increase in technical efficiency in the current period for the first and second ranked products, and a 0.65% increase in technical efficiency of all other products produced by the firm. Across 10 robustness checks our estimate of 1.05% ranges between 0.84% up to 1.17%. Without instruments we find only one-tenth the effect, which is consistent with lagged import penetration being higher in product markets where domestic innovations in technical efficiency are lower (and vice versa).

As an additional exercise, we calculate the long-run changes in the value of produced output due to a change in the previous period's input share by multiplying the log change in technical efficiency by the product's current revenue, and then scaling it up to account for future output gains arising due to the high persistence of the technical efficiency process

[2]Dhingra (2013) and Eckel et al. (2015) show that firms respond to trade liberalization by undertaking R&D activities that lead to greater increases in technical efficiencies or improved quality depending on the nature of the good and the initial level of firm efficiency.

as the AR(1) coefficient is estimated to be 0.9 across almost all specifications instrumented or not. Of the 65,242 positive and negative changes the average change is a little over 22 thousand euros, and while most changes are positive almost 35% of the realized changes are negative because import shares decrease in many cases. There is a tremendous amount of variation across industries in these changes with some of the biggest negative changes ranging from -1.8 to -2.5 million euros and the some of the biggest positive changes ranges between 2.2 and 2.5 million euros. Aggregating over the entire sample period the overall gain in the value of output due to increased import competition is on the order of 1.4 billion euros, almost 2.5% of average annual value of manufacturing output in Belgium over this period.

The closest empirical findings to ours are from De Loecker, Goldberg, Khandelwal, and Pavcnik (2016)[3] (DLGKP henceforth), who use manufacturing data on multi-product production from India to estimate the effect of trade liberalization on firm-product marginal costs. They assume multi-product firms have the same production function coefficients than single-product firms, and then allocate inputs based on input optimization theory. Their setup generates a firm-level technical efficiency but their model implies separate marginal costs for each firm-product.[4] Similar to our findings, they find that marginal costs are on average declining as the within-firm product revenue share increases and that increases in trade liberalization are associated with reductions in product-specific marginal costs. They also provide a solution to the input pricing heterogeneity bias by including output price and market share in their control function approach.

Our approach is complementary to theirs but rests on different assumptions. The main difference between our approach and DLGKP is that we include multiproduct firms in our estimation of production functions. DLGKP estimate the parameters of the production function for single product firms only within a 2-digit industry and assume that multi-product firms face the same technology and share the same parameters than single product firms for the product that they make. The second difference is that we do not need to retrieve the input allocation shares, as the theory behind Diewert-Lau allows for a flexible functional form that conditions the production of a specific product to aggregate input use and the production of other goods. Third, as a consequence of our methodology, we

[3] Garcia Marin and Voigtländer (2019) follow a similar strategy to properly measure learning-by-exporting effect. They are also interested in the pass-through: they find that marginal costs declined substantially after export entry for new entrants, while markups remained stable – so that falling prices explain why revenue-based productivity measures typically found no improvement after export entry. For incumbent exporters however, the pass through was not complete, so that prices declined less than marginal costs and markups increased on average.

[4] Several follow-up papers using multi-product data extend the De Loecker et al (2016) methodology on important economic dimensions. See e.g. Valmari (2016), Gong and Sickles (2018), Orr (2019), Itoga (2019) and the discussion in Dhyne et al. (2020).

obtain a firm-product measure of productivity. DLGKP have a firm-level measure, but also derive a firm-product level measure of efficiency, marginal cost.

Our paper is also closely linked and complementary to recent theoretical and empirical developments regarding how multi product firms react to trade liberalization or demand shocks and how it affects aggregate productivity. Mayer, Melitz and Ottaviano (2016) analyze how demand shocks in export markets affect French multi-product exporters to reallocate the mix of products sold in those destinations and show that positive shocks are associated with skewing export sales towards their best performing products. The aggregate implications are quite large, as they estimate that this within firm adjustment of product portfolios is associated with a 12% productivity gain over their period of analysis. While their focus is on export markets, we look at firms' reaction to increased competition on their domestic market. We also suggest a new metric for productivity that varies at the firm-product level.

The rest of the paper is structured as follows. Section 2 describes the detailed quarterly firm-product dataset that we build. In Section 3, we explain the methodology that we use to estimate the multi-product production functions. Section 4 formalizes and parameterizes the system of simultaneous production equations that comes out of the theory of Section 3. Section 5 addresses simultaneity, Section 6 presents our results, and Section 7 concludes.

2 Product Quantities, Prices, and Import Shares

We construct quarterly 8-digit firm-product observations on quantities sold, unit prices, and import shares from 1997–2007 using the Belgian PRODCOM survey and the Belgian data on international trade transactions. We construct quarterly measures of inputs used in production using the Value Added Tax (VAT) declarations, the National Social Security database, and data from the Belgian Central Balance Sheet Office.

2.1 The Belgian PRODCOM survey

The first data set is firm-product level production data (PRODCOM) collected by Statistics Belgium.[5] It has been used in recent papers like Bernard et al. (forthcoming) and Amiti, Konings and Itskhoki (2018). The survey is designed to cover at least 90% of production value in each NACE 4-digit industry by including all Belgium firms with a

[5]See http://statbel.fgov.be/fr/statistiques/collecte_donnees/enquetes/prodcom/ and http://statbel.fgov.be/nl/statistieken/gegevensinzameling/enquetes/prodcom/ for more details in French and Dutch, or Eurostat in English (http://ec.europa.eu/eurostat/web/prodcom).

minimum of 10 employees or total revenue above 2.5 million Euros.[6] The sampled firms are required to disclose monthly product-specific revenues and quantities sold of all products at the PRODCOM 8 digit level (e.g. 15.96.10.00 for "Beer made from malt", 26.51.11.00 for "Cement clinker"). We keep only firms that are classified by NACE as have their principal business activities in manufacturing. We aggregate revenues and quantities to the quarterly level and calculate the associated quarterly unit price. We restrict our analysis to the period from 1995-2007 because it is the main period of trade liberalization and because in 2008 PRODCOM both significantly reduced its sample size and changed its classification system. For each firm within each 4-digit industry we compute the median ratios of total revenue over employment, capital over employment, total revenue over materials and wage bill over labor (average wage), and we exclude those observations more than five times the interquartile range below or above the median. Finally, we keep only firm-product observations where the share of the product's revenue in the firm's total revenue is at least 5%.

The Value Added Tax revenue data provides us with a separate check against the revenue numbers firms report to PRODCOM. Comparing the tax administrative data revenue numbers with the revenue numbers reported in the PRODCOM data, we find that between 85% and 90% of firms report similar values for both. We exclude firms if they do not report a total value of production to PRODCOM that is at least 90% of the revenue they report to the tax authorities.

Table 1 shows the average revenue share of products in firms' portfolios when they are producing a different number of products at two levels of aggregation (8-digit and 2-digit PRODCOM). We observe 137,453 firm-product observations between 1997-2007. As has been noted in other product-level data sets the majority of firms produce multiple products.[7] At the 8-digit level of disaggregation multi-product firms are responsible for 73% of total value of manufacturing output. Most firms produce between one and five products and these firms account for 75% of the value of manufacturing output. For firms producing two goods the core good accounts for 77.5% of revenue. Similarly for firms producing three goods 69.5% of revenue comes from the core product. Even for firms producing six or more goods the core good is responsible for 49.4% of revenue. At the 2-digit level of aggregation the fraction of manufacturing revenue coming from single product firms jumps to 78% and the fraction of manufacturing revenue from firms producing three or more goods falls to 3%, suggesting firms specialize by typically producing goods within the same 2-digit category.

[6]NACE is a French acronym for the European Statistical Classification of Economic Activities.

[7]See e.g. Bernard et. al (2010) or Goldberg et. al (2010).

2.2 Firm Input Measurements

For tax liability purposes, Belgian firms have to report every quarter in their VAT fiscal declarations both their sales revenues and their input purchases. Using this information, we construct quarterly measures for intermediate input use and investment in capital (purchases of durable goods). For measures of firm employment, we use data from the National Social Security declarations where firms report on a quarterly basis their level of employment and their total wage bill. We construct a quarterly measure of capital using as initial value the total fixed assets data from the Central Balance Sheet Office, which records annual measures of firm assets for all Belgian firms. We then use standard perpetual inventory methods to build out a capital stock for each firm-quarter.[8]

2.3 The Increase in Import Shares: 1997-2007

The competitive environment in Europe changed significantly over the 1997-2007 period with the implementation of the Single Market Plan within the European Union in 1993 and with the entry in 2001 of China into the World Trade Organization. We construct two separate measures of import shares by combining information from the PRODCOM database with the Belgian international trade data, which contains the quarterly values and quantities of all imports and exports by Belgium firms at the 8-digit level.[9]

Let M_{ijt} denote the quantity of imports of firm i of good j at time t and let $M_{jt} = \sum_{i \in \text{Importers}} M_{ijt}$ be the total quantity of imports of product j at the 8-digit level. Let Q_{jt} denote the total domestic quantity sold of product j. Our first measure of import

[8] In order to build the capital stock, we assume a constant depreciation rate of 8% per year for all firms. Real capital stock is computed using the quarterly deflator of fixed capital gross accumulation. The initial capital stock in $t = t_0$, where period t_0 represents the 4th quarter of the first year of observation of the firm, is given by

$$K_{t_0} = \frac{Total\ fixed\ assets_{first\ year\ of\ observation}}{P_{K;t_0}}$$

The capital stock in the subsequent periods is given by

$$K_t = (1 - 0.0194)\, K_{t-1} + \frac{I_t}{P_{K;t}}$$

We assume that the new investment is not readily available for production and that it takes one year from the time of investment for a new unit of capital to be fully operational.

[9] International trade data are recorded at the CN8 level, while PRODCOM is recorded at the PRODCOM level. We use the concordance tables by Eurostat between nomenclatures and over time. We also follow Bernard et al. (forthcoming) to use a classification consistent over time.

penetration is given as[10]:

$$IS_{1jt} = \frac{M_{jt}}{Q_{jt} + M_{jt}}.$$

Belgium is a small open economy with a relatively large harbor and a significant fraction of the products entering Belgium are subsequently re-exported to other countries.[11] To account for re-exporting we develop a second measure based on net imports. Continuing to work in quantity units we define net imports at the firm level as $Max\{M_{ijt} - E_{ijt}, 0\}$ where E_{ijt} is the physical quantity of exports of good j from firm i at time t. Our second import share measure is then given as

$$IS_{2jt} = \frac{\sum_{i \in \text{Importers}} Max\{M_{ijt} - E_{ijt}, 0\}}{Q_{jt} + \sum_{i \in \text{Importers}} Max\{M_{ijt} - E_{ijt}, 0\}}.$$

Table 2 shows the changes in import shares at the 8-digit product level between 1997 and 2007 using IS_{2jt}, the "export-corrected" measure of imports, which is our preferred measure. The table shows the percentiles for all 8 digit-products pooled together and by 2-digit industries. The mean change across all products is an increase of 0.043. This mean hides the tremendous heterogeneity in the underlying changes with most changes positive but many changes negative. The 10th percentile change is -0.21 and the 90th percentile is 0.368. The 25th percentile is -0.04 and the 75th percentiles is 0.136. This pattern is reasonably robust across all of the 2-digit industries and across our two measures of import competition and it suggests that there is a role for increases *and decreases* in competition to both increase and decrease technical efficiencies.

3 Empirical framework

3.1 Multi-product transformation function

The methodology is based on Diewert (1973) and Lau (1976) and uses the concept of multi-product transformation function. Diewert shows that "under mild regularity conditions, there will exist a multi-product transformation function that relates the output of any good j to the output of all the other goods a firm produces and to aggregate input use.

[10]We also compute a similar measures is given in value instead of quantity:

$$IS_{3jt} = \frac{MV_{jt}}{Y_{jt} + MV_{jt}}$$

where Y_{jt} represents the value of production of good j in quarter t as measured in PRODCOM and MV_{jt} represents the value of imports of good j in quarter t as measured in the trade dataset.

[11]Duprez (2014) shows that 30% of Belgian exports in 2010 are re-exports of imported goods not processed in Belgium.

This functional form significantly simplifies the empirical analysis, as it does not require product-level use of inputs. It is also conditional on the firm's product portfolio choice.

Start by considering the simple example of a firm producing only two products a and b. Assuming Cobb-Douglas production function, and taking logs, the multi-product transformation function for product a by firm i in time t can be written as:

$$q_{i,t}^{a} = \beta_{l}^{a} l_{i,t} + \beta_{k}^{a} k_{i,t} + \beta_{m}^{a} m_{i,t} + \boldsymbol{\gamma_a q_{i,t}^{b}} + \omega_{i,t}^{a} + \eta_{i,t}^{a}$$

where $q_{i,t}^{a}$ is the quantity of good a, $q_{i,t}^{b}$ is the quantity of good b, $l_{i,t}$, $k_{i,t}$ and $m_{i,t}$ are the firm's aggregate input use (labor, capital amd material), $\omega_{i,t}^{a}$ is the technical efficiency at producing good a, and $\eta_{i,t}^{a}$ is an i.i.d. shock specific to the given environment. There is a similar equation for good b. One difficulty with this setting though is that we need enough firms jointly producing goods a and b in order to estimate such a production function. In a small open economy, there will typically be a small number of firms producing a given mix of products. This is discussed in details in Dhyne et al. (2020) where they test the method in a variety of given environments, such as bread and cake, or different choices of furniture.

For researchers interested in using data for a larger subset of firms, this is not very practical, so we would like to be able to generalize the approach. In order to do so, we will need to make some restrictive assumptions about the aggregation of the other products that a firm makes aside from the referenced products. Generalizing to N-product firms, the multi-product transformation function for product j (conditional on producing a subset of products $-j$) can be written as:

$$q_{i,t}^{j} = \beta_{l}^{j} l_{i,t} + \beta_{k}^{j} k_{i,t} + \beta_{m}^{j} m_{i,t} + \boldsymbol{\gamma_{-j}^{j} q_{i,t}^{-j}} + \omega_{i,t}^{j} + \eta_{i,t}^{j}$$

where in this case $q_{i,t}^{j}$ is the quantity of good j and $q_{i,t}^{-j}$ is a **vector** of the physical quantity of all the other goods produced by the firm. $\omega_{i,t}^{j}$ is the technical efficiency of product j and $\eta_{i,t}^{j}$ is an i.i.d. shock specific to the environment where the firm operates (researchers typically consider a 2-digit industry, as we discuss later).

To generalize our approach to many environments, we propose a quantity index, as suggested by Roberts and Supina (2000).[12] We consider various methods of aggregation of $q_{i,t}^{-j}$. Our main specification uses revenues of all the other goods produced by the firm deflated by a firm-level price index. We also experimented with alternative quantity aggregations.

When we estimate our multi-product transformation function, we use quantity at the 8-digit product level. We follow the previous literature by estimating the production

[12]See de Roux et al. (2020) for a related discussion with Colombian data.

function for each 2 digit industry level (see e.g. De Loecker et al., 2016). Our coefficients will therefore be the same for all firms within at the 2-digit level. We refer to this approach as the "generalized Diewert-Lau method".

One enormous advantage is that it provides a very flexible structure, that allows for complementarities between products in the production function. The quantity index allows the estimation to be generalized to many environments, as in most firm level empirical papers in industrial organization and trade. The fact that the coefficient of $q_{i,t}^{-j}$ is assumed to be homogeneous within a 2-digit industry explicitly implies a similar production function and technology within broad industry groups. This assumption can be relaxed by looking at smaller but more homogeneous subset of firms and products, or separate the quantity index in a small subset of sub-indexes, as we discuss in the next subsection.

3.2 Input and Output Indices

The difficulty of dealing with multi product firms is similar with inputs. Most firms produce output using only some of all available inputs recorded in disaggregated firm-level input data. In order to circumvent this "zeros" issue researchers have aggregated across inputs within firms to create a smaller number of non-zero input aggregates, like capital, intermediate inputs, or labor.[13] Suppose there are G goods over which to aggregate denoted $(m_1, \ldots, m_G)$ and let Q_{m_g} denote quantity used (or produced) of good m_g (we suppress the time index). The input index q^* that is almost universally used weights the quantity of the input by the input's price P_{m_g} and deflates it by an input deflator P_m common to all firms within a subset (typically a 2-digit or 4-digit industry):

$$q^* = log(\frac{\sum_{g=1}^{G} P_{m_g} Q_{m_g}}{P_m}).$$

In place of estimating the G unrestricted coefficients β_g $g = 1, \ldots, G$ on $log(Q_{m_g})$ $g = 1, \ldots, G$, only one coefficient β^G associated with the quantity index q^* is estimated. Letting $s_l = \frac{P_{m_g} Q_{m_l}}{\sum_{g=1}^{G} P_{m_g} Q_{m_g}}$ the index achieves this parsimony by restricting the elasticity of output with respect to input l (β_l) to be proportional to β^G:

$$\beta_l = s_l * \beta^G, \ \ l = 1, \ldots G.$$

so an input with twice the expenditure share of another input in the input category will have twice the output elasticity. We use this index for all of our inputs.

[13] Capital is an aggregate mix of the value of different kinds of machines, buildings, and/or vehicles used by the firm. The intermediate input aggregate sums across all kinds of different materials weighting by their price. Labor is also sometimes aggregated by weighting the different labor types with their wage to get the labor aggregate.

The output-side aggregation restriction is analogous to the input-side restriction. Consider a firm that produces good j and a potentially large number of other products $-j$. We construct several output aggregators for the production function for q_j instead of treating the other goods as a vector.[14]

Our main aggregator[15] is the analog to the input aggregator (with the only difference being that it excludes good j) and is given by

$$q^*_{-j} = log(\frac{\sum_{g \neq j} P_{m_g} Q_{m_g}}{P_{-j}}).$$

where P_{-j} is a firm-level price deflator constructed by using the observed prices of all the other goods produced by the firm, as in Eslava et al.(2004) and Smeets and Warzynski (2013).[16] This simplifies our estimation but imposes several potentially strong assumptions.

The first one is that we impose the coefficients of the transformation function to be the same within a 2-digit industry, so we rule out heterogeneity of behavior across products within our subset. For inputs, this is similar to what the literature has been doing for the last 50 years. Adding the output aggregator extends the same logic to this additional regressor. This assumption could easily be relaxed by imposing these common coefficients for a smaller but more homogeneous set of firms, as in Dhyne et al., 2014 and Dhyne et al., 2018, where it is then safer to assume that the production function and the technology used are similar within the subset. The problem to overcome then becomes the sample size. Alternatively, we could also break up the aggregator in several (but not too many) subcomponents that make sense in a specific context.

Second, in practice, there will be important heterogeneity in product characteristics within a 2-digit product code and even within a 8-digit product code. We deal with it

[14] Roberts and Supina (2000) use a similar quantity index when they estimate cost functions.

[15] A second aggregator sums all units of the goods and then takes logs:

$$q^*_{-j} = log(\sum_{g \neq j}^{G} Q_{m_g}),$$

Aggregating quantities within a subset can be justified if the output produced are relatively similar and use a similar production function, what is the case for most firms, but not all.

[16] If P_{igt} and $P_{ig(t-1)}$ are the unit values of good g produced by firm i at times t and $t-1$, respectively, then the weighted average of the growth in output price is defined as

$$\Delta P_{i(-j)t} = \sum_{g \neq j} \bar{s}_{igt} \Delta \ln(P_{igt}),$$

where $\Delta \ln(P_{igt}) = \ln P_{igt} - \ln P_{ig(t-1)}$ and $\bar{s}_{igt} = \frac{s_{igt}+s_{ig(t-1)}}{2}$ (s_{igt} and s_{igt-1} are the revenue shares of product g at time t and $t-1$, respectively). The price index for each firm is then $\ln P_{i(-j)t} = \ln P_{i(-j)t-1} + \Delta P_{i(-j)t}$, where the price for the reference year is standardized ($P_{i'0} = 100$).

by adding product dummies and by adding product price in the control function like De Loecker et al. (2016), as explained in subsection 4.4.

4 Estimation

To address the issue of simultaneity (Marschak and Andrews (1944)) we extend the Wooldridge (2009) formulation of Olley and Pakes (1995) (OP) and Levinsohn and Petrin (2003) to the multi-product production setting by allowing for one technical efficiency shock for each product made by the firm.

4.1 Single-product production setting

In the single product case, we have for q_t:

$$q_t = \beta_l l_t + \beta_k k_t + \beta_m m_t + \epsilon_t \tag{1}$$

where we have replaced the shock with its two components, i.e. $\varepsilon_t = \omega_t + \eta_t$. η_t is assumed to be i.i.d. error upon which the firm does not act (like measurement error or specification error). ω_t is the technical efficiency shock, a state variable observed by the firm but unobserved to the econometrician. ω_t is assumed to be first-order Markov and is the source of the simultaneity problem as firm observe their shock before choosing their freely variable inputs l_t and m_t. k_t also responds to ω_t but with a lag as investments made in period $t-1$ come online in period t. This assumption allows k_t to be correlated with expected value of ω_t given ω_{t-1}. as ω_{t-1} - denoted $E[\omega_t|\omega_{t-1}]$ - but maintains that the innovation in the productivity shock $\xi_t = \omega_t - E[\omega_t|\omega_{t-1}]$ is unknown at the time the investment decision was made in $t-1$ and is therefore uncorrelated with current k_t.

The control function approaches of OP and LP both provide weak conditions under which there exists a proxy variable $h_t(k_t, \omega_t)$ that is a function of both state variables and that is monotonic in ω_t given k_t. The variables may include either investment (OP) or materials, fuels, electricity, or services (LP) (e.g.). Given the monotonocity there exists some function $g(\cdot)$,

$$\omega_t = g(k_t, h_t)$$

allowing ω_t to be written as a function of k_t and h_t. Wooldridge (2009) uses a single index restriction to approximate unobserved productivity, writing

$$\omega_t = g(k_t, h_t) = \mathbf{c}(k_t, h_t)'\beta_\omega$$

where $\mathbf{c}(k_t, h_t)$ is a known vector function of (k_t, h_t) chosen by researchers with parameter vector β_ω to be estimated. The conditional expectation $E[\omega_t|\omega_{t-1}]$ can then be written as

$$E[\omega_t|\omega_{t-1}] = f(\mathbf{c}(k_{t-1}, h_{t-1})'\beta_\omega)$$

for some unknown function $f(\cdot)$, which Wooldridge (2009) approximates using a polynomial.

Replacing ω_t with its expectation and innovation, the estimating equation becomes

$$q_t = \beta_l l_t + \beta_k k_t + \beta_m m_t + E[\omega_t|\omega_{,t-1}] + \xi_t + \epsilon_t \tag{2}$$

For expositional transparency, we use only the first-order approximation term for $f(\cdot)$, which yields our error term

$$[\xi_t + \epsilon_t](\theta) = q_t - \beta_l l_t - \beta_k k_t - \beta_m m_t - \mathbf{c}(h_{t-1}, k_{t-1})'\beta_\omega \tag{3}$$

with the parameters to $\beta = (\beta_l, \beta_k, \beta_m, \beta_\omega)$.[17]

We formulate the moment condition using materials m_t as the proxy but any other available proxy cited above could also be used here. The only change would be the set of conditioning variables. For the special case when m_t is the proxy a sufficient set of conditioning variables given as (e.g.) $x_t = (k_t, k_{t-1}, m_{t-1}, m_{t-2}, l_{t-1})$. Let θ_0 denote the true parameter value. Wooldridge shows that the conditional moment restriction

$$s(x_t;\theta) \equiv E[[\xi_t + \epsilon_t](\theta)|x_t] \text{ and } s(x_t;\theta_0) = 0$$

is sufficient for identification of β in the single product case (up to a rank condition on the instruments).[18] ξ_t is not correlated with k_t, so k_t can serve as an instrument for itself. Lagged labor l_{t-1} and twice lagged materials m_{t-2} serve as instruments for l_t and m_t.

4.2 Multi-product production setting

In the multi-product case we have a system of M_t output equations:

$$q_{jt} = \beta_0^j + \beta_l^j l_t + \beta_k^j k_t + \beta_m^j m_t + \gamma_{-j}^j{}' q_{-jt} + \varepsilon_{jt} \qquad j = 1 \cdots M \tag{4}$$

We denote the vector of technical efficiency shocks as $\omega_t = (\omega_{1t}, \omega_{2t}, \ldots, \omega_{M_t})$. Choices of inputs will now generally be based not only on ω_{jt} but also on all of the other technical efficiency shocks ω_{-jt}. This frustrates the "inverting out" of ω_t that allows one to express ω_t as a function of k_t and a single proxy h_t as is done in the single product case.

We adopt suggestions from Petropoulos (2001) and Ackerberg, Benkard, Berry, and Pakes (2007) to allow for multiple unobserved technical efficiency shocks. Suppose we observe (at least) one proxy variable for every technical efficiency shock. Let $\mathbf{h}_t = (h_{1t}, \ldots, h_{Lt})$ denote the $1XL$ vector of available proxies. Each of these variables will

[17] The first-order approximation would add another parameter in front of $\mathbf{c}(h_{t-1}, k_{t-1})'\beta_\omega$ but this parameter is already subsumed in β_ω and is therefore not separately identified.

[18] The Wooldridge formulation is robust to the Ackerberg, Caves, and Frazer (2015) criticism of OP/LP.

generally be a function of k_t and $(\omega_{1t}, \omega_{2t}, \ldots, \omega_{M_t})$ and we write $\mathbf{h}_t(k_t, \omega_t)$. If the multivariate function $\mathbf{h}_t(k_t, \omega_t)$ is a bijection in ω_t conditional on k_t - one-to-one and onto - then we can invert the proxy variables to get the $1XL$ vector of functions $\omega_t = \mathbf{g}(k_t, \mathbf{h}_t)$. Included in this vector of functions is

$$\omega_{jt} = g_j(k_t, \mathbf{h}_t), \qquad j = 1 \cdots M$$

which then motivates including a function of (k_t, h_t) in the estimation to control for ω_{jt}.

The rest of the estimation proceeds in a manner similar to the single-product case. We use the same single index restriction to approximate unobserved productivity, so we have

$$\omega_{jt} = g_j(k_t, \mathbf{h}_t) = \mathbf{c}_j(k_t, \mathbf{h}_t)'\beta_{\omega_j}$$

where $\mathbf{c}_j(k_t, \mathbf{h}_t)$ is a known vector function of $(k_t, \mathbf{h}_t)$ chosen by researchers. $E[\omega_{jt}|\omega_{t-1}]$ is now given as

$$E[\omega_{jt}|\omega_{t-1}] = f_j(\mathbf{c}_j(k_{t-1}, \mathbf{h}_{t-1})'\beta_{\omega_j})$$

for some unknown function $f_j(\cdot)$. Again we use only the first-order approximation term for $f_j(\cdot)$ to keep exposition to a minimum.

Re-expressing in terms of firm's expectations we have

$$q_{jt} = \beta_l^j l_t + \beta_k^j k_t + \beta_m^j m_t + \gamma_{-j}^j{}' q_{-jt} + E[\omega_{jt}|\omega_{t-1}] + \xi_{jt} + \epsilon_{jt} \tag{5}$$

with $\xi_{jt} = \omega_{jt} - E[\omega_{jt}|\omega_{t-1}]$. The error is

$$[\xi_{jt} + \epsilon_{jt}](\theta) = q_{jt} - \beta_l^j l_t - \beta_k^j k_t - \beta_m^j m_t - \gamma_{-j}^j{}' q_{-jt} - \mathbf{c}_j(k_{t-1}, \mathbf{h}_{t-1})'\beta_{\omega_j}$$

with the new parameters γ_{-j}^j added to $\beta^j = (\beta_l^j, \beta_k^j, \beta_m^j, \gamma_{-j}^j, \beta_{\omega_j})$.

An additional key difference from the single product case is the need for instruments for q_{-jt}, which might either be lagged values of q_{-jt} or inputs lagged even further back. Let the set of conditioning variables be given as (e.g.) $x_{jt} = (q_{-j,t-1}, k_t, k_{t-1}, \mathbf{h}_{t-1}, m_{t-1}, l_{t-1})$.[19] Let θ_0 denote the true parameter value. The conditional moment restriction

$$s(x_{jt}; \theta) \quad \equiv \quad E[[\xi_{jt} + \epsilon_{jt}](\theta)|x_{jt}] \text{ and } s(x_{jt}; \theta_0) = 0$$

continues to be sufficient for identification of β as long as a rank condition holds.

[19] If h_t contains m_t (l_t) then one would add m_{t-2} (l_{t-2}) to the conditioning set.

4.3 Dealing with input pricing heterogeneity

Our left hand side variable is the firm's physical production of a given product. Therefore, our measure of productivity does not suffer from the so called output price heterogeneity bias (see e.g. Klette and Griliches, 1996 and De Loecker, 2011 for a discussion). However, two of our left hand side variables (material and capital) are measured in monetary values and deflated with an industry level deflator (see footnote 6 for the construction of capital). To deal with this issue, we follow the suggestion of De Loecker et al. (2016) and add price and market share in our control function when estimating the production function.

5 The link between technical efficiency improvements, import competition, and changes in gross output

We estimate three different specifications to investigate the relationship between technical efficiency and import shares. We use the import share net of re-exporting for our preferred results and show robustness of our results to our second import share index. We also discuss the mapping of changes in import shares into the implied long-term changes in the value of output due to these changes in competition.

In our first specification, we regress current firm-product technical efficiency on last quarter's technical efficiency and last quarter's import share, including 8-digit product indicator variables (ν_j), and year-quarter indicator variables (δ_t),

$$\omega_{ijt} = \rho\, \omega_{ij(t-1)} + \alpha_1 IS_{j(t-1)} + \nu_j + \delta_t + \eta_{ijt} \tag{6}$$

where η_{ijt} denotes the innovation in the firm-product technical efficiency conditional on last period's technical efficiency, import share, and the time and product fixed effects.

We map changes in import shares into changes in output as follows. Letting Δ denote the one period change operator. The units of the technical efficiency term are in the units of output, so the immediate short term impact on the growth rate of output induced by $\Delta IS_{j(t-1)} = IS_{j(t-1)} - IS_{j(t-2)}$ is given by $\Delta\omega_{ijt} = \alpha_1\, \Delta IS_{j(t-1)}$. An approximation to the short-term value of this change is then given by

$$PQ_{ijt} * \alpha_1\, \Delta\omega_{ijt},$$

where PQ_{ijt} denotes our approximation to the average revenue from period $t-1$ to t generated by the particular product. Alternative approximations might use last periods revenue or the simple average of this period's revenue and last period's revenue. Finally, if the AR(1) term ρ is greater than zero but less than one then this suggests approximating the long-term change in the value of output - denoted $\Delta Value_{ijt}$ - as

$$\Delta Value_{ijt} = \frac{PQ_{ijt} * \alpha_1 \, \Delta IS_{j(t-1)}}{(1-\rho)}. \tag{7}$$

Once we have estimates of α_1 and ρ we can compute this quantity for every firm-product in every time period.

In our second specification we include indicator variables that denote the revenue rank of the product in the firm's portfolio to investigate whether within-a-firm product rank and technical efficiency are correlated. The omitted variable is the core (highest revenue) product, $Rank^2_{ijt}$ is an indicator for the second product, $Rank^3_{ijt}$ is an indicator for the third product, and $Rank^4_{ijt}$ is an indicator that is equal to one for any product ranked lower than third. The estimation equation is

$$\omega_{ijt} = \rho \, \omega_{ij(t-1)} + \alpha_1 IS_{j(t-1)} + \sum_{k=2}^{4} \alpha_k Rank^k_{ijt} + \nu_j + \delta_t + \eta_{ijt} \tag{8}$$

Note that $\Delta Value_{ijt}$ in this setup is exactly the same as in the first setting above.

In our third specification we interact these rank indicators with the lagged product-level import shares in order to investigate whether the competitive effects vary by product rank. This will also allow for the $\Delta Value_{ijt}$ to vary by product rank holding the change in import share constant. The estimation equation is given as

$$\omega_{ijt} = \rho \, \omega_{ij(t-1)} + \alpha_1 IS_{j(t-1)} + \sum_{k=2}^{4} (\alpha_k + \alpha_{3+k} IS_{j(t-1)}) \, Rank^k_{ijt} + \nu_j + \delta_t + \eta_{ijt}. \tag{9}$$

For a product that ranks first the formulation for $\Delta Value_{ijt}$ remains as above but for a product that ranked (e.g.) second in revenues in a firm's portfolio the new expression for $\Delta Value_{ijt}$ is given as

$$\Delta Value_{ijt} = \frac{PQ_{ijt} * (\alpha_1 + \alpha_5) \, \Delta IS_{j(t-1)}}{(1-\rho)}, \tag{10}$$

and similarly for other lower ranking products.

We estimate these equations using ordinary least squares and using instrumental variables for the import share for a total of six primary specifications. As noted in De Loecker (2013), we could have estimated all of these parameters in one step along with the production function parameters to achieve possible efficiency gains. We did not do so because the one-step approach does not make apparent the quality of the instruments for the import share and we want the first stage F-statistic test for weak instruments to be very transparent. Also, in our results most of our production function estimates and our estimates from the equations above are fairly precise.

5.1 Instruments for Import Share

The import shares that enter into equations 7-9 are functions of the quantities of imports at the 8-digit level. If these quantities are correlated with the *innovations* in the firm-product technical efficiencies after controlling for last period's technical efficiency shock and time and 8-digit product-level fixed effects then we need instruments that are correlated with the shares but uncorrelated with the innovations. For example, if imports shares are increasing in 8-digit product categories in which domestic producers are becoming less technically efficient then import shares will be negatively correlated with the technical efficiency shocks, biasing the effect of import competition on technical efficiency down.

We use two different instruments. Our first instrument for the import share makes use of tariffs obtained from the World Bank WITS website.[20] Over our sample time period the "effectively applied tariffs" on Chinese goods applied by the European Union are significantly reduced for many goods as a result of China's entry into the World Trade Organization.[21] The World Bank aggregates tariffs to the HS6 level and we use this same HS6-level tariff for all 8-digit level goods in that category.[22] In the spirit of Hummels et. al. (2014) we focus more on HS6-level product categories where China has a significant pre-sample presence by weighting the HS6-level tariffs by the import share of China at the HS6 level in 1995. Our second instrument is also based on Hummels et. al (2014). For each good j at time t we calculate the total world exports net of those coming from Belgium using the BACI database from CEPII.[23] This variable includes world-wide shocks to export supply for good j that vary over time and products. Positive shocks to world export supply for good j - like decreases in transportation costs for the good - should be positively correlated with the total import share of good j in Belgium. World export supply net of Belgium exports is a valid instrument for the import share if the world-wide supply shocks are uncorrelated with the *innovations* in firm-product technical efficiencies. This condition is a slightly weaker condition than required by Hummels et al (2014) where the *levels* of productivity must be uncorrelated with the world-wide shock holding other controls constant.

[20] See *http://wits.worldbank.org/wits/wits/witshelp/Welcome.htm.*

[21] From the WITS website "WITS uses the concept of effectively applied tariff which is defined as the lowest available tariff. If a preferential tariff exists, it will be used as the effectively applied tariff. Otherwise, the MFN applied tariff will be used."

[22] We use conversion tables from Eurostat to identify the HS6-level product category to which each of our 8-digit level PRODCOM goods' belongs.

[23] BACI is the World trade database developed by the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). The original data is provided by the United Nations Statistical Division (COMTRADE database). BACI is constructed using a harmonization procedure that enables researchers to link import shares directly to HS 6-digit product disaggregation level.

6 Results

We report multi-product production function estimates and then relate the implied firm-product technical efficiencies to changes in import penetration. We then map realized changes in import shares to changes in aggregate manufacturing output. We compare our findings with what we would find if instead we used the single product production approximation to multi-output production.

6.1 Estimation at the firm-product level

We first start by estimating firm-product productivity using our Diewert-Lau hybrid method. Our left hand side variable is the physical quantity of a given good produced by a given firm. Goods are defined at the 8-digit product level or PRODCOM8. Our right hand side variables consist of firm-level inputs plus a quantity aggregate reflecting the physical production of all the other goods produced by the firm. The firm-level inputs are expressed in quantity for labor (as the number of workers) and in monetary values for capital and materials. As mentioned in the previous section, we are concerned that using inputs (deflated by an industry-wide price index) measured in monetary terms will introduce a bias in our estimation. This is especially relevant in our case as we use quantity on the left hand side but values on the right hand side for some of the inputs. We therefore follow a strategy very similar to De Loecker et. al (2016) by adding a linear function of firm-product output prices in our control function.[24]

Our baseline specification relies on a Cobb-Douglas production function. The method we use to address the simultaneity bias is the Wooldridge modified version of the mix Olley and Pakes and Levinsohn and Petrin (2003) estimator, as explained in subsection 5.2. This means that we use both investment and materials as proxies, and we refer to this estimator as the Wooldridge-OPLP estimator. Using only material does not affect our results. Alternative production functions and estimators are used in the robustness checks.

While our unit of analysis is an 8-digit product (PRODCOM8), we pool our estimations at the 2-digit product level (PRODCOM2). We therefore assume parameters to be constant within the subset, which is a common practice in the literature.[25] Belgium is a small country and there are few disaggregated products made by many firms. Our method is also data demanding. Pooling products together allows us to reach a reasonable

[24]Experimenting by adding market share, or using a non linear function of output prices did not affect our results.

[25]In previous versions, we pooled products belonging to the same 4-digit level (see Dhyne et al., 2014) and for a very limited set of products for which we had enough observations. Our results were robust to the pooling specification.

number of data points that we need for our estimations. All of our specifications include both 8-digit product indicator variables and year-quarter indicator variables. Finally, we should note that the use of quarterly data allows us to beef up the number of product-level observations. However, our results are robust if we run the analysis with yearly data.

The quantity aggregate used in our baseline for the output of the other goods produced by the firm is the log of the revenues of all the other goods deflated by the quarterly producer price index. Other alternatives are investigated in the robustness section, as explained in subsection 4.3.

Table 3 reports the results of our production function estimates for the 12 largest 2-digit product groups, which represents 1,655 different 8-digit products or 70% of all products made in Belgium. Our largest product group is food and beverages with 52,573 firm-product-quarter observations while our smallest product group is electrical machinery with 4,437 firm-product-quarter observations.[26] The quantity aggregate coefficient is the correct sign (negative) and significant for all 12 industries and ranges between -0.082 for paper and -0.145 for apparel. The interpretation for apparel is that - holding all input levels constant at their current levels - an increase in the firm's apparel output index of one percent comes at the expense on average of 0.14 percent of the good under consideration. On the input side 29 out of 36 coefficients are statistically significant, 35 of the 36 coefficients have the correct (non-negative) sign, and in the one case where capital is negative it is not significant.

In the multi-product setting, returns to scale can be defined in a variety of ways depending upon what feature of production is of interest. If we hold the other outputs constant and increase all inputs by one percent, we get a range for most industries of an increase in output of the good under consideration between 0.8 and 1, which is the sum of the coefficients on all three inputs. Above, we report that "returns" to output of a good If we hold inputs constant and increase the other-output index by one percent ranges from -0.08 to -0.14. If we increase all inputs and the output index by one percent - the sum of all coefficients - then we get a range of increases that principally lie between 0.7 and 0.9. In the single-product case researchers frequently report returns to scale close to one but comparisons to the multi-product case are frustrated by the fact that they are estimating different function, the latter of which holds other outputs constant and the former of which does not.

[26]The 2-digit PRODCOM product categories are the same as the European industry codes (NACE).

6.2 The link between technical efficiency and import competition

Table 4 presents results from the OLS and IV regressions of technical efficiency on import shares. All specifications include 8-digit product indicators and quarterly-time indicator variables. Our ten alternative estimates for α_1 range from 0.84 to 1.17 and are all statistically significant.

6.2.1 Non-instrumented Results

In column 1 we regress firm-product technical efficiency (in logs) on lagged firm-product technical efficiency (in logs) and lagged product import share. Changes in import share are positively correlated with technical efficiency but the magnitude is small; the estimated value of α_1 from equation (12) is estimated to be 0.10, implying an increase of 10% in the import share with a 1.0% increase in firm-product technical efficiency. Since the average change in shares is 4.7%, this OLS estimate suggests import competition has played a relatively minor role in promoting economic growth.

We find a high persistence in firm-product technical efficiency over time with a coefficient of 0.91 for lagged productivity that is statistically significant at 1%. This estimated value for ρ is approximately the same for all of the OLS and IV specifications we have estimated and it suggests changes in technical efficiency are long-lived.

In column 2, we investigate whether the technical efficiency associated with a product is related to the share of revenue that the product generates for the firm by including share-rank indicators. The left out good is the firm's "core" product, that is, the product that generates the most revenue for the firm. Products that generate less revenue are not produced in as technically efficient a manner, with the second ranking product's technical efficiency 9.3% less than the core product, the third ranking product 20.9% less, and the fourth and above ranked products 32.3% less. All rank indicator variables are statistically significant at 1%. While the exact magnitudes of these differences do vary across our OLS and IV specifications the finding of this ordering of technical efficiencies by share-rank is very robust.

Column 3 adds interactions between import share and the rank of the product to test whether the magnitude of the change in technical efficiency due to a change in import shares varies by share-rank. The lead coefficient α_1 is still small at 0.12 and significant at 1% and slightly higher than in the previous specifications, where it represented the average effect across all products. The interactions between import share and product rank are all negative, with -0.01 for the second product (but not statistically significant), -0.03 for the third product (significant at 1%) and -0.12 for products ranked more than

3 (significant at 1%). Thus the OLS results suggest changes in import shares impact the first, second, and third products similarly but do not affect products ranked higher than three.

6.2.2 Instrumented Results

Columns 4, 5, and 6 are the IV analogs to columns 1-3. They use the same price-weighted quantity index in the W-OPLP production function estimation. Our first-stage F-statistics from the regressions of import shares on our two instruments reject the hypothesis of weak instruments at the 1% level in all three IV regressions.

Column 4 shows estimates from the regression of technical efficiency on last period's technical efficiency and the lagged instrumented import share. Relative to column 1 the estimate of α_1 increases almost *ninefold* from 0.10 to 0.87 and is significant at the 10% level. When we add the share-rank indicators in column 5 the estimate of α_1 goes up to 0.99 and is significant at the 5% level. When we add the interactions of the share-rank indicators with the instrumented lagged import share in column 6 the estimate of α_1 climbs to 1.05 and remains significant at 5%. The increase from 0.12 to 1.05 when we move from OLS to IV is consistent with lagged import penetration being higher in product markets where domestic innovations in technical efficiency are lower (and vice versa).

In column 6 the coefficients on the share-rank indicators decrease only a bit relative to OLS. However the coefficients on the interactions tell a different story from OLS as all products - regardless of the product revenue ranking - have technical efficiency increasing in response to increases in import competition. A 1% increase in the lagged import share is associated with a 1% percent increase in technical efficiency in the current period of both the first and second ranked products and a 0.65% increase in technical efficiency of all other products produced by the firm. All three coefficients are statistically significant at 1%. Recall that this impact is only the short-term effect because the estimated AR(1) coefficient is 0.89 and strongly significant.

Column 7 presents the first of ten robustness checks. We estimate the production function parameters with the W-OPLP estimator but using the unweighted quantity index instead of the price-weighted quantity index. The estimated coefficient on α_1 drops slightly to 1.01 and remains significant at the 5% level. The remaining point estimates are very similar to those from column 6. Table 5 and table A1 contain the other nine robustness checks. The estimates for α_1 range from 0.84 to 1.17 and seven of the nine are significant at the 5% level (the other two are significant at the 10% level). For the most part the other coefficients are very similar across these specifications. Readers not interested in these details can skip directly to Section 7.3.

For comparison Column 1 of table 5 reprints the results from our preferred specification (column 6 of table 4). All nine specifications use the price-weighted quantity index, and except for columns 2 and 3, all of these specifications estimate the production function parameters with the W-OPLP estimator. In column 2 we estimate the production function but address simultaneity using just materials as the proxy (the Wooldridge-LP estimator). We find an estimate of α_1 of 1.06. In column 3 we ignore simultaneity and use OLS to estimate the production function parameters. We find the estimated coefficient is 0.84, the lowest of all of our alternative estimates. Column 4 uses our alternative measure of the import share that does not adjust for re-export. For this specification we estimate a value of α_1 of 0.93.[27] Column 5 does not include the product's output price in the estimation of the production functions and we find an estimate of 0.89 for α_1. Column 6 allows the price-weighted quantity index and its squared value to enter the production function during estimation, as argued by Diewert (1973), and the coefficient increases to 1.17, the largest estimate of α_1 across all eleven specifications.

We currently pool single and multi-product firms. Column 1 of table A1 reports results for only multi-product firms and Column 2 uses both single- and multi-product firms - the full sample - but includes an indicator variable for multi-product firms in the import share regression. The respective α_1's are 1.08 and 1.11 and both are significant at the 5% level.

Firms that are active in international markets may respond differently to increases in import competition relative to those that only sell in the domestic market. Column 3 of table A1 includes two indicator variables, one for whether the firm producing the product imports and one for whether they export. The estimate of α_1 is 1.02 and significant at the 5% level. Column 4 of table A1 includes two indicator variables, one for whether the firm imports goods in the same 8-digit category as the good it is producing and one for whether it exports that particular good. Both variables are lagged by one quarter. The estimate is 1.01 and again significant.

We also find two additional side results in line with previous papers in the literature. Firms that import appear to be slightly more efficient at making their goods (column 3), and exported goods appear to be produced slightly more efficiently as well (column 4).

[27] In previous versions, we also experimented with measures of import shares in value instead of quantity, and found similar results. Results are available from the authors.

6.3 Changes in the Value of Output due to Changes in Import Competition

Equation 16 shows how we translate changes in import shares into changes in the value of manufacturing output for any product j. The expected percentage change in technical efficiency in the current period due to a change in the lagged import share is given by multiplying our preferred estimate of α_1 of 1.05 by the change in the lagged import share for that 8-digit product category. We multiply this expected change in technical efficiency in the current period by the current revenue of the product to estimate the total expected change in product revenue this period. The AR(1) coefficient of 0.89 implies these changes are highly persistent and we account for future gains in technical efficiency by scaling up this estimated change in current revenue by $\frac{1}{1-0.89}$. By design the total lifetime change in revenues will be positive in years when the lagged import share increases and negative when the import share decreases.[28]

Table 6 reports the entire distribution of 65,242 changes in the long-run value of produced output due to changes in the previous period's input share from 1997-2007. There is a tremendous amount of dispersion in the changes in the value of output due to changes in import shares. Almost 35% of the realized changes are negative because import shares decrease in many cases (see Table 2). On average changes in prior year's input share leads to an increase in the long-run value of output of over 22,000 euros. Across industries the largest average change is 96,000 euros in Electrical Machinery followed by Apparel (75,000) and Basic Metals (71,000). The median changes in import shares are close to zero and this leads to the median changes in the value of output to be close to zero across all 11 2-digit industries. Both the positive and negative changes can be very large for products with the biggest revenues, as in industries like Machinery and Equipment, Basic Metals, and Electrical Machinery. Across these industries the 10th percentile of the distribution in these industries ranges between -1.8 to -2.5 million euros and the 90th percentile changes ranges between 2.2 and 2.5 million euros.

In table 7 we aggregate the positive and negative changes separately across industries in each year from 1997 to 2007. On average the value of increased output due to increases in import shares ranges from 1.1 to 1.4 billion euros in any given year and the decreases range from -1.1 to -1.4 billion euros. These numbers are not small relative to the overall average annual total value of real output in Belgian manufacturing of 55 billion euros. The net changes in every year are positive except for 1997 and most years range from

[28] We did not have enough variation to allow for precise estimation of different coefficients on increases and decreases in import shares but we could not reject that they were significantly different from one another.

between 100 and 300 million euros. Aggregating over the entire sample period the overall gain in the value of output due to increased import competition is on the order of 1.4 billion euros, almost 2.5% of average annual output.

7 Conclusion

We develop a new approach to estimate firm-product technical efficiencies for multi-product firms using detailed quarterly data on inputs and on the physical quantities of goods produced by firms. We use our estimates of 8-digit firm-product technical efficiencies to study the link between productivity and import competition. Our results show a strong positive relationship between firm-product technical efficiency and import competition, pointing towards the disciplinary effect of competition on efficiency. Over the sample period we find an aggregate effect on Belgian manufacturing of over 1.2 billion euros. Consistent with several theoretical papers in international trade, we find that firms are most technically efficient at the goods that generate them the most revenue. We also find that while all products' technical efficiencies benefit from increased competition, the "core" products experience the biggest increases in response to increased competition.

While our main finding is that increased import competition leads to higher productivity, we do not analyze in this paper the channels through which firms generate these productivity gains. Therefore, our results as such provide indirect evidence in favor of recent extensions of multi product firms models that suggest that firms adapt their innovation strategy when facing trade liberalization (see e.g. Dhingra, 2013; Eckel et al., 2015). We leave this line of investigation for future research.

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Table 1: Average share of a firm's revenue derived by its individual products, 1997 to 2007

Product ranking within a firm determined by its share of the firm's total revenue.

Number of products produced by the firm at the Prodcom 8-digit level

	1	2	3	4	5	More than 5	N
Product rank							
1	100	77.5	69.5	64.2	57.8	49.4	
2		22.5	23.0	23.5	23.6	22.4	
3			7.5	9.1	11.1	11.8	
4				3.2	5.3	6.7	
5					2.2	3.9	
6+						5.8	
Share of manufacturing output	26.4	19.0	12.8	11.7	4.1	26.0	100
# observations	59,510	33,955	15,078	9,246	4,906	12,119	134,814

Number of products produced by the firm at the Prodcom 2-digit level

	1	2	3	4	5	More than 5	N
Product rank							
1	100	82.1	74.4	74.1	63.8	65.4	
2		17.9	20.2	19.2	22.8	17.5	
3			5.4	5.1	7.9	9.3	
4				1.6	3.8	4.5	
5					1.6	3.1	
6+						0.2	
Share of manufacturing output	78.4	16.3	3.4	1.4	0.3	0.2	100
# observations	117,598	14,669	1,884	481	129	53	134,814

Note: For any product rank i each column j reports the average share (in %) of the i-th product in total output for firms producing j products.

Table 2: Changes in import share defined in terms of "re-export" corrected quantities (I_{2jt}) from 1997 to 2007 at the 8-digit product level

Distribution of changes reported for each 2-digit product category

Code	Product category	Mean	Mean (weighted)	10th	25th	Median	75th	90th	# products
24	Chemicals	0.027	0.073	-0.297	-0.098	0.002	0.140	0.381	240
15	Food and beverages	0.008	-0.015	-0.202	-0.096	0.004	0.098	0.228	215
28	Fabricated metal products	0.172	0.196	-0.176	0.001	0.122	0.389	0.575	103
29	Machinery and equipment	0.062	0.070	-0.290	-0.034	0.019	0.185	0.493	93
25	Rubber and plastic products	0.028	0.058	-0.284	-0.116	0.020	0.164	0.322	81
18	Apparel	0.114	0.194	-0.008	0.006	0.060	0.177	0.323	68
27	Basic metals	0.002	0.014	-0.303	-0.036	0.020	0.104	0.269	62
26	Non metallic mineral	0.090	0.038	-0.112	-0.007	0.047	0.193	0.347	49
21	Paper	0.047	-0.004	-0.270	-0.037	0.040	0.181	0.443	47
17	Textile	0.003	-0.030	-0.318	-0.186	0.002	0.112	0.372	45
31	Electrical machinery	0.064	0.022	-0.347	-0.062	0.028	0.193	0.478	29
	All products	0.051	0.043	-0.216	-0.040	0.020	0.164	0.409	1075

Note: The weighted means weight by the product's 8-digit revenue share of the total 2-digit industry revenue.

Table 3: Multi-product production function estimates at 2-digit Prodcom level

Dependent variable q_{ijt} is log of the quantity sold in physical units at the 8-digit product level of good j by firm i at time t
All specifications include quarter-year and product dummies and a constant term

	(1) Food & beverages 15	(2) Fab. metal 28	(3) Other manuf. 36	(4) Chemicals 24	(5) Non metallic mineral 26	(6) Rubber & plastic 25	(7) Machinery & equip. 29	(8) Textile 17	(9) Apparel 18	(10) Paper 21	(11) Basic metals 27	(12) Electrical machinery 31
$q_{(-j)}$	-0.107***	-0.097***	-0.110***	-0.100***	-0.086***	-0.096***	-0.107***	-0.097***	-0.145***	-0.082***	-0.113***	-0.085***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.001)	(0.002)	(0.003)
l	0.148***	0.388***	0.346***	0.037*	0.320***	0.043*	0.390***	0.179***	0.257***	0.305***	0.169***	0.475***
	(0.010)	(0.016)	(0.022)	(0.021)	(0.016)	(0.025)	(0.030)	(0.022)	(0.023)	(0.031)	(0.027)	(0.045)
m	0.443***	0.379***	0.658***	0.634***	0.439***	0.761***	0.178*	0.698***	0.507***	0.535***	0.629***	0.474***
	(0.049)	(0.062)	(0.077)	(0.071)	(0.074)	(0.098)	(0.102)	(0.105)	(0.059)	(0.116)	(0.114)	(0.128)
k	0.089**	0.115*	0.152*	0.085	0.109	0.132*	0.067	0.166*	-0.131	0.161	0.060	0.000
	(0.039)	(0.059)	(0.080)	(0.091)	(0.075)	(0.078)	(0.104)	(0.100)	(0.146)	(0.102)	(0.116)	(0.123)
# obs.	47,125	17,309	12,673	13,742	11,036	11,106	11,138	9,512	6,008	5,465	5,551	3,984

Note: Each column reports the estimated coefficients using a modified variant of the Wooldrige-Mixed OP-LP estimator. Explanatory variables are in logs and include firm-level labor, the standard real indices for materials and for capital - i.e. the dollar value of each - and a firm level index of the output of its other goods $q_{i(-j)t}$ given by the revenue of all other products produced by the firm. We include the product's price as an additional control (see Estimation section and see Appendix for results that do not include price). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: The link between firm-product technical efficiency, import competition and product rank
Dependent variable is the estimated firm-product technical efficiency residual
Product ranking within a firm determined by its share of the firm's total revenue

	using price weighted quantity index						using unweighted quantity index
	OLS			IV			IV
Dep. var.: technical efficiency	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged import share	0.108***	0.101***	0.123***	0.878*	0.996**	1.055**	1.012**
	(0.013)	(0.013)	(0.014)	(0.501)	(0.494)	(0.460)	(0.474)
Second product		-0.093***	-0.090***		-0.094***	-0.089***	-0.110***
		(0.003)	(0.004)		(0.004)	(0.020)	(0.020)
Third product		-0.209***	-0.200***		-0.211***	-0.094***	-0.096***
		(0.004)	(0.005)		(0.005)	(0.025)	(0.026)
Product above rank 3		-0.323***	-0.287***		-0.325***	-0.195***	-0.194***
		(0.005)	(0.007)		(0.007)	(0.025)	(0.026)
Lagged import share x 2nd prod.			-0.014			-0.034	0.015
			(0.011)			(0.075)	(0.076)
Lagged import share x 3rd prod.			-0.039***			-0.398***	-0.384***
			(0.014)			(0.086)	(0.088)
Lagged import share x higher rank prod.			-0.122***			-0.422***	-0.410***
			(0.016)			(0.080)	(0.082)
Lagged technical efficiency	0.913***	0.889***	0.889***	0.915***	0.893***	0.894***	0.900***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
First stage F-statistic				55.36***	55.73***	16.09***	15.89***
# obs.	165,800	165,800	165,800	106,243	106,243	106,243	106,243

Note: Import shares are computed controlling for re-export. The first three columns report OLS estimates. The next three columns show the estimates where import share is instrumented by Chinese tariffs weighted by the share of China in the pre-sample period and world export supply. Column (7) is similar to column (6) but uses the TFP estimates from a specification with an alternative unweighted quantity index. All specifications include quarter-year and product dummies and a constant term (not reported). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The link between firm-product technical efficiency, import competition and product rank
Robustness to production function estimators

Dep. var.: technical efficiency	(1) Wooldridge-OPLP	(2) Wooldridge-LP	(3) OLS	(4) Import share in quantity unadjusted for re-export	(5) without price control	(6) with quadratic term for $q_{(-j)}$
Lagged import share	1.055**	1.069**	0.849*	0.936**	0.894*	1.171**
	(0.460)	(0.459)	(0.472)	(0.420)	(0.477)	(0.547)
Second product	-0.089***	-0.088***	-0.096***	-0.091***	-0.090***	-0.074***
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.023)
Third product	-0.094***	-0.091***	-0.127***	-0.083***	-0.123***	-0.067**
	(0.025)	(0.025)	(0.026)	(0.029)	(0.026)	(0.030)
Product above rank 3	-0.195***	-0.197***	-0.235***	-0.177***	-0.216***	-0.182***
	(0.025)	(0.025)	(0.026)	(0.029)	(0.026)	(0.030)
Lagged import share x 2nd prod.	-0.034	-0.042	-0.069	-0.022	-0.070	0.071
	(0.075)	(0.075)	(0.075)	(0.070)	(0.076)	(0.089)
Lagged import share x 3rd prod.	-0.398***	-0.417***	-0.405***	-0.385***	-0.389***	-0.327***
	(0.086)	(0.086)	(0.087)	(0.085)	(0.088)	(0.103)
Lagged import share x higher rank prod.	-0.422***	-0.430***	-0.452***	-0.424***	-0.456***	-0.296***
	(0.080)	(0.080)	(0.081)	(0.080)	(0.082)	(0.095)
Lagged technical efficiency	0.894***	0.892***	0.870***	0.893***	0.878***	0.876***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
# obs.	106,243	106,243	106,243	106,243	106,243	106,243

Note: This table reports results for the estimates in column 6 of table 4 using four alternative methods of estimating the production function estimates and the implied technical efficiency residuals. As before all production function specifications include quarter-year and product dummies and a constant term (not reported). Column (1) uses the same specification as column 6 in table 4. Column (2) uses the TFP measure from the Wooldridge-Levinsohn&Petrin estimator with price control. Column (3) uses ordinary least squares estimates of TFP. The next four columns use the Wooldridge OPLP estimator used in table 4. Column (4) uses an import share measure in quantity and that does not control for reexport. Column (5) uses the TFP estimates from the Wooldridge-OPLP estimator that does *not* include the product's output price as an control. Column (6) includes a quadratic term for the revenues of the other goods produced by the firm when estimating the production function parameters. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: The distribution of estimated annual changes in the value of 8-digit firm-product output attributable to changes in import shares, 1997-2007
Thousands of Euros

Code	Product category	10th	25th	Median	75th	90th	# obs	Mean
24	Chemicals	-971.6	-53.3	0.0	55.2	936.4	10005.0	10.8
15	Food and beverages	-281.1	-30.5	-0.1	21.4	250.7	22186.0	-5.9
28	Fabricated metal products	-517.7	-100.6	0.1	137.1	691.2	6063.0	53.8
29	Machinery and equipment	-2536.6	-185.4	0.1	277.1	2241.2	2180.0	17.7
25	Rubber and plastic products	-953.8	-105.5	0.7	158.1	1070.3	4820.0	28.0
18	Apparel	-71.9	-3.1	1.4	52.1	308.7	4708.0	75.7
27	Basic metals	-1924.4	-154.0	0.2	282.2	2509.1	2113.0	71.2
26	Non metallic mineral	-343.7	-41.8	0.8	78.9	431.9	4091.0	23.6
21	Paper	-1165.2	-99.9	0.2	141.6	1156.4	2799.0	20.1
17	Textile	-879.0	-106.9	0.5	121.3	826.3	2741.0	9.8
31	Electrical machinery	-1878.8	-208.9	0.1	344.0	2589.4	656.0	96.5
	All products	-538.3	-46.7	0.1	63.6	625.9	65242.0	22.6

Note: The table uses the estimates in column 6 in table 4 along with the realized changes in import shares to calculate the estimated change in output value. The change in output value is calculated by first multiplying the change in firm-product technical efficiency by the coefficient on import share to get the change in the growth rate in output due to the change in the import share. In order to account for the time series persistence in technical efficiency implied by the AR(1) term we scale additional value in output by $\frac{1}{1-\hat{\rho}}$, where $\hat{\rho}$ is the estimated value of the AR(1) coefficient from column 6 of table 4.

Table 7: Aggregate manufacturing gains and losses from increases and decreases in import competition, 1997-2007
Millions of Euros

	Firm-product gains with increases in import share (1)	Frm-product losses with decreases in import share (2)	Total Change (1)+(2)
1997	1,122	-1,473	-351
1998	1,246	-1,105	141
1999	1,376	-1,237	138
2000	1,317	-1,245	72
2001	1,407	-1,369	38
2002	1,369	-1,095	273
2003	1,407	-1,191	216
2004	1,372	-1,002	370
2005	1,278	-1,033	245
2006	1,357	-1,140	217
2007	1,263	-1,147	116
Total	14,514	-13,038	1,476

Note: The table reports the sum of all estimated productivity gains, losses and net gains at the annual level across all 2-digit manufacturing industries reported in Table 5.

Table A1: The link between firm-product technical efficiency, import competition and product rank
Other checks on robustness to production function estimation and importing/exporting

Dep. var.: technical efficiency	(1) Only multi-product firms	(2) All firms pooled with multi-product indicator in production estimation	(3) Does the firm import or export ?	(4) Is the product imported or exported by the firm ?
Lagged import share	1.086**	1.114**	1.020**	1.012**
	(0.439)	(0.459)	(0.469)	(0.468)
Second product	-0.136***	-0.159***	-0.090***	-0.090***
	(0.020)	(0.020)	(0.020)	(0.020)
Third product	-0.140***	-0.170***	-0.095***	-0.094***
	(0.027)	(0.026)	(0.025)	(0.025)
Product above rank 3	-0.242***	-0.267***	-0.197***	-0.197***
	(0.027)	(0.026)	(0.025)	(0.025)
Lagged import share x 2nd prod.	-0.116	0.023	-0.030	-0.029
	(0.077)	(0.075)	(0.074)	(0.074)
Lagged import share x 3rd prod.	-0.512***	-0.332***	-0.397***	-0.398***
	(0.092)	(0.086)	(0.086)	(0.086)
Lagged import share x higher rank prod.	-0.565***	-0.376***	-0.419***	-0.419***
	(0.087)	(0.080)	(0.080)	(0.080)
Multi-product indicator		0.149***		
		(0.005)		
Lagged Importer indicator			0.017**	-0.004
			(0.007)	(0.005)
Lagged exporter indicator			0.006	0.025***
			(0.007)	(0.006)
Lagged technical efficiency	0.873***	0.885***	0.892***	0.892***
	(0.003)	(0.003)	(0.003)	(0.003)
# obs.	84,493	106,243	106,243	106,243

Note: Column (1) considers only multi-product firms. Column (2) considers all firms but adds an indicator variable for multi-product firms when estimating the production function parameters. Column (3) includes two indicator variables, one for whether the firm is an importer, the other for whether the firm is an exporter. In column (4), the import and export indicators are on if the firm is exporting or importing that specific product. All specifications include quarter-year and product dummies and a constant term (not reported). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.