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 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 use theory and empirical techniques developed in Dhyne et al. (2017) for multi-product production estimation to estimate firm-product quarterly technical efficiencies. This theory avoids requiring multi-product production to be a collection of single-product (SP) production functions, and it does not require an allocation rule of aggregated inputs for these single product production functions. We find that a 0.01 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" good 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 most profitable (see e.g. Aghion and Howitt, 1996 and Holmes and Schmitz, 2010 for a recent review). 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).

In this paper we estimate the impact of import competition on Belgian *firm-product technical efficiencies* from 1997 to 2007. Bernard, Redding and Schott (2010, 2011), Mayer, Melitz and Ottaviano (2014), and others have reported that most firms produce multiple products. We follow a novel estimation mehdology by Dhyne, Petrin, Smeets and Warzynski (2018) (DPSW2018 henceforth) who extend Diewert (1973) and Lau (1976) to show that the multi-product production possibilities set with J outputs and K inputs can be completely characterized by J equations, with one equation for each output j. This result implies the multi-product production possibilities can be recovered by regressing each firm-product output on each of the firm's aggregate inputs capital, labor, and materials, and the levels of each of their other outputs. The collection of these estimated equations describes the vectors of outputs that can be achieved by different levels of inputs, and for any vector of outputs the vectors of inputs that can achieve that vector of outputs. The residuals from each of these equations are the unrestricted firm-product technical efficiencies. This approach has the added advantage that it does not require multi-product production to be a collection of single-product production functions.

We relate these changes in estimated technical efficiencies to changes in (instrumented) import shares and find that technical efficiency increases a full percentage point for every 0.01 increase in import penetration. The average change in import share increased by 0.05 suggesting 5% gains on average, with some changes like Apparel and Fabricated Metal Products experiencing increases as large as 11.4% and 17.1% on average. We then translate these change in technical efficiency into the changes in both the value of firm-product and aggregate output over the sample period. Of the 65,242 changes the average change in the value output due to changes in competition was a little over 22 thousand euros for each product. although these averages are significantly higher for some industries, with Fabricated Metal Products, Basic Metals, Apparel, and Electric Machinery averaging 53.8, 71.2, 75.7, and 96.5 thousand 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.

Our estimates of firm-product technical efficiencies are can be directly related to changes in competitive conditions for that particular 8-digit product category, allowing us explore implications of the recent theoretical models of 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. More recently, extensions of these models by Dhingra (2013), Eckel et al. (2015), and Mayer, Melitz and Ottaviano (2016) explore how - within a firm - resources are reallocated across different products in the face of external shocks.

Our main empirical specification regresses the estimated firm-product technical efficiencies 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, 8-digit product fixed effects, and quarter-specific fixed effects. If import penetration is 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 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 above we find that product rankings on average line 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).

The approach neither requires us to assume that multi-product production is a collection of single-product production functions, nor does it require us to have a rule for allocating aggregated firm-level input measures across these single product production categories. DPSW (2017) test the former assumption in the context of their setup where it is not imposed and reject the single-product production function approximation to multi-product production. They also find that using single-product production functions causes the results we find in this paper to disappear - import penetration has no impact on firm-product technical efficiency - because the estimated technical efficiency residuals using single-product production functions are measured with so much error that the result is attenuated away.

The closest related paper to ours is De Loecker, Goldberg, Khandelwal, and Pavcnik (2016).[1] They estimate how changes in product-specific marginal costs are related to increases in import competition. Consistent with our findings they report that marginal costs do appear to decline in the face of increases in import competition. The key difference between our approach to estimation and their approach is that we do not assume that single product firms and multi product firms have the same production technology, therefore clarifying a channel for economies of scope. They then use firm-optimization conditions to allocate the aggregate measures of capital, labor, and materials to each of these production functions to recover a firm-product specific markup, which is their main purpose.

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 describes estimation of multi-product production functions in the face of simultaneity. Section 5 describes how estimate the impact of increased import competition, 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.

[1] Garcia Marin and Voiglander (forthcoming) 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.

2.1 The Belgian PRODCOM survey

The first data set is firm-product level production data (PRODCOM) collected by Statistics Belgium.[2] 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 minimum of 10 employees or total revenue above 2.5 million Euros.[3] 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 1997-2007 because it is a period of dramatic trade liberalization and because in 2008 PRODCOM both significantly reduced its sample size and changed its classification system. We also do some standard cleaning to exclude outliers. 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 only keep in our estimations 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 134,814 firm-product observations between 1997-2007. As has been noted in other product-level data sets, the majority of firms produce multiple products.[4] 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

[2] 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*)

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

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

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.

2.2 Firm Input Measurements

Quarterly measurements of firms inputs from 1997 to 2007 are obtained from the VAT firm fiscal declarations, the National Social Security database, and the Central Balance Sheet Office database. For tax liability purposes, Belgian firms have to report 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. To construct a quarterly measure of capital, we start with data from the Central Balance Sheet Office, which records annual measures of firm assets for all Belgian firms. For the first year a firm is present in our data, we take the total fixed assets as reported in the annual account as their starting capital stock. We then use standard perpetual inventory methods to build out a capital stock for each firm-quarter.[5]

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

[5]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.

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.[6]

We construct two import share indices. Our preferred measure corrects for the fact that Belgium is a small open economy on the North Sea in Central Europe and a significant fraction of the products entering Belgium are subsequently re-exported to other countries.[7] Our second measure is based on total imports including those that are re-exported.

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. For expositional purposes we start with our second measure of import penetration given as[8]:

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

Our preferred measure is based on net imports. Continuing to work in quantity units we define net imports at the firm level as $Max\left\{M_{ijt} - E_{ijt}, 0\right\}$ where E_{ijt} is the physical quantity of exports of good j from firm i at time t. This export-corrected import share measure is then given as

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

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

[6]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.

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

[8]We also compute a similar measures 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.

competition and it suggests that there is a role for increases *and decreases* in competition to both increase and decrease technical efficiencies.

3 Multi-Product Production

The primitive of production analysis is the firm's production possibilities set T. With M outputs and N inputs the firm's production possibilities set T lives on the non-negative orthant of R^{M+N}. It contains all of the combinations of M non-negative outputs $q = (q_1, q_2, \ldots, q_M)$ that can be produced by using N non-negative inputs $x = (x_1, x_2, \ldots, x_N)$ so if $(\tilde{q}, \tilde{x}) \in T$ then $\tilde{q} = (\tilde{q_1}, \ldots, \tilde{q_J})$ is achievable using $\tilde{x} = (\tilde{x_1}, \ldots, \tilde{x_N})$. The existence theorem from DPSW (2018) - Theorem 3.1 below - building on Diewert and Lau motivates characterizing the production possibilities set by using a first- (or higher) order approximation to M production equations which can be written as:

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

where (l_t, k_t, m_t) denote total labor, capital, and materials used in the production of all goods, q_{-j} denoted the vector of outputs excluding good j, and with all variables in logs. Holding all outputs except good j constant, β_l^j (e.g.) gives the increase in output j given a one-percent increase in labor. Holding all inputs constant γ_k^j (e.g.) gives the decrease in output of good j given a one-percent increase in the output of good k. We briefly review the theory behind multi-product production. Readers not interested in these or estimation details can skip directly to the results in Section 5.

For good j produced by the firm, let the output production of other goods be denoted by q_{-j}. For any (q_{-j}, x), if $max\{q_j \,|\, (q_j, q_{-j}, x) \in T$ is finite, then Diewert (1973) defines the multi-product production function as

$$q_j^* = F_j(q_{-j}, x) \equiv max\{q_j \,|\, (q_j, q_{-j}, x) \in T\}.$$

[9] The single-product production function is the special case where

$$q_j^* = F_j(x) \equiv max\{q_j \,|\, (q_j, x) \in T\}.$$

We divide outputs and inputs (q_{-j}, x) into those that are variable v in the short-run and those that are not, denoted by K. We sometimes abuse notation by expressing (q_{-j}, x) as (v, K) and by writing $F_j(v, K)$. The existence result uses a mix of assumptions from Diewert (1973) and Lau (1976) to show that the production possibilities set is fully characterized by the M output equations given by $F_j(q_{-j}, x)$ $j = 1, \ldots, M$. Formulated

[9] If no positive output of q_j is possible given (q_{-j}, x) then he assigns $F_j(q_{-j}, x) = -\infty$.

as $F_j(\nu, K)$ $j = 1, \ldots, M$ the result also yields necessary conditions on each of these j equations. The result maintains five conditions on the production possibilities set T - P.1-P.5 - and are each briefly discussed below after we restate the theorem..

Theorem 3.1 (The Transformation Function) *Under P.1-P.5 the function $F_j(q_{-j}, x)$ is an extended real-valued function defined for each $(q_{-j}, x) \geq (0_{M-1}, 0_N)$ and is non-negative on the set where it is finite. $F_j(q_{-j}, x)$ is non-decreasing in x holding q_{-j} constant and non-increasing in q_{-j} holding x constant. $F_j(v, K)$ is concave in v for all K and quasi-concave in K for all v.*

Conditions P.1 and P.2 are weak regularity conditions on T that require the production set to be non-empty, closed, and bounded. Condition P.3 is a free disposal condition that says that, if you can produce q_j given (q_{-j}, x), then you can produce q_j with any $x^{'} \geq x$. Condition P.4 is the free disposal condition on outputs that says if you can produce q_j given (q_{-j}, x) then given (q_{-j}, x) you can produce any level of output $q_j^{'}$ such that $0 \leq q_j^{'} \leq q_j$. These free disposal conditions imply that output for good j is weakly increasing in any input holding all other inputs and outputs q_j constant, and that output of good j is weakly decreasing in any other one output holding all other outputs and inputs constant.

Condition P.5 extends Diewert (1973)'s convexity on T assumption - which rules out increasing rules to scale - to Lau (1976)'s setting of disjoint biconvexity, under which convexity holds but less restrictively. Under disjoint biconvexity we have convexity of the freely variable inputs v holding fixed inputs K constant, and convexity in the fixed variables K holding freely variable inputs v constant. Convexity in the elements of v (conditional on any K) results in a production function that is concave in v holding K constant. For the elements in K convexity in K given v results in the production function being quasi-concave in K given v.

4 Estimation

These M equations yield M technical efficiency terms, one for each product produced. 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.

4.1 Single-product production setting

We review the standard proxy approach in the single-product production setup. We have for q_t:

$$q_t = \beta_l l_t + \beta_k k_t + \beta_m m_t + \omega_t + \epsilon_t \tag{2}$$

where we have replaced the shock with its two components, i.e. $\varepsilon_t = \omega_t + \eta_t$. ϵ_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. For estimation 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

$$q_t = \beta_l l_t + \beta_k k_t + \beta_m m_t + E[\omega_t|\omega_{,t-1}] + \xi_t + \epsilon_t \tag{3}$$

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

$$[\xi_t + \epsilon_t](\theta) = q_t - \beta_l l_t - \beta_k k_t - \beta_m m_t - \mathbf{c}(h_{t-1}, k_{t-1})'\beta_\omega \tag{4}$$

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

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. 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).[10] In equation (13) a function of m_{t-1} and k_{t-1} conditions out $E[\omega_t|\omega_{t-1}]$. 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:

$$q_{jt} = \beta_0^j + \beta_l^j l_t + \beta_k^j k_t + \beta_m^j m_t + \gamma_{-j}^j{\prime} q_{-jt} + \omega_{jt} + \eta_{jt} \qquad j = 1 \cdots M \tag{5}$$

We denote the vector of technical efficiency shocks as $\omega_t = (\omega_{1t}, \omega_{2t}, \ldots, \omega_{M_t})$ and assume $E[\omega_t|\omega_{t-1}] = \omega_{t-1}$. 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.

DPSW (2018) extend 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 generally be a function of k_t and $(\omega_{1t}, \omega_{2t}, \ldots, \omega_{M_t})$ and we write the vector of proxies as $\mathbf{h}_t(k_t, \omega_t)$. Conditional on k_t if $\mathbf{h}_t(k_t, \omega_t)$ is one-to-one and onto in ω_t 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}.[11]

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

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

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

[11]DPSW(2018) use cost minimization and the implicit function theorem to prove $\mathbf{h}_t(k_t, \omega_t)$ is a bijection as long as $\frac{\partial q_j^2}{\partial x \partial \omega'}$ is full rank for each output production function $q_j(\cdot)$.

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

$$q_{jt} = \beta_l^j l_t + \beta_k^j k_t + \beta_m^j m_t + \gamma_{-j}^j{}' q_{-jt} + E[\omega_{jt}|\omega_{t-1}] + \xi_{jt} + \epsilon_{jt} \tag{6}$$

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.) $x_{jt} = (q_{-j,t-1}, k_t, k_{t-1}, \mathbf{h}_{t-1}, m_{t-1}, l_{t-1})$.[12] Let θ_0 denote the true parameter value. The conditional moment restriction

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

continues to be sufficient for identification of β as long as a rank condition holds. In the appendix we develop this setup for the case of two-product production for interested readers.

4.3 Input and Output Indices

Most firms produce output using only some of all available inputs recorded in disaggregated firm-level input data. An implication of Theorem 3.1 is different input tuples represent different production functions, but estimating separate production function parameters for each input tuple places prohibitively high demands on the data. In our data the same issue arises with multiple outputs as firms in our 2-digit industries produce only a small number of all possible goods in that 2-digit category.

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. Suppose there are G goods over which to aggregate and let and

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

let M_g denote quantity used of that input. The input index M^* that is almost universally used weights the quantity of the input by the input's price P_g:

$$M^* = log(\sum_{g=1}^{G} P_g M_g).$$

In place of estimating the G unrestricted coefficients - one for each $log(M_g)$ $g = 1, \ldots, G$ - only one coefficient β^M associated with the quantity index M^* is estimated, implying $G-1$ restrictions on the underlying production function parameters. We use these input aggregates for all of our inputs.[13]

One aggregator that we use in our analysis[14] 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).[15]

One might be concerned that we are using the prices of the other goods in the aggregator, and these might be endogenous. Therefore, we also tested with an alternative output aggregator using physical quantities denoted q'^*_{-j} that sums the logged units of each output except j:

$$q'^*_{-j} = \sum_{g\neq j} log(Q_g),$$

[13]Capital is an aggregate mix of the value of investments in 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.

[14]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 - see more discussion on this below and in Dhyne et al., 2018).

[15]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 ($P_{i'0} = 100$).

which implies all elements of the vector γ^j_{-j} are equal to some common value γ^j. The estimation equations become

$$q_{jt} = \beta^j_0 + \beta^j_l l_t + \beta^j_k k_t + \beta^j_m m_t + \gamma^j_{-j} q^*_{-jt} + \varepsilon_{jt} \qquad j = 1 \cdots M \tag{7}$$

where now there is only one coefficient γ^j_{-j} to estimate for each good j. Results are very similar, as shown in the online appendix.

These various aggregation mechanisms simplify our estimation but also impose several potentially strong assumptions, as discussed in details in Dhyne et al. (2018). 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 discussed in Dhyne et al., 2014, 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 by adding product dummies and by adding product price in the control function like De Loecker et al. (2016), as explained in the next subsection.

4.4 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 in our control function when estimating the production function.[16]

[16]We also added market share as additional variable with very little difference for our results.

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

5.1 Main specifications

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 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),

$$\omega_{ijt} = \rho\, \omega_{ij(t-1)} + \alpha_1 IS_{j(t-1)} + \nu_j + \delta_t + \eta_{ijt} \tag{8}$$

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. The units of the technical efficiency are the log 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

$$\Delta\omega_{ijt} = \frac{\Delta q_{ijt}}{q_{ijt}} = \alpha_1\, \Delta IS_{j(t-1)}.$$

An approximation to the short-term value of output due to this change is given by

$$p_{ijt} q_{ijt} * \frac{\Delta q_{ijt}}{q_{ijt}} = P_{ijt} \Delta q_{ijt}$$

which we calculate by multiplying the current revenue of the product by $\Delta\omega_{ijt}$.[17] 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

$$\Delta Value_{ijt} = \frac{P_{ijt} \Delta q_{ijt}}{(1-\rho)}. \tag{9}$$

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

[17] Alternative approximations might use last periods revenue or the simple average of this period's revenue and last period's revenue.

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

$$\omega_{ijt} = \rho\,\omega_{ij(t-1)} + \alpha_1 IS_{j(t-1)} + \sum_{k=2}^{4} \alpha_k Rank^k_{ijt} + \nu_j + \delta_t + \eta_{ijt} \tag{10}$$

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

$$\omega_{ijt} = \rho\,\omega_{ij(t-1)} + \alpha_1 IS_{j(t-1)} + \sum_{k=2}^{4} (\alpha_k + \alpha_{3+k} IS_{j(t-1)})\, Rank^k_{ijt} + \nu_j + \delta_t + \eta_{ijt}. \tag{11}$$

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

$$\Delta Value_{ijt} = \frac{p_{ijt} q_{ijt} * (\alpha_1 + \alpha_5)\, \Delta IS_{j(t-1)}}{(1-\rho)}, \tag{12}$$

and similarly for other lower ranking products.

5.2 Instruments for Import Share

The import shares that enter into equations 8, 10, and 11 are functions of the quantities of imports at the 8-digit level. 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.[18] 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. 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.[19] In the spirit of Hummels et. al. (2014) we focus more on HS6-level

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

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

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.[20] 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 weaker than required by Hummels et al (2014) where the *levels* of productivity must be uncorrelated with the world-wide shock holding other controls constant.

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.

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. Our baseline specification relies on a Cobb-Douglas production function and we assume production function parameters are the same at the 2-digit product level (PRODCOM2). We use both investment and materials as proxies, and we refer to this estimator as the Wooldridge-OPLP estimator.[21] Alternative production functions and estimators are explored in the robustness section below.

[20]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.

[21]As discussed in subsection 4.4, we experimented with including the price in the control function following the suggestion of De Loecker et. al. (2016). We found that, while it affected the coefficients of our production function, it made little difference in our findings of the impact of increased import penetration on changes in output. See robustness table 5.

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.[22] 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.

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 0.11, implying an increase of 10% in the import share with a 1.1% 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

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

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), -0.04 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 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 *eightfold* from 0.11 to 0.88 and is significant at the 10% level. When we add the share-rank indicators in column 5 the estimate of α_1 goes up close to 1 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.

6.2.3 Robustness Results

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 6.3.

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 1.07. In column 3 we ignore simultaneity and use OLS to estimate the production function parameters. We find the estimated coefficient is 0.85, 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 0.94.[23] 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

[23] 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.

5% level. In addition, multi-product firms are also shown to be more efficient than single product firms.

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 it exports. 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).

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

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.[24]

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 22,600 euros. Across industries the largest average change is 96,500 euros in Electrical Machinery followed by Apparel (75,700) and Basic Metals (71,200). The median changes in import shares are

[24]We tested whether the coefficients are the same for increases and decreases in import shares and could not reject that they were the same.

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 from minima between -1.8 to -2.5 million euros and the 90th percentile changes ranges to maxima between 2.2 and 2.6 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 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

In this paper, we apply 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. Consistent with several theory models, 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 attempt to identify the exact channel 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. We leave this line of investigation for future research.

References

[1] Ackerberg, D., Benkard, L., Berry, S., and Pakes, A. Econometric Tools for Analyzing Market Outcomes. Chapter 63 in Handbook of Econometrics: Volume 6A, Edited by J. Heckman and E. Leamer, North Holland 2007.

[2] Ackerberg, D., K. Caves, and G. Frazer, 2015. Identification Properties of Recent Production Function Estimators. Econometrica 83, 2411-2451.

[3] Aghion, P., and P. Howitt, 1996. *Endogenous Growth Theory.* MIT Press.

[4] Bernard, A., E. Blanchard, I. Van Beveren, and H. Vandenbussche, 2012. Multi-Product Exporters, Carry-Along Trade and the Margins of Trade. NBER Working Paper #18246.

[5] Bernard, A., S. Redding, and P. Schott, 2010. Multiple-Product Firms and Product Switching. American Economic Review 100, 70-97.

[6] Bernard, A., S. Redding, and P. Schott, 2011. Multi-product Firms and Trade Liberalization. Quarterly Journal of Economics 126, 1271-1318.

[7] De Loecker, J., 2011. Product Differentiation, Multi-Product Firms and Estimating the Impact of Trade Liberalization on Productivity. Econometrica 79, 1407-1451.

[8] De Loecker, J., P. Goldberg, A. Khandelwal, and N. Pavcnik, 2016. Prices, markups and Trade Reform. Econometrica 84, 445-510.

[9] Dhingra, S., 2013. Trading away wide brands for cheap brands. American Economic Review 103, 2554–84.

[10] Dhyne, E., A. Petrin, and F. Warzynski, 2014. Deregulation and Spillovers in Multi-Product Production Settings. Working paper.

[11] Dhyne, E., A. Petrin, V. Smeets and F. Warzynski, 2018. A Transformation Function Approach to Estimate Firm-Product Technical Efficiency. Under revision.

[12] Diewert, W. 1973. Functional Forms for Profit and Transformation Functions. Journal of Economic Theory 6, pp. 284-316.

[13] Duprez, C. 2014. Value Creation in Exports: A Diagnostic for Belgium. NBB Economic Review, September 2014, pp. 25-39.

[14] Eckel, C., Iacovone, L., Javorcik, B., and Neary, J. P., 2015. Multi-product firms at home and away: Cost- versus quality-based competence. Journal of International Economics 95, 216–232.

[15] Eckel, C. and Neary, P. J., 2010. Multi-Product Firms and Flexible Manufacturing in the Global Economy. Review of Economic Studies 77, 188–217.

[16] Eslava, M., Haltiwanger, J., Kugler, A. and Kugler, M., 2004. The effects of structural reforms on productivity and profitability enhancing reallocation: evidence from Colombia. Journal of Development Economics 75, 333–371.

[17] Foster, L., J. Haltiwanger, and C. Syverson, 2008. Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? American Economic Review 98, 394-425.

[18] Garcia Marin, A. and Voigtländer, N., (forthcoming). Exporting and plant-level efficiency gains: It's in the measure. Journal of Political Economy.

[19] Goldberg, P., A. Khandelwal, N. Pavcnik, and P. Topalova, 2010a. Imported Intermediate Input and Domestic Product Growth: Evidence from India. Quarterly Journal of Economics 126, 1727-1767.

[20] Goldberg, P., A. Khandelwal, N. Pavcnik, and P. Topalova, 2010b. Multiproduct Firms and Product Turnover in the Developing World: Evidence from India. Review of Economics and Statistics 92, 1042-1049.

[21] Holmes, T. and T. Schmitz, 2010. Competition and Productivity: A Review of Evidence. Annual Review of Economics 2, 619-642.

[22] Hummels, D., R. JÃ¸rgensen, J. Munch, and C. Xiang, 2014. The Wage Effects of Offshoring: Evidence from Danish Matched Worker-firm Data. American Economic Review 104, 1597â€“1629.

[23] Klette, T. J. and Z. Griliches, 1996. The Inconsistency of Common Scale Estimators When Output Prices Are Unobserved and Endogenous. Journal of Applied Econometrics 11, 343-361.

[24] Lau, L., 1976. A Characterization of the Normalized Restricted Profit Function. Journal of Economic Theory 12, 131-163.

[25] Levinsohn, J., and A. Petrin, 2003. Estimating Production Functions Using Inputs to Control for Unobservables. Review of Economic Studies 70, 317-341.

[26] Lileeva, A. and D. Trefler, 2010. Improved Access to Foreign Markets Raises Plant-Level Productivity... for Some Plants. Quarterly Journal of Economics 125, 1051-1099.

[27] Mayer, T., M. Melitz, and G. Ottaviano, 2014. Market Size, Competition, and the Product Mix of Exporters. American Economic Review 104, 495-536.

[28] Mayer, T., M. Melitz, and G. Ottaviano, 2016. Product Mix and Firm Productivity Responses to Trade Competition. Work in progress.

[29] Olley, S., and A. Pakes, 1996. The Dynamics of Productivity in the Telecommunications Industry. Econometrica 64, 1263-1297.

[30] Pavcnik, N., 2002. Estimating Production Functions Using Inputs to Control for Unobservables. Review of Economic Studies 70, 317-341.

[31] Petropoulos, W, 2000. Industry Productivity Dynamics with Capacity Utilization and Differentiated Products, University of Michigan Ph.D.

[32] Roberts, M. and D. Supina, 2000. Output price and markup dispersion in micro data: the roles of producer heterogeneity and noise. Industrial Organization 9, 1-36.

[33] Smeets, V. and Warzynski, F., 2013. Estimating productivity with multi-product firms, pricing heterogeneity and the role of international trade. Journal of International Economics 90, 237-244.

[34] Wooldridge, J. M., 2009. On estimating firm-level production functions using proxy variables to control for unobservables. Economics Letters 104, 112-114.

Appendix: Two product case

We follow the discussion in Dhyne, Petrin, and Warzynski (2016) who show how to estimate the production possibilities set for bread and cakes, a two-product production process. In the case of two-product production we have an equation for good 1

$$q_{1t} = \beta_l^1 l_t + \beta_k^1 k_t + \beta_m^1 m_t + \gamma^1 q_{2t} + \omega_{1t} + \epsilon_{1t} \tag{13}$$

and an equation for good 2

$$q_{2t} = \beta_l^2 l_t + \beta_k^2 k_t + \beta_m^2 m_t + \gamma^2 q_{1t} + \omega_{2t} + \epsilon_{2t}. \tag{14}$$

We use as our two proxies investment and materials, and we write these input demands as $i_t(k_t, \omega_{1t}, \omega_{2t})$ and $m_t = m(k_t, \omega_{1t}, \omega_{2t})$. If the bivariate function (i_t, m_t) is one-to-one and onto with $(\omega_{1t}, \omega_{2t})$ then this bivariate bijection can be inverted and there exist functions $g_1(\cdot)$ and $g_2(\cdot)$ such that $\omega_{1t} = g_1(k_t, i_t, m_t)$ and $\omega_{2t} = g_2(k_t, i_t, m_t)$. For either j we approximate

$$\omega_j = g_j(k_t, i_t, m_t) = \mathbf{c}_j(k_t, i_t, m_t)'\beta_{\omega_j}$$

where $\mathbf{c_j}(k_t, i_t, m_t)$ is a known vector function of (k_t, i_t, m_t) chosen by researchers. The nonparametric conditional mean function for either j is given as

$$E[\omega_{jt}|\omega_{t-1}] = f_j(\mathbf{c_j}(k_{t-1}, i_{t-1}, m_{t-1})'\beta_{\omega_j}) \quad j = 1, 2$$

for some unknown functions $f_1(\cdot)$ and $f_2(\cdot)$. The error now becomes

$$[\xi_{jt} + \epsilon_{jt}](\theta) = q_{jt} - \beta_l^j l_t - \beta_k^j k_t - \beta_m^j m_t - \gamma_{-j}^j q_{-jt} - f_j(\mathbf{c_j}(k_{t-1}, i_{t-1}, m_{t-1})'\beta_\omega) \quad j = 1, 2.$$

Let the set of conditioning variables be given as (e.g.) $x_{jt} = (q_{-j,t-1}, k_t, k_{t-1}, i_{t-1}, m_{t-1}, m_{t-2})$. Let θ_0 denote the true parameter value. The conditional moment restrictions for each equation are given as

$$s(x_{jt};\theta) \equiv E[[\xi_{jt} + \epsilon_{jt}](\theta)|x_{jt}] \text{ and } s(x_{jt};\theta_0) = 0 \quad j = 1, 2.$$

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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Food & beverages	Fab. metal	Other manuf.	Chemicals	Non metallic mineral	Rubber & plastic	Machinery & equip.	Textile	Apparel	Paper	Basic metals	Electrical machinery
	15	28	36	24	26	25	29	17	18	21	27	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 subsection 4.4 for more discussion and online 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	10,005	10.8
15	Food and beverages	-281.1	-30.5	-0.1	21.4	250.7	22,186	-5.9
28	Fabricated metal products	-517.7	-100.6	0.1	137.1	691.2	6,063	53.8
29	Machinery and equipment	-2,536.6	-185.4	0.1	277.1	2,241.2	2,180	17.7
25	Rubber and plastic products	-953.8	-105.5	0.7	158.1	1,070.3	4,820	28.0
18	Apparel	-71.9	-3.1	1.4	52.1	308.7	4,708	75.7
27	Basic metals	-1,924.4	-154.0	0.2	282.2	2,509.1	2,113	71.2
26	Non metallic mineral	-343.7	-41.8	0.8	78.9	431.9	4,091	23.6
21	Paper	-1,165.2	-99.9	0.2	141.6	1,156.4	2,799	20.1
17	Textile	-879.0	-106.9	0.5	121.3	826.3	2,741	9.8
31	Electrical machinery	-1,878.8	-208.9	0.1	344.0	2,589.4	656	96.5
	All products	-538.3	-46.7	0.1	63.6	625.9	65,242	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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.