Estimating firm product quality using trade data*

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Abstract

We propose a new instrumental variable strategy to estimate product quality at the firm-level, using trade data. Interacting firm importing shares by country with real exchange rates (RER), we obtain a cost shifter that varies across firms and is arguably orthogonal to product quality. We use this import weighted RER as an instrument for export prices and we identify firm-level quality from residual export variations, after controlling for prices. Our quality estimates correlate sensibly to firm characteristics (e.g. wages) and to alternative measures of quality available for some rare sectors. By contrast, our estimates are not always consistent with prices, a popular proxy for quality. We show for instance that firms add products to their export portfolio when their quality increases, as expected, while simultaneously their prices decrease. This suggests that our empirical strategy, by delivering quality estimates which, unlike prices, are not polluted with productivity variations, should contribute to future research on the link between firm-level product quality and globalization.

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1 Introduction

Trade economists have long investigated the role played by product quality in shaping the patterns of trade at the macroeconomic level. A more recent literature has emphasized the importance of product quality at the microeconomic level: in addition to being one of the main sources of firm heterogeneity,[1] the quality supplied by firms impacts the relative demand for inputs, which makes it decisive to understand the link between globalization and inequalities.[2] These findings triggered an increasing demand from trade economists for disaggregated data on product quality. However, despite this need, estimating firm-level quality on trade data remains an empirical challenge: traditional techniques developed in Industrial Organization cannot be applied to datasets in which product characteristics are not observed,[3] which is typically the case with international trade data.[4]

In this paper, we propose and implement a new empirical methodology to estimate product quality at the firm level. We create a new instrument for prices, based on exchange rate variations interacted with firm-specific importing shares, that allows us to consistently estimate demand equations in the absence of observable product characteristics. Implementing this methodology using customs data from France, we first document the reliability of our estimation: we compare the estimated price elasticities and measures of quality with industry and firm characteristics as well as alternative measures of quality. Then, we employ the obtained quality measures to study the link between export performance and quality: we show that firms which add products or destinations in their portfolio simultaneously exhibit an increasing quality. Importantly, using a common proxy for quality, prices, to study this question leads to a different conclusion.

The main contribution of this paper is to provide a new method to estimate quality using trade data. We estimate quality from the demand side. The main challenge one faces when estimating demand functions is to deal with the endogeneity of prices: prices are likely to be correlated to demand shocks, because quality is costly to produce.[5] Consequently, researchers have used unit values or prices as proxies for quality, or have estimated demand equations in contexts where unobserved vertical differentiation is limited.[6] To address this endogeneity issue, we construct a novel instrument for prices, exploiting fluctuations in exchange rates. These fluctuations, interacted with firm-specific import shares, shift a firm's costs of importing goods. As the firm passes importing cost variations to its consumers, the instrument generates firm-specific export price and sales variations. These variations are arguably exogenous to unobserved demand shocks (e.g., quality shocks) and allow us to identify the price-elasticity of exports. Quality is then identified at the firm, destination, product, year level, from the residual variations of

[1]See Roberts, Xu, Fan, and Zhang (2012) and Hottman, Redding, and Weinstein (2016) for empirical quantifications of the relative importance of different sources of heterogeneity at the firm level.

[2]Verhoogen (2008) and Brambilla et al. (2012) document the consequences of trade openness on wage inequality.

[3]Industrial Organization has developed strategies to back out quality by estimating a demand equation. In this approach, the presence of omitted product characteristics challenges the identification as these characteristics are likely to be correlated with the price of the product which induces an endogeneity bias.

[4]Exceptions include Crozet et al. (2012) and Garcia-Marin (2014) who use expert ratings of quality of Champagne and wine, as quality measures.

[5]See, e.g., Hallak and Sivadasan (2013), Johnson (2012) and Kugler and Verhoogen (2012) for trade models where quality is costly and endogenous at the firm-level.

[6]Broda and Weinstein (2010) and Handbury (2012) use barcode-level data, that features no quality variation within barcode across time, whereas Foster, Haltiwanger, and Syverson (2008) restrict their analysis to homogeneous products.

demand once price variations have been controlled for; a strategy that is present throughout the literature.

The implementation of this method using customs data from France, supports the validity of the procedure. First, we find that the import-weighted exchange rate, our instrument, is strongly and positively correlated to export prices charged by firms. This is consistent with the assumption we make to motivate the instrumentation, namely that exchange rates shift a firm's production costs. Second, in order to evaluate the ability of our instrument to correct for the endogeneity of prices, we estimate the demand equation using both ordinary least squares and instrumental techniques. Our instrumental variable procedure affects the estimates of price-elasticities consistently with a correction of an omitted variable bias: while ordinary least squares estimates deliver a low (in absolute value) price-elasticity (0.8), the instrumental variable approach produces estimates consistent with the existing studies in the industrial organization literature, ranging from 1.3 to 2.1, depending on the specification.

We then investigate the properties of the quality estimates obtained from the procedure. We show that the dispersion of these estimates within a market is positively correlated with existing measures of vertical differentiation. Moreover, we directly relate our quality measure to existing measures of quality at the firm-level. A natural benchmark is provided by Crozet et al. (2012) who use one of the very few "direct" measure of firm-specific quality present in the literature, by relying on ratings attributed by an expert to a sample of French Champagne producers. We compare these ratings with our estimated quality of exported Champagne and find a positive and strongly significant correlation. Similarly, we find that the obtained quality measures are intuitively correlated with firms characteristics and in particular the average wage paid by firms.

Finally, we compare our estimated quality measures with export prices, the most commonly employed proxy for quality. We show that prices and quality are positively correlated in the cross-section of firms, as well as over time within a firm. However, this correlation is significantly stronger for vertically differentiated markets. In other words, prices are informative on quality, but less so in more homogeneous sectors. Then, we show that this imperfect correlation between prices and quality can be misleading when studying the role of quality in explaining export performance. In particular, we show that firms adding destinations or varieties to their portfolio do so as they experience an increase in the estimated quality of their products. On the contrary, using prices to study this question leads to contradictory answers as prices tend to increase with the addition of a destination, and decrease with the addition of a product. We argue these results highlight the superiority of our measure over prices that conflate many factors other than vertical differentiation.

This paper is directly related to the literature aiming to measure quality using trade data. Most of the literature back up quality measures from the estimation of a demand system, following the tradition in Industrial Organization.[7] In particular, we can cite Hallak and Schott (2011) and Khandelwal (2010) who rely on an instrumental variable approach to identify quality at the

[7] Most notable contributions in IO include Berry, Levinsohn, and Pakes (1995) and Berry (1994). These papers have contributed to the estimation of structural demand parameters by introducing demand systems exhibiting more sophisticated substitution patterns. However, the structure included in these papers does not solve the issue that prices are endogenous to quality in the demand equation. Therefore, these structural empirical models do not dispense from finding an instrument for prices, but can usually rely on product characteristics that control for mosts of the variation in quality across goods.

country-product level using trade data. To be applied at the firm-product level, their methods require an instrument for prices which varies across firms. We provide such an instrument. Gervais (2015) and Roberts et al. (2012) also estimate quality at the firm level by instrumenting prices. However, these studies use instruments, respectively physical productivity and wages, which are questionable if quality varies over time, within the firm. By contrast, our instrument is robust to time-varying quality. Because of the difficulty of estimating demand equations at the firm level, in the absence of product characteristics, researchers have relied on alternative strategies: Khandelwal, Schott, and Wei (2013) construct quality by calibrating price-elasticity with estimates from Broda and Weinstein (2006). The relevancy of these price-elasticities estimates is open to question as they are obtained from country-level data. Alternatively, demand equations have been estimated in contexts where unobserved vertical differentiation is limited: for instance, Broda and Weinstein (2010) and Handbury (2012) use barcode-level data, whereas Foster et al. (2008) restrict their analysis to homogeneous products.

Moreover, a number of papers have used prices to investigate the role played by quality in explaining export performance across firms. Most of these papers used output and input prices as proxy for quality: we can cite for instance Kugler and Verhoogen (2012) and Manova and Zhang (2012a) that document quality variations across firms, and within firm across destinations, using firm-level or customs data. While the use of prices is appropriate in the context of their studies,[8] we believe the use of prices as proxy for quality can be problematic in other situations. Indeed, while product quality usually increases the cost of a good, many other factors determine the price charged by a firm for its product. Moreover, the presence of multi-products firms makes the use of prices even more so challenging since firms self-select their set of products based on their quality. Manova and Zhang (2012b) studies the complexity of the relationship between prices and product quality in the context of multi-product firms.

Finally, the use of exchange rates as an instrument for prices links our paper to Berman, Martin, and Mayer (2012) and Amiti, Itskhoki, and Konings (2014). These studies empirically analyze the firm-level pass-through from exchange rates to export prices. However, while both works are interested in the heterogeneity of the pass-through across firms, we only use the effect of exchange rates on export prices as a first stage to a demand function estimation. Moreover, our first stage results are consistent with Amiti et al. (2014) since we find that firms with larger imports have a larger pass-through. More recently, Amiti, Itskhoki, and Konings (2016) studies the price setting of firms in response to shocks on their costs and the prices of their competitors. In this context, they also use exchange rates to obtain exogenous variations in the cost of imported inputs.

This paper is structured as follows. In the next section, we derive a simple model of demand with vertically-differentiated goods and present our identification strategy to consistently estimate demand equations using trade data. In section 3, we describe the French customs data used for the implementation and show the results of the estimation. Section 4 describes the relevancy of the quality estimates we obtain by relating them to existing measures. Moreover, we explore the link between these measures and prices to show that using prices as proxy can be misleading

[8] The positive correlation between prices and export performance they show clearly points toward a positive effect of product quality on firms' performance. However, a negative relationship would not imply a negative role for product quality.

in some contexts. Finally, section 5 concludes.

2 Quality Estimation Strategy

In this section, we present a novel strategy to estimate the quality of exports at the firm-product-destination-year level, using customs data. Since we identify quality from the demand side, this section introduces a demand system with constant elasticity of substitution (CES) in which the quality of a product acts as a utility shifter. This implies that variations in the quality of exported goods over time and across firms will be revealed from variations in sales that cannot be explained by price movements.

In order to identify the demand system and infer product quality measures, we then present a new instrument for the price of firms' exports. This instrument is obtained by interacting firm-specific importing shares with real exchange rates. We argue that this instrument is exogenous to quality choices made by firms and measurement errors on prices, which constitutes an improvements relative to existing instruments in the literature, allowing us to consistently estimate demand functions using trade data.

2.1 An Empirical Model of Demand

Let us consider a global economy composed of a collection of destination markets d. In each market, the representative consumer allocates her revenue over the different varieties of each product g. Our definition of product categories follows the structure of French customs data, namely a product corresponds to a 8 digit position of the Combined Nomenclature (CN). A variety is defined as an unique combination of a destination market d, a producing firm f and a product g.

Representative consumers have two tier preferences. The lower level of the utility function aggregates consumptions of varieties by product. The upper level aggregates consumptions across products. We assume that the lower part of the utility function displays a constant elasticity of substitution (CES) across varieties, while we do not need to impose any functional form on the upper level. It follows that an expression of the utility of the representative consumer in market d at year t is

$$\begin{aligned} U_{dt} &= U\left(C_{1dt}, .., C_{Gdt}\right), \\ C_{gdt} &= \left[\sum_{f\in\Omega_{gdt}} \left(q_{fgdt}\, x_{fgdt}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \qquad \forall\, g = 1..G, \end{aligned} \tag{1}$$

with $U(.)$ a well-behaved utility function, C_{gdt} the CES aggregate consumption of product g in destination d at year t, Ω_{gdt} the set of varieties of good g available to consumers, σ the elasticity of substitution across varieties within a product category and x_{fgdt} and q_{fgdt} respectively the aggregate physical consumption and the quality of variety fgd at year t.[9]

[9]We assume a unique elasticity of substitution to present the model, but will be able to partially relax this assumption across industries in the empirical application.

Utility function (1) imposes no restriction on the patterns of substitutability across product category. However, varieties are equally substitutable within product categories.[10] In equation (1), quality is modeled as a utility shifter, i.e. a number of units of utility per physical unit of good. This implicitly defines quality as an index containing any characteristic of a variety which raises consumers' valuation of it. These characteristics may be tangible (e.g. size, color) as well as intangible (e.g. reputation, quality of the customer service, brand name). This broad definition is consistent with most of the literature in international trade and quality.[11]

The representative consumer allocates her total expenditure, E_{dt}, across goods and varieties, in order to maximize her utility (1). This behavior results in the following aggregate demand function for variety fgd:

$$s_{fgdt} = {p^*_{fgdt}}^{1-\sigma} q^{\sigma-1}_{fgdt} P^{\sigma-1}_{gdt} E_{gdt}, \tag{2}$$

with s_{fgdt} the sales of variety fgd in value and E_{gdt} the expenditure optimally allocated to good g. p^*_{fgdt} is the price of variety fgd faced by consumers in destination d, labeled in market d's currency. P_{gdt} is the price index of good g in market d at year t.[12] In order to properly grasp the properties of demand function (2), it is worth noting that $-\sigma$ is not the own price elasticity of variety fgd's demand. It is rather the own price elasticity *keeping constant the price index* P_{gdt} *and the aggregate expenditure* E_{gdt}. In a monopolistic competition setting, firms are atomistic and their individual decisions do not influence these aggregate variables. However, with non-atomistic firms, individual prices may have an aggregate impact, and thus the own price elasticity may differ from $-\sigma$ and be heterogeneous across firms.

Producing firms are located in different countries and we assume that exporting involves iceberg trade costs. From the point of view of a specific exporting country (France in our application), domestic firms need to ship $\tau_{gdt} \geq 1$ units of good g for one unit to reach the consumer in market d at year t. So for varieties exported from home to market d, the customer price in d currency (p^*_{fgdt}) is linked to the FOB (Free on Board) price in home currency (p_{fgdt}) by the following relationship:

$$p^*_{fgdt} = \frac{\tau_{dt}}{e_{dt}} p_{fgdt}, \tag{3}$$

with e_{dt} the direct nominal exchange rate from home currency (Euro in the application) to market d's, i.e. that one unit of d currency buys e_{dt} units of home currency. Plugging (3) and

[10] This feature is shared by most estimations of demand systems with vertically differentiated goods using trade data. In the nested logit specification of Khandelwal (2010) for instance, the cross price elasticity is the same for any two varieties within a nest, irrespective of their quality, after controlling for their market shares.

[11] Because of the wide range of product attributes potentially captured by our concept of "quality", some papers have adopted a more conservative terminology. For instance, Roberts et al. (2012) refer to the variety-specific utility shifter as a "demand index", Foster et al. (2008) to "demand fundamental" and Hottman et al. (2016) to "product appeal".

[12] The price index verifies:

$$P_{gdt} = \left(\sum_{f \in \Omega_{gdt}} \left(\frac{p^*_{fgdt}}{q_{fgdt}} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

log-linearizing, we can re-express demand function (2) for domestic firms as follows:

$$\log s_{fgdt} = (1-\sigma)\log p_{fgdt} + \lambda_{fgdt} + \mu_{gdt} \tag{4}$$

$$\text{with} \quad \begin{cases} \lambda_{fgdt} \equiv (\sigma-1)\left(\log q_{fgdt} - \overline{\log q}_{gdt}\right) \\ \mu_{gdt} \equiv \log\left(\frac{\tau_{gdt}}{e_{gdt}}\right)^{1-\sigma} + \log P_{gdt} + \log E_{gdt} + (\sigma-1)\overline{\log q}_{gdt} \end{cases}$$

and $\overline{\log q}_{gdt} \equiv \frac{1}{\mathcal{H}_{gdt}}\sum_{f\in\mathcal{H}_{gdt}} \log q_{fgdt}$ the average log-quality of good g supplied by domestic firms to market d at year t, $\mathcal{H}_{gdt}$ being the set of firms exporting good g from home to country d at year t.

Equation (4) is the one that we bring to the data. In (4), $\log s_{fgdt}$ and $\log p_{fgdt}$ are observable to the econometrician while $(1-\sigma)$, λ_{fgdt} and μ_{gdt} have to be estimated. One can see from (4) that the demand shifter of a firm contains a variety-specific as well as a market-specific term (respectively λ_{fgdt} and μ_{gdt}). The latter term will be estimated by including destination-product-year fixed effects in the regression. This term is not informative on quality as it conflates the average quality of domestic exports with other aggregate variables. Thus, the estimation developed in this paper identifies quality from λ_{fgdt}, the variety-specific part of the demand shifter. Incidentally, the presence of quality in the demand shifter also causes the potential endogeneity of prices as we discuss further below.

From the structural expression of λ_{fgdt} in (4), one can see that our strategy does not deliver an absolute measure of quality. Instead, we obtain a measure of quality which is relative to the average quality supplied by domestic firms to a market. A corollary is that λ_{fgdt} will not be suited to analyze variations in the aggregate quality of domestic exports, but rather how firms move relative to each other along the quality ladder across markets and over time. Moreover, because we assume that all firms have the same elasticity within a category, any deviation in the elasticity across firms will be attributed to our quality measure. Therefore, our quality measure will also capture the relative market power of firms.

Next subsection describes the estimation of demand function (4) with a focus on our treatment of the endogeneity of prices.

2.2 Dealing with Price Endogeneity

In our setup, the endogeneity of prices comes from two mechanisms. First, we face a well-known simultaneity problem as prices are likely to be correlated to quality, which is in the residual of the demand function. Assuming that high quality varieties are more costly to produce, this correlation would result from firms passing on the cost of quality to consumers. This endogeneity channel leads ordinary least squares to underestimate the price-elasticity of demand, σ. Indeed, when a firm increases the quality of its products, the effect of prices on demand is compensated with the greater appeal of the good to consumers.

A second source of endogeneity, more specific to international trade data, comes from the construction of prices. Because prices are not directly observed, we follow the standard practice and use unit values as a proxy for prices. Unit values are obtained by dividing the value of a shipment by the physical quantity shipped. The use of this proxy may generate an attenuation bias due to the measurement error contained in the price variable.[13]

Existing Methods Existing literature has used different empirical strategies to deal with price endogeneity. In particular, the literature in Industrial Organization has developed estimation procedures with instruments for prices. For instance, Berry et al. (1995) use competitors' product characteristics, Hausman (1996) and Nevo (2000) use product's price on other markets, while Foster et al. (2008) rely on estimated physical productivities. However, these instruments are not valid in the presence of *unobserved* vertical differentiation.[14] As a consequence, these instruments cannot be used in our context. Indeed, trade data contain no product characteristics, except for the classification in product categories. Despite a narrow definition of these categories (8-digit CN classification present in our data has around 8,000 positions), there is still a wide scope for (unobserved) vertical differentiation within each category.[15]

Some strategies for demand estimation with trade data exist at the country level. Khandelwal (2010) and Hallak and Schott (2011) use instrumental variables approaches. Their strategy are not suited to firm-level demand estimation as their instruments vary at the market level, not across firms within a market. Feenstra (1994) and Broda and Weinstein (2010) respectively develop and refine a very influential demand estimation using country-level trade data. Their identification exploits the heteroskedasticity of supply and demand shocks. Although there strategy could be applied to firm-level trade data, it involves an orthogonality assumption between demand and supply shocks which is likely to be violated in the presence of vertical differentiation (e.g., if quality is costly).

Literature on demand estimation with trade data is scarcer at the firm-level. Roberts et al. (2012) and Gervais (2015) use firms' wages and physical productivities as instruments for prices. These instruments are only valid if product quality is constant over time within the firm. For instance, if a firm upgrades its quality, it might need more workers per physical unit of output. In that case physical productivity is (negatively) correlated to quality and IV estimates of σ would be biased downward. Khandelwal et al. (2013) construct a firm-level quality measure by calibrating a CES demand system with price-elasticity estimates from Broda and Weinstein (2006). Conceptually, this approach raises two concerns. First, it implicitly inherits the identifying assumptions from Broda and Weinstein (2006). We explained above that these assumptions are problematic in the presence of vertical differentiation. Second, Broda and Weinstein (2006) estimates are obtained from country-level data. Elasticity may differ at the micro and the macro level,[16] which would generate biases in estimated firm-level quality.

[13]This attenuation bias will certainly be magnified by the flow fixed effects we use in our estimation. In fact, in the time series of a trade flow, the measurement error may represent a larger share of the variation of unit values than in the cross-section.

[14]Berry et al. (1995), Hausman (1996) and Nevo (2000) all study specific markets, for which they clearly observe different varieties of a good, as well as their characteristics, reducing the possibility for unobserved quality differences. In a different setup, Foster et al. (2008) and Handbury (2012) estimate demand functions for a wide range of products, but either restrict their analysis to homogeneous products or use barcode-level data, which rule out the possibility of unobserved quality differences.

[15] Consider cars, for instance. This product category contains multiple cn8 position, among which positions 8703 21 10 and 8703 21 90, which respectively stand for 'new and used vehicles, with spark-ignition internal combustion reciprocating piston engine'. There is clearly room for vertical differentiation across different exporting firms within each one of these two positions.

[16]See Imbs and Méjean (2015) or Chetty (2012) for instances where the price elasticity depends on the level of aggregation considered.

Because existing methods do not lend themselves to our exercise, we develop a new instrumental strategy, robust to unobserved and time-varying quality differences within product categories.

A New Instrument for Prices at the Firm-level The approach developed in this paper takes advantage of the information coming from the importing activity of exporters. We use real exchange rates fluctuations faced by importing firms to instrument prices of exported goods. The basic idea is that real exchange rate shocks on a firm's imports are cost shocks. As the firm passes these cost shocks through to its export prices, sales adjust and the demand function is identified. In order to generate firm-specific exchange rate shocks, we take advantage of the fact that the spatial structure of imports varies across firms

To gain insight into the identification, let us study the example of two firms selling in a same market. One firm imports from the United States, while the other imports from Europe. An appreciation of the dollar would induce an increase of the export price of the former, leaving unchanged the price of the latter. The response of these firms' relative sales to the change in their relative prices identifies the price-elasticity of demand. This example also conveys the intuition of our main identifying assumption: relative real exchange rate shocks across firms should be exogenous to relative demand shocks. Next subsection discusses this assumption. It acknowledges situations where it is likely to be violated and adjusts the econometric specification accordingly.

Formally, our instrument is the import-weighted real exchange rate of a firm f at time t:

$$\overline{RER}_{ft} = \sum_s \omega_{sf} \times \log(\text{rer}_{st}), \tag{5}$$

with $\omega_{sf} = \frac{\sum_{t=1}^{T} m_{sft}}{\sum_{s=1}^{S}\sum_{t=1}^{T} m_{sft}}$ the average share of imports m_{sft} from source country s, in the total imports of firm f,[17] and with rer_{st} the real exchange rate from home (France in our application) to country s at time t. The exchange rate rer_{st} is defined using direct quotation, such that an increase of this variable implies larger costs for a firm. Moreover, the real term is computed using CPI indices. The formula of rer_{st} is:

$$\text{rer}_{st} = \text{er}_{st}\frac{\text{CPI}_{st}}{\text{CPI}_{France,t}}.$$

In addition to this main instrument, we develop three others to account for potential heterogeneity across firms. First, we interact our main instrument with the share of import expenditures in the total exports of the firm. We called this second instrument $\overline{RER}_{ft}^{imp}$, which aims to capture the larger exposure to exchange rate movements of firms that heavily rely on imports for their inputs. Second, the pass-through from our instrument to export prices may be limited by the fact that firms hedge against currency risk. To illustrate this point, consider two French firms exporting to the US: firm A imports from China while firm B simultaneously imports and exports to China. We expect that firm B will not pass through an appreciation of the Yuan as

[17] In next section, we come back on the importance of using time-invariant weights to compute the import-weighted exchange rate.

much as firm A, since she is naturally hedged against Yuan fluctuations because of her exporting activity in China. Consequently, we create the instrument $\overline{RER}_{ft}^{h}$ taking into account this degree of hedging of a firm, by using the product of importing and exporting weights for a same country to compute the firm-level weighted exchange rates. Finally, the pass-through of this cost shock will be limited if some firms display significant market shares within their product category. If an individual firm has an impact on the price index of the category, Amiti et al. (2014) shows that the market share of the firm is a sufficient statistic to describe the heterogeneity in pass-through. Therefore, we create an additional instrument, $\overline{RER}_{ft}^{ms}$, from the interaction of the import-weighted exchange rates and the average market share of the firm in the product category. Formally, these three additional instruments are defined as follows.

$$\overline{RER}_{ft}^{imp} = \overline{RER}_{ft} \times \log\left(\frac{\sum_{s=1}^{S}\sum_{t=1}^{T} m_{sft}}{\sum_{d=1}^{D}\sum_{t=1}^{T} s_{dft}}\right) \tag{6}$$

$$\overline{RER}_{ft}^{h} = \sum_{s} \omega_{sf} \times \omega_{sf}^{\exp} \times \log(\mathrm{rer}_{st}) \tag{7}$$

$$\overline{RER}_{fdt}^{ms} = \overline{RER}_{ft} \times \frac{\sum_{t=1}^{T} s_{dft}}{\sum_{f\in\mathcal{H}_{gdt}}\sum_{t=1}^{T} s_{dft}}, \tag{8}$$

with $\omega_{sf}^{\exp}$ the exporting weight of a firm toward destination s. We expect the pass-through from the RER on imports to export prices to be increasing with $\overline{RER}_{ft}^{imp}$ but decreasing with $\overline{RER}_{ft}^{h}$ and $\overline{RER}_{fdt}^{ms}$.

We conclude the presentation of the instruments with three remarks. First, the instrument is orthogonal to measurement errors on unit values as its construction does not involve information on exports. Therefore, our instrumental strategy deals with the measurement errors problem existing when estimating demand functions using unit values.

Second, similar instruments have been used in a series of recent international trade contributions (see Brambilla et al. (2012) or Bastos et al. (2014)). In these papers, the export-weighted exchange rate generates exogenous change in firms' destination portfolio. In our case, the import-weighted average exchange rate creates exogenous firm-specific cost shifters due to the mechanical increase of the price of imported inputs.

Lastly, we are not the first paper looking at the pass-through from the cost of imported input to export prices. Amiti et al. (2014) and Berman et al. (2012) run the same type of regression using respectively Belgian and French customs data. However, the motivation for their analysis differs greatly from ours. While, they are interested in the heterogeneity of the pass-through across firms, we only use the effect of exchange rates on export prices as a first stage to a demand function estimation.

2.3 Discussion of the Identification

There are a few mechanisms that could affect the exogeneity of the instrument. First of all, the instrument is constructed from import shares, which are potentially endogenous to quality. Put simply, higher quality firms most likely import from countries with a stronger currency, from where they can source higher quality inputs. So we expect the instrument to be positively correlated to quality in the cross-section of firms. If not controlled for, this correlation would induce the price elasticity of demand (which is negative) to be biased upward.[18] To fix this problem, we add variety-specific fixed effects (as defined above, a variety is a firm × product category × destination combination) to our demand estimation. As a result, identification is in the time series of a variety. Since the instrument is constructed using average import shares, its time series variations are fully driven by (firm-specific) exchange rates dynamics and not contaminated by (endogenous) import share dynamics.

Another potential problem comes from the dual impact of exchange rates variations on firm performances. While a change in exchange rates can increase input prices, it can also affect the competitiveness of firms on foreign markets. This is a concern to us as it suggests that our instrument could be correlated to a firm's demand shifter. In reality, this is not an issue with the structural demand equation we consider. As one can see from the demand function (4), the competitiveness effect will be fully captured by destination-product-year fixed effect μ_{gdt}.

A last threat to the identification could arise from the fact that exchange rate variations directly cause quality adjustments. Bastos, Silva, and Verhoogen (2014) show that an exchange rate shock may induce a firm to upgrade its quality if it improves its competitiveness in rich destination markets. Similarly, Bas and Strauss-Kahn (2015) show that a change in tariffs or exchange rates on imported goods can lead firms to adjust their product quality. This import side effect is based on the premise that source countries produce inputs of different qualities. When an exchange rate shock makes imports from high (low) input quality countries more affordable, a firm upgrades (downgrades) the quality of its imported inputs, and output quality adjusts accordingly.

Remark that even if firm-level quality adjustments actually arise as the real exchange rate fluctuates and firms re-balance their export and imports; it is not clear what sign of the resulting correlation between quality and our instrument, if any, would be. An increase in $\overline{RER}_{ft}$ can equally result from the appreciation of the currency of a rich source country as of the currency of a poor source country. So the existence of a bias on price-elasticity is unclear. However, we take a conservative approach and neutralize the effect of exchange rates on quality by adding controls to the estimation. Namely, we incorporate the import weighted average GDP per capita of the firm as well as the export weighted average GDP per capita to the demand equation. The formula of these controls is:

$$\begin{cases} \overline{gdpc}_{ft}^{\text{exp}} & = \sum_s \omega_{sft}^{\text{exp}} \times \log(\text{gdpc}_{st}) \\ \overline{gdpc}_{ft}^{\text{imp}} & = \sum_s \omega_{sft}^{\text{imp}} \times \log(\text{gdpc}_{st}) \end{cases} . \tag{9}$$

These terms aim to capture quality adjustments following changes in the set of countries the firm imports from and exports to. The implicit assumption here is that GDP per Capita proxies the quality of inputs supplied by a country.[19] In the mechanism described above, exchange rates are suspected to affect quality only through an impact on a firm's spatial structure of imports.

[18]In the cross-section of firms, the instrument is likely to be positively correlated to quality. So, provided that higher quality goods are more expensive, an increase in the value of the instrument is associated to an increase in both prices and the demand shifter. Hence the upward bias.

[19]In line with this assumption, Schott (2004) shows evidence that richer countries specialize in the export of higher quality goods.

Controlling for that structure of exports thus makes the instrument orthogonal to the demand residual.

Finally, we add two controls in the specification to account for the partial-year effects that might contaminate our quality measures. Recent papers such as Berthou and Vicard (2015) and Bernard, Massari, Reyes, and Taglioni (2014) have documented that the construction of trade statistics in calendar year leads to systematic lower sales when a firm enters or exits a market. This effect comes from the fact that firms are likely to enter or exit at any time, leading to partial calendar years. To account for these systematic deviations, we add specific dummies, $entry_{fpdt}$ and $exit_{fpdt}$, which are equal to one when a firm respectively enters or exits a new market.

Consistently with the above discussion, our econometric specification will proceed in two steps. In a first step, we regress the exported price of the firm on the sets of instruments, RER_{ft}, variety and market fixed effects, and the controls defined in equation (9). Formally, the first stage is

$$\log p_{fgdt} = \eta RER_{ft} + \beta \overline{gdpc}_{ft} + entry_{fpdt} + exit_{fpdt} + \delta_{fgd} + \delta_{gdt} + u_{fgdt} \tag{10}$$

with RER_{ft} a vector containing different sets of instruments and $\overline{gdpc}_{ft}$ a vector containing the two controls defined in equation (9), δ_{fgd} and δ_{gdt} are respectively variety and market-year fixed effects, and u is the residual term. Using the predicted values of exporting prices from this first stage, we can then estimate the structural equation (4) in a second stage:

$$\log r_{fgdt} = (1-\sigma)\widehat{\log p}_{fgdt} + \alpha \overline{gdpc}_{ft} + entry_{fpdt} + exit_{fpdt} + \gamma_{fgd} + \gamma_{gdt} + \varepsilon_{fgdt} \tag{11}$$

in which γ_{fgd} and γ_{gdt} are variety and market-year fixed effects. The estimation of this equation will be consistent if the structural error ε is orthogonal to our set of instruments. As we argue in the previous paragraphs, we believe this condition is reasonable with our specification. In equation (11), demand equation is identical to structural demand equation (4) except that we now impose our measure of quality, λ_{fgdt}, to take following form:

$$\lambda_{fgdt} = \hat{\alpha}\overline{gdpc}_{ft} + \hat{\gamma}_{fgd} + \hat{\varepsilon}_{fgdt}. \tag{12}$$

In the next section, we implement this methodology using French customs data. Then, we assess its effectiveness by comparing our estimates of the elasticity of demand, and the product quality to existing measures.

3 Data and Demand Estimation Results

In this section, we apply our estimation strategy to French exporting firms using customs data. We start by describing the data we use, and provide descriptive statistics showing that they suit our exercise. Then, we report results on price elasticity. The estimates obtained from our empirical procedure are almost systematically larger, in absolute values, than corresponding OLS estimates. This is strongly suggestive that the use of our IV estimation corrects the endogeneity bias described in section 2.2. Finally, we estimate product quality by separately estimating demand function (4) for different categories of goods.

3.1 Data

We exploit firm-level trade data collected by French customs administration. These data provide a comprehensive record of the yearly values and quantities exported and imported by French firms from 1997 to 2010. Trade flows are disaggregated at the firm, country and eight-digit product category of the combined nomenclature.[20] Imports and exports are reported separately.

Information on quantities in trade data is known to be noisy. In order to mitigate this issue, we clean the data along various dimensions. First, we drop quantities equal to one or two, since we suspect them to be subject to rounding errors or to be poorly reported by firms. Secondly, we drop prices which variations are "suspiciously" large between years, destinations, and relatively to competing products.[21] Finally, because of changes in the HS classification across years, we apply the algorithm described in Pierce and Schott (2012) in order to obtain well-defined and time invariant product categories.

Descriptive Statistics The empirical strategy described in the previous section requires large variations in the data. First, our set of instruments relies on variations across firms in the set of countries they import from. Second, the large number of fixed effects included in the regression requires enough observations to identify variations across varieties within markets and across time within varieties. Table 1 provides information on the amount of variation contained in the data.

TABLE 1: Descriptive Statistics

	p5	p25	p50	p75	p95	mean
# **Sources by Firm**	1	2	5	10	25	7.80
# **Years by Firm-CN8-Destination**	1	1	1	2	7	2.21
# **Firms by CN8-Destination-Year**	1	1	2	4	19	5.22
# **Observations**			17 790 534			

Notes: An observation is an export flow at the firm, nc8 product, destination, year level.

First, table 1 reports the number of source countries per firm over the period: more than 50 percent of firms import from at least 5 sources and the average number of source countries per firm is equal to 7.8.[22] This is reassuring that there is substantial variation across firms regarding their exposure to exchanges rates movements. Second, rows two and three reports the numbers of observations by market and varieties. Even though many observations will not contribute to the identification, more than 25% of the firm-destination-product fixed effect and more than 50% of the destination product year fixed effects are identified. Finally, we report the number of

[20] Only annual values which exceeds a legal threshold are included in the dataset. For instance, in 2002, this threshold was 100,000 euros. This cutoff is unlikely to significantly affect our study since, this same year, the total values of flows contained in the dataset represented roughly 98 percent of the aggregated estimates of French international trade.

[21] Appendix A provides the details of the cleaning procedure.

[22] Table 10 in appendix B report similar statistics for the raw dataset. The difference in sample size mainly comes from the cleaning procedure and the fact that our estimation is on the subset of exporting firms which simultaneously import. Since these firms are larger than the average exporter, our final sample still contains 70% of total French exports.

observations in the last row of table 1: the size of the dataset remains large after this cleaning procedure with almost 18 millions observations.

The instrument crosses two informational sources: import shares and real exchange rates. Figure 1 provides information on the latter source by reporting the 1996-2010 evolution of real exchange rates for the top 5 importer of French Goods over the period. Even though the real exchange rate movements of Euro zone countries are solely due to inflation after 1999, this figure shows large and non-monotonic movements in exchange rates: this is likely to affect firms that import relatively more from these specific countries.

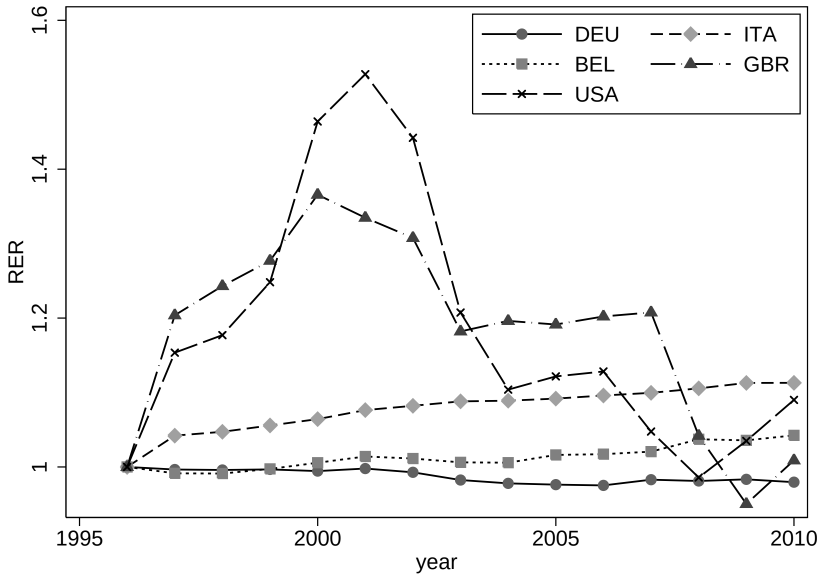

Figure 1: RER 1995-2010-Top Source Countries

Notes: Real exchange rates are calculated as $e_{Euro,st} \times \frac{\mathrm{CPI}_{st}}{\mathrm{CPI}_{France,t}}$ where $e_{Euro,st}$ is the direct nominal exchange rate from Euro to j's currency at date t. CPI is the consumer price index. After 1999, Real-exchange-rate movements of Euro zone countries are solely due to inflation. 1996 real exchange rates are normalized to one.

3.2 Estimation Algorithm

Estimation of linear equations with two sets of high-dimensional fixed effects and unbalanced panel, as is the case in our estimation, is cumbersome. Because the panel is unbalanced along these two dimensions, the two sets of fixed effects are not orthogonal. Consequently, variables included in the regression need to be simultaneously projected on these two sets of fixed effects, as one cannot rely on successive projections. In order to do so, we rely on the algorithm developed in Correia et al. (2016). This algorithm first demeans the variables along the two sets of fixed effects. Parameters of interest are then estimated using demeaned variables.

We estimate the model using the limited information maximum likelihood estimator (LIML). Unlike the two-stage least square estimator (2SLS), LIML has the virtue to be approximately unbiased in the presence of weak instruments, even when more than one instrument is employed in the first stage.[23] In practice, this means that weak instruments will translate into large standard errors rather than biased coefficients: this more conservative approach will be important when we separately estimate demand functions across industries, some of these industries being more prone to weak instruments.

3.3 Pooled Industries Results

In order to describe the effectiveness of our instrumental strategy, we first present results obtained by pooling the data before moving on to separately estimating the model on different industries.

The pooled results are reported in table 2. Panel A and panel B respectively contain first stage and second stage results. All regressions in this table are obtained including firm-destination-cn8 product fixed effects and destination-cn8 product-year fixed effects. Standard errors are clustered at the firm-year level. The smaller number of observations in table 2 than in the descriptive statistics from table 1 comes from observations which drop out of the regression because at least one of the two fixed effects is not identified.

First of all, table 2 shows the relevancy of our sets of instruments. The main instrument, $\overline{RER}_{ft}$, has a positive and significant effect on the export price charged by firms: on average a firm's export prices increase by 0.16 percent when its RER on imports increase by 1 percent.[24] Moreover, the additional instruments included in specifications (4) and (5) all have the expected signs. Firms with larger share on imports in their total output will be more affected by an increase in their average real exchange rate. On the contrary, firms with large market shares in the destination market, or a strong correlation between their sets of destination and source countries, will not adjust their export prices as much when facing an increase in cost of their inputs. As a consequence of this relevancy, the first stage of the procedure is strong enough to avoid issues related to weak instruments. The Kleibergen-Paap F-statistic is systematically above the thresholds commonly used to detect weak instruments, even though this statistic does decrease with the number of instruments used in the regressions.[25] Finally, a drawback comes from the rejection of the over-identification assumptions. While this rejection might cast some doubts on the set instruments, it is likely to reflect the possible heterogeneity in firms' responses to the exchange rates shocks that is captured by our different instruments.[26]

Turning to the second stage, we start by reporting the estimation of the demand equation using ordinary least squares (OLS). The purpose of this specification is to serve as a reference point to assess the impact of instrumenting on the instrument. Since the estimated coefficient is $1 - \hat{\sigma}^{OLS} = 0.21$, the OLS estimated price-elasticity of demand is $\hat{\sigma}^{OLS} = 0.79$. By contrast, all the specifications using instrumental variables lead to a larger elasticity in absolute values. For

[23] See, e.g, Mariano (2001) and Angrist and Pischke (2008).

[24] This number is consistent with the literature. In fact, considering a pass-through from RER on imports to import prices of 0.79 (Amiti, Itskhoki, and Konings (2014)), a pass-though of import prices to marginal production cost of 0.33 (the share of imports in the total cost of exporters in Amiti, Itskhoki, and Konings (2014)) and a pass-though of production costs to export prices of 0.79 as well, one gets a pass-through from RER on imports to export prices of 0.21, which is sensibly comparable to the 0.16 that we get.

[25] When separately estimating demand functions by industries, specifications (4) will be used to limit the decrease of the Kleibergen-Paap F statistic.

[26] We believe that adding more instruments to capture this heterogeneity leads to a modification of the local average treatment effect (LATE) estimated in the second stage, hence modifying the point estimates in the second stage and rejecting the overidentification assumptions.

Table 2: 2SLS Results on Pooled Data

	Dependent variable: log price export					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV1	IV2	IV3	IV4	IV5
Panel A (1^{st} **STAGE)**	*Dependent variable: log price export*					
$\overline{RER}_{ft}$		0.16***	0.16***	0.16***	0.17***	0.13***
		(0.012)	(0.012)	(0.012)	(0.013)	(0.011)
$\overline{RER}_{ft}^{imp}$				0.029***	0.029***	
				(0.0043)	(0.0043)	
$\overline{RER}_{ft}^{ms}$					-0.060	
					(0.040)	
$\overline{RER}_{ft}^{h}$					-0.14*	
					(0.055)	
$\overline{gpdc}_{ft}^{\mathbf{exp}}$			0.0060***	0.0060***	0.0060***	0.0057***
			(0.0016)	(0.0016)	(0.0016)	(0.0016)
$\overline{gpdc}_{ft}^{\mathbf{imp}}$			0.0065***	0.0065***	0.0065***	0.0068***
			(0.0011)	(0.0012)	(0.0011)	(0.0012)
$Entry_{fpdt}$			0.0063***	0.0063***	0.0063***	0.0062***
			(0.00068)	(0.00068)	(0.00068)	(0.00068)
$Exit_{fpdt}$			0.0021**	0.0021**	0.0021**	0.0022**
			(0.00068)	(0.00068)	(0.00068)	(0.00068)
Panel B (2^{nd} **STAGE)**	*Dependent variable: log export sales*					
Log price $(1-\hat{\sigma})$	**0.21***	**-1.04***	**-0.63***	**-0.38**	**-0.42**	**-0.33**
	(0.0032)	(0.29)	(0.26)	(0.26)	(0.26)	(0.32)
$\overline{gpdc}_{ft}^{\mathbf{exp}}$			0.14***	0.14***	0.14***	0.14***
			(0.0068)	(0.0067)	(0.0067)	(0.0067)
$\overline{gpdc}_{ft}^{\mathbf{imp}}$			0.011*	0.0093*	0.0096*	0.0090
			(0.00477)	(0.0047)	(0.0047)	(0.0049)
$Entry_{fpdt}$			-0.60***	-0.60***	-0.60***	-0.60***
			(0.00378)	(0.0037)	(0.0038)	(0.0039)
$Exit_{fpdt}$			-0.68***	-0.69***	-0.69***	-0.69***
			(0.00362)	(0.0036)	(0.0036)	(0.0036)
Import weights		Average	Average	Average	Average	Initial
N	11 484 981					
Kleibergen-Paap F-stat		172.5	172.3	100.7	51.75	136.7
Overid. p-value				0.0000909	0.000570	

Notes: Firm×prod×dest and prod×dest×year fixed effects fixed effects are included in all regressions. Firm×year-level clustered standard errors in parentheses. The estimation is carried out using a Limited information maximum likelihood (LIML) estimator.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

instance, the elasticity estimated with a single instrument and no control is equal to 2.04. The inclusion of controls and multiple instruments tend to reduce the estimated elasticity, even though these differences are not significant. Overall, our estimates of the price-elasticity of demand ($\hat{\sigma}$) range from 1.3 to 2, which is in the lower end of the recent findings in the literature.[27]

[27] Recent papers estimating firm-level demand functions include Nevo (2000), who finds estimates between 2.2 and 4.2 in the cereal industry, Dubé (2004) who gets estimates between 2.11 and 3.61 in the soft drinks industry.

Finally, two additional points validate our instrumental strategy. First, the inclusion of the controls does not affect the strength of the first stage. This rules out the reallocation of firm trade across differentially rich markets as a potential source of endogeneity of the instrument. Incidentally, the coefficients on the GDP per capita variables are consistent with theory. As predicted in Bastos, Silva, and Verhoogen (2014), following an increase in the average GDP per capita of its destinations, a firm should upgrade its product, generating a positive impact on prices and on sales. Similarly, the average gdp per capita of source countries is positively correlated with output prices and sales, suggesting that $\overline{gdpc}_{ft}^{\text{imp}}$ actually proxy for the quality of imported inputs. Second, we report in the sixth and last column of table 2 the results using the initial import weights to construct the average real exchange rates.[28] Therefore, column (6) reveals that results are robust to this alternative, and arguably more exogenous, definition of import shares.

3.4 Demand Estimation by Industry

In this section, we describe the results obtained by replicating the instrumentation strategy separately for fifteen product categories. The estimations all include $\overline{RER}_{ft}$ and $\overline{RER}_{ft}^{imp}$ as instruments, the four controls ($\overline{gpdc}_{ft}^{\textbf{imp}}$, $\overline{gpdc}_{ft}^{\textbf{exp}}$, $Entry_{fpdt}$, $Exit_{fpdt}$), and the two sets of fixed effects. Standard errors are clustered at the firm-year level and IV estimates are obtained by LIML. For each product category, we report the IV and OLS estimates of the price-elasticities of demand, as well as the first-stage F statistic (Kleibergen-Paap) of the instrumental variable procedure and the number of observations. The results of this procedure are displayed in table 3.

For most industries, the estimated price elasticities in the IV specification are larger relative to the OLS. This confirms that the instrument does correct for endogeneity as expected. However, due to the reduction in the number of observations, some industries do not have a strong enough first stage which translates in a F-statistic that does not exceed the critical value conventionally adopted to reject weak instruments.[29] In particular, two industries ('Mineral products' and 'Stone, Glass') appear problematic with very low F-stat, and accordingly very large standard errors. This result is not surprising as these industries mostly import commodities with little price variation across firms, which implies small firm-specific variations of the instrument. Even though we will include these industries in the construction of our quality measures, the results presented in the rest of the paper are robust to their exclusion.[30]

Finally, in order to make sense of the price-elasticity variation across sectors, we compare our estimates to those obtained by Soderbery (2015) in a paper that refines the estimation strategy by Broda and Weinstein (2006). Soderbery (2015) estimates are demand elasticities

Some recent studies estimate firm-level price-elasticities for several industries. Foster, Haltiwanger, and Syverson (2008) obtains a mean estimate of 2.41 with eleven homogeneous industries, Handbury (2012) finds a mean of 1.97 with 149 industries, and Gervais (2015) a median of 2.11 with 504 products.

[28]For each firm, we construct the instrument using the import weights from the first year she appears in the data.

[29]In our case, i.e with two instruments, the critical value tabulated by Stock and Yogo (2005) is 8.68. It corresponds to the rejection rate of the Wald test that the second stage coefficient is equal to zero being at most 10% when the true rejection rate should be the standard 5%. See Baum, Schaffer, Stillman et al. (2007) for details.

[30]See appendix B for tables showing results excluding these industries.

TABLE 3: Price-elasticity estimates ($\hat{\sigma}$) for different product categories

Product categories	**OLS**		**IV**			
	Coef ($\hat{\sigma}$)	SE	Coef ($\hat{\sigma}$)	SE	F-stat	**N**
Wood, Wood products	0.75	(0.0078)	**-0.43**	(1.15)	3.38	542 027
Chemicals and Allied	0.89	(0.0068)	**0.54**	(0.55)	20.10	1 077 303
Metals	0.76	(0.0068)	**0.82***	(0.43)	26.58	898 802
Textiles	0.71	(0.0098)	**0.85****	(0.42)	34.49	2 706 228
Machinery, Electrical	0.81	(0.0040)	**1.17*****	(0.29)	52.56	1 750 361
Foodstuffs	0.91	(0.010)	**1.35***	(0.80)	10.19	691 680
Plastics, Rubbers	0.86	(0.0066)	**1.36*****	(0.42)	29.31	798 010
Miscellaneous	0.77	(0.0054)	**1.52**	(1.45)	11.83	962 737
Vegetable Products	0.82	(0.012)	**1.66**	(1.17)	8.31	459 494
Raw Hides, Skins, Leather	0.72	(0.011)	**2.49*****	(0.72)	12.13	266 967
Animal Products	0.85	(0.017)	**2.67**	(2.66)	3.02	397 747
Footwear, Headgear	0.70	(0.017)	**4.25*****	(1.58)	6.69	265 214
Mineral Products	0.80	(0.028)	**4.42**	(8.53)	0.31	73 545
Transportation	0.79	(0.012)	**5.68**	(3.69)	4.14	299 216
Stone, Glass	0.79	(0.0096)	**10.4**	(12.13)	0.42	295 650

Notes: The estimates are obtained by estimating equation (4) separately for each industry. Controls for GDP per capita ($\overline{gpdc}_{ft}^{\mathbf{exp}}$ and $\overline{gpdc}_{ft}^{\mathbf{imp}}$) and for partial years ($Entry_{fpdt}$ and $Exit_{fpdt}$) are included in all regressions. Firm×Prod×Dest and Prod×Dest×Year fixed effects are included in all regressions. Standard errors are clustered at the firm-year level. IV specifications use $\overline{RER}_{ft}$ and $\overline{RER}_{ft}^{ms}$ as instruments. Last column reports the value of the Kleibergen-Paap F-stat. * p<0.1, ** p<0.05, *** p<0.01

faced by countries (not firms) on their exports and are defined at the 4-digit level. We therefore aggregate them up to the 1-digit level using a simple arithmetic mean. As plotted, in figure 2, the correlation between the two sets of price elasticities is positive, although non-significant, which should not come as a surprise given the small number of data points (15).

4 Analysis of Estimated Quality

In this section, we describe the quality measures obtained from the demand estimation. We start by briefly describing the variations of the quality measure along different dimensions. Then, in order to assess the relevance of our measure, we document its correlation with existing but sporadic measures of quality, firm-level data and industry-level measures of vertical differentiation. Finally, we show in which contexts this measure might be preferred to other variables commonly used to proxy product quality.

As a first way to describe our estimates of quality, we provide a variance decomposition in table 4. Here, it is important to remember that the quality measure is obtained at the firm × product category × destination × year level. Moreover, quality is defined relatively to the average quality in the market. Therefore, it defines a position over the quality ladder in a market, rather than an absolute quality which can be compared across markets. A first observation comes from the fact that firm-specific variation in quality only explains 17 percent

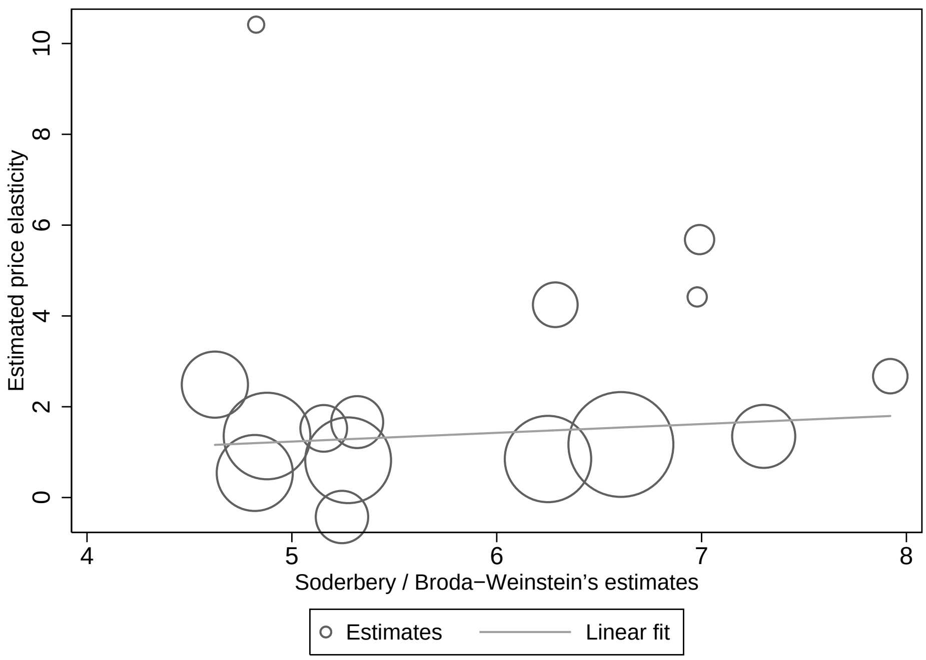

FIGURE 2: Estimated price elasticity and existing estimates

Notes: Each circle corresponds to a product category in Table 3. The size of a circle is proportional to the inverse of the standard error of the estimates. The vertical axis is equal to the estimated price-elasticities while the horizontal axis is the demand elasticity estimates from Soderbery (2015), improving on Broda and Weinstein (2006). The line is the predicted value of an OLS regression using the inverse of standard errors as weights. The coefficient of this regression is equal to 0.19 but is not statistically significant using standard criteria.

of the total variation. However, one can see from table 4 that the dispersion of quality is well predicted by variety-specific effects. Indeed, 59 percent of this quality dispersion is captured by time-invariant variety-specific effects, and 75 percent by time-variant variety fixed effect. From this table, it seems that the quality level of a product is strongly correlated across destinations for a specific good. However, it is also suggestive of the presence of market-specific tastes, or of the fact that firms adjust the quality to their product depending on the country they serve, which would explain the remaining variation in quality across destinations.

TABLE 4: Variance decomposition of the quality measure

	Firm FE	Firm×year FE	Firm×prod FE	Firm×prod×year FE
R^2	0.17	0.24	0.59	0.75

Notes: Each R^2 is obtained from the separate regression of the quality measures on fixed effects only.

Having briefly described the sources of variation of this measure, we next document its consistency with existing measures of vertical differentiation.

4.1 Consistency tests

Comparison with expert assessed quality First, we relate the estimated quality to one of the only objective product quality measure existing in the literature. Crozet et al. (2012) take advantage of expert ratings for Champagne to analyze the importance of quality in explaining international trade flows at the firm level. These expert assessed ratings (initially from Juhlin (2008)) are expressed in number of stars ranging from 1 to 5, one being the lowest quality. We non-parametrically regress our revealed measure of quality for Champagne exports over the number of stars.[31]

TABLE 5: Correlation with Ratings of Champagne

	Dependent variable: estimated quality
2 Stars	0.263*
	(0.140)
3 Stars	0.397**
	(0.177)
4 Stars	1.152***
	(0.196)
5 Stars	1.371***
	(0.151)

Notes: Champagne ratings from Juhlin (2008). A larger number of star means a higher expert assessed quality. We drop non-Champagne exports of Champagne producers. Standard errors in parentheses are clustered at the firm level. *** $p < 0.1$, *** $p < 0.01$, *** $p < 0.01$

From table 5 it appears that our measure of quality is monotonically increasing with the number of stars assigned by Juhlin (2008). Even though Champagne is a specific good in many dimensions, and cannot assess the overall quality of our measure, this is convincing of the relevancy of our measure of quality.

Correlation with firms' characteristics In order to further confirm the relevancy of our quality measure, we relate its estimated value to firms' characteristics. We merge the estimated qualities with firm-level data from France.[32] Therefore, we are able to inspect how our quality measure is related to firm characteristics and in particular the average wage of workers employed by the firm. Table 6 inspects these correlations.

Table 6 shows that quality is strongly correlated with the average wage of the firm. In order to control for the size of the firm, we also add as regressors the number of employees and the total stock of capital employed by the firm. Adding these controls do not affect the correlation between

[31] We thank the authors for sharing their data

[32] We use the dataset BRN, that covers all French firms with revenue larger than 763 Keuros, and is constructed from reports of French firms to the tax administration.This dataset has been widely used in the literature (see Eaton et al. 2011 or Berman et al. 2012 for instance).

Table 6: Correlation with firms' characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: estimated quality					
	No fixed effects		Dest, prod, year FE		Dest×prod×year FE	
log(wage)	0.096***	0.017**	0.34***	0.28***	0.38***	0.32***
	(0.0058)	(0.0059)	(0.0099)	(0.0090)	(0.011)	(0.0100)
log(employment)		-0.0016		0.016**		0.023***
		(0.0049)		(0.0051)		(0.0056)
log(capital)		0.077***		0.082***		0.093***
		(0.0034)		(0.0034)		(0.0038)
N	12 613 235	12 433 294	12 613 215	12 433 270	12 520 593	12 330 042

Notes: The variable log($wage$) is obtained by taking the logarithm of the total wage bill divided by the number of employees. Specifications (1), (3) and (5) have a non-reported constant. Standard errors in parentheses are clustered at the firm-year level. *** $p < 0.1$, *** $p < 0.01$, *** $p < 0.01$

quality and average wage. Moreover, this link is even stronger when we include destinations, product and year fixed effects, such that firms with higher wages systematically have higher product quality, relative to other exporting firms in the same market. These results provide further evidence that our measure captures heterogeneity across firms that is related to vertical differentiation and product quality differences.

Length of quality ladders and vertical differentiation As a final test of our quality estimation, we construct a market specific measure of the "length" of the quality ladder. Following Khandelwal (2010), for any product, destination, year combination, this length is obtained by taking the difference between the 95th and the 5th percentile of the quality distribution. This measure may be interpreted as a revealed measure of the degree of vertical differentiation in a market. We start by verifying that this measure is correlated with the quality ladders obtained by Khandelwal (2010). In his work, these measures are obtained at the industry level by comparing exporting countries' qualities in the US market. In contrast, we obtain this measure by comparing French exporters' qualities in different industries and destinations. Second, because this measure describe the extent of vertical differentiation in a market, we compare it to Sutton (2001)'s alternative measure of vertical differentiation, which uses the average of industry-level R&D and advertising expenditures to sales.

Table 7 shows the positive link between the quality ladders constructed from our quality measures, and the ones from Khandelwal (2010) and Sutton (2001)'s measure. This positive correlation is not significant in all specifications, but removing the markets in which the number of firms is too small to realistically compare 5th and 95th percentile leads to a significant and large correlation with these two measures. This correlation is stable as we control for market destinations and time fixed effects such that the identification is obtained across product categories in the same country at the same time.

These different tests demonstrate the relevancy of our measure to describe the quality of the good produced by the firm, and the vertical differentiation across firms. In order to further

TABLE 7: Length of quality ladders and vertical differentiation

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: quality ladders					
	All markets		More than 5 firms		More than 20 firms	
Khandelwal (2010)'s ladders	0.079	0.082	0.35	0.35	0.63*	0.63*
	(0.11)	(0.11)	(0.19)	(0.19)	(0.30)	(0.30)
N	1 384 266	1 384 173	509 505	509 245	128 670	128 480
Sutton (2001)'s measure	7.99**	8.14**	10.9*	11.2*	14.4*	14.6*
	(3.05)	(3.05)	(4.97)	(4.98)	(6.95)	(6.94)
N	1 516 190	1 516 111	552 950	552 722	137 254	137 082
Dest FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No
Dest×year FE	No	Yes	No	Yes	No	Yes

Notes: Each coefficient in the table comes from separate regressions. Khandelwal (2010)'s measure is averaged from 10-digit product categories to 6-digit categories. Sutton (2001)'s measure is converted from ISIC rev.2 to 6 digit product classification. Standard errors in parentheses are clustered at the 6-digit product level. *** $p < 0.1$, *** $p < 0.01$, *** $p < 0.01$

demonstrate the relevance of our measure, we show in the next subsection why this measure might be preferable to using prices, a popular proxy for quality.

4.2 How well do Prices proxy for Quality?

As highlighted in the introduction, the absence of product quality measures has led researchers to use proxies, directly available in many datasets, to measure quality. Among these proxies, the price of a good is probably the most common in studies aiming to describe product quality at a microeconomic level. However, an important drawback of this proxy is that it conflates many factors that are not related to product quality, and ignores characteristics that are not accounted in the price of a good but still enter the consumers' valuation of a good. In particular, firms with low productivity, and therefore high price, will be characterized as producing high quality goods using price as a proxy for quality.

In this subsection, we confirm this imperfect relationship between prices and quality. First, we show that prices and our quality measures are more correlated in industries with large vertical differentiation. In these industries, variations in prices rely more on quality variations than cost variations, which generates a stronger correlation with our quality measures. Second, we describe a situation in which using prices as proxy for quality can be misleading: unlike prices, we show that the quality measure of a firm increases as this firm increases its number of destinations or varieties.

Prices and vertical differentiation In table 8, we display the correlation between prices and our measures of quality across firms. All regressions include destination×product×year fixed effects such that the relation is identified within a market. We can see from this table that export prices and quality measures are positively correlated, justifying the use of prices as a proxy for quality. This positive correlation is significant in the cross-section of firms within a market, but also when tracking firms over time: firms which moves their prices over time simultaneously move their quality in the same direction (specifications (2), (4) and (6)).

Table 8: Correlation between prices and quality

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: log price					
	All markets		More than 5 firms		More than 20 firms	
Quality	0.054***	0.044***	0.050***	0.043***	0.046***	0.040***
	(0.00037)	(0.00026)	(0.00043)	(0.00029)	(0.00065)	(0.00041)
Quality × quality lad.	0.0079***	0.0083***	0.0083***	0.0087***	0.010***	0.011***
	(0.000092)	(0.000091)	(0.00011)	(0.00011)	(0.00024)	(0.00023)
Firm×Prod×year FE	No	Yes	No	Yes	No	Yes
N	18 867 461	13 153 066	15 124 335	11 085 058	9 530 823	7 201 815

Notes: Quality ladder is the difference between the 95th and 5th percentiles of the quality distribution within a market, normalized to have a mean of zero and a variance of one. Each regression includes product×dest×year fixed effects. Standard errors in parentheses are clustered at the product×dest×year level. *** $p < 0.1$, *** $p < 0.01$, *** $p < 0.01$

If prices and quality measures are correlated across and within firms, table 8 also shows that this correlation is stronger in markets with a larger degree of differentiation. The coefficient on the interaction between quality and quality ladder shows that market with a wide quality ladder also displays a stronger link between prices and quality: in these markets with differentiation, dispersion in prices are strongly linked with the quality content of a product.

Prices, quality and extensive margin Despite the positive relationship between prices and quality measures, the use of prices as proxy for quality can lead to erroneous conclusions. In this section, we show this is case when studying the link between the extensive margins of a firms (its number of destinations and products) and its product quality.

Recent research in international trade has studied the link between quality and export performance. While prices are often positively correlated with export performance in developing countries (see Kugler and Verhoogen (2012) or Manova and Zhang (2012a) for instance), the positive correlation in developed economies is less established. The main reason for this ambivalence comes from the fact that prices conflates productivity and quality, with opposite predictions on the link between prices and export performance. On the contrary, a measure of product quality should be positively correlated with measures of performance.

We test this relationship by looking at the link between prices, quality and the number of destinations or varieties of a firm. Table 9 shows regressions of the measure of quality or the price of a good on the number of destinations or varieties a firm is exporting. Importantly, we include market fixed effects to identify this relationship within a specific market. Moreover, an additional complication comes from the fact that adding a new destination or a new variety might lead to a decrease of the average quality exported by the firm.[33] To account for this endogenous sorting, we identify the link between quality and the extensive margin within a specific firm-destination-product dimension: we use both fixed effects and first difference to look at the change in quality for existing destinations or products. In other words, we capture the change in quality of existing destinations or varieties when new destinations or products are added: if quality is positively correlated with export performance, the quality of existing varieties should increase as the firm expands its scope.

TABLE 9: Quality and extensive margins

	(1)	(2)	(3)	(4)
Dependent variable:	*estimated quality*		*log price*	
log(# destinations)	0.58***	0.48***	0.0060***	0.0062***
	(0.0039)	(0.0042)	(0.00077)	(0.00055)
log(# products)	0.34***	0.31***	-0.0027***	-0.0014**
	(0.0032)	(0.0033)	(0.00070)	(0.00047)
Firm-dest-product FE	Yes	No	Yes	No
First difference	No	Yes	No	Yes
N	13 153 066	8 090 727	13 153 066	8 090 727

Notes: Each coefficient is obtained from a separate regression. Each regression includes product×dest×year fixed effects. Standard errors in parentheses are clustered at the firm×year level. *** $p < 0.1$, *** $p < 0.01$, *** $p < 0.01$

Table 9 shows that this correlation is indeed positive when using our measure of quality. The addition of a destination or a variety takes place simultaneously to an increase in the quality of existing destinations and varieties. However, this prediction is mixed when looking at prices: while expanding to a new destination is associated with a price increase in existing destinations, existing products see a price reduction as a new product is introduced. This mixed result highlights the drawbacks of prices: by conflating many factors, they might lead to somewhat conflicting conclusions. In this specific context, the addition of new destination in a firm portfolio seems to be mostly driven by demand factors, while the addition of new goods is correlated with price reductions at the firm level. By contrast, the use of estimated quality measures clearly shows that product quality is postively associated with the export performance of the firm.

5 Conclusion

A recent literature has evidenced that product quality has implications for key economic outcomes such as firms' profitability or welfare inequalities. These findings make it crucial to understand

[33] This can be easily seen in a model in which firms have a core-product of higher quality. In this framework, adding a product generates a reduction in the average quality produced because this additional variety (or destination) is of lower quality. Manova and Zhang (2012b) develops such a model.

the determinants of quality at the firm-level. In this paper, we have provided a necessary tool to pursue this research agenda. Namely, we have proposed a novel strategy to estimate time-varying quality at the firm-level. Our strategy is robust to unobserved vertical differentiation and only requires firm-product level information on prices, sales and imports by country.

We first show that the measures of quality obtained from this method are consistently related to a range of measures: estimated quality is positively correlated with the average wage paid by firms, with direct measures of product quality from outside sources, and index of vertical differentiation constructed from these quality measures are correlated with existing indices.

To highlight the relevancy of this work, we then study the link at the firm level between product quality and export performance. We show that the most common proxy for quality, export prices, displays a nuanced relationship between quality and exporters' scope. Instead, when using the estimated quality measures, we show that firms adding varieties to a market or destinations to their portfolio do so as the quality of their existing varieties increase, implying a positive link between export performance and quality. In light of these results, we believe that the methodology developed in this paper could help exploring existing and new questions in which the quality of the good produced by exporters plays an important role.

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Appendices

A Data Cleaning

We perform two main operations to prepare the final sample. First, we harmonize the product codes across time to obtain consistent categories across time. Then, we clean the dataset to take into account the existence of measurement errors in trade data.

Harmonization The product category used by custom authorities are regularly updated to follow the changes in product characteristics. This means that we need to account for these changes to maintain a coherent set of product categories across time. To implement this, we follow the procedure from Van Beveren, Bernard, and Vandenbussche (2012) which applies the methodology from Pierce and Schott (2012) to European statistics. This allows us to obtain consistent product categories from 1997 to 2010.

Cleaning Data on quantities are known to be subject to measurement errors, which could lead to spurious relationships between quantities and prices (computed by dividing values with quantities). Moreover, the customs statistics from France allows exporters to declare the quantities in two different units: the weight or a supplementary unit that is product specific and more relevant to describe the quantities of certain types of goods. Therefore, we decide to use the supplementary unit when at least 80 percent of firms in the category are providing this unit. Otherwise, we use the weight of the good as quantity.

This allows us to compute the price as the export value divided by quantity. Then, because of the potential measurement errors in prices, we clean the prices according to the following dimensions:

- Observations are dropped for prices for which variations across times differ from a factor three or more. Formally, observations are dropped if $\frac{p_{fpdt}}{p_{fpdt-1}} > 3$ or $\frac{p_{fpdt}}{p_{fpdt-1}} < \frac{1}{3}$
- Observations are dropped for prices which differ from a factor two or more from the mean across all destinations. Formally, observations are dropped if $\frac{p_{fpdt}}{p_{fp\bullet t}} > 3$ or $\frac{p_{fpdt}}{p_{fp\bullet t}} < \frac{1}{3}$
- Extreme quantiles of the price distributions are censored: for each market (product $\times$ destination $\times$ year), observations below the 1st percentile, and beyond the 99th percentile are dropped.

B Additional tables

Table 10: Descriptive Statistics, Raw Data

	p5	p25	p50	p75	p95	mean
# **Sources by Firm**	0	0	0	3	16	3.233
# **Years by Firm-CN8-Destination**	1	1	1	3	7	2.277
# **Firms by CN8-Destination-Year**	1	1	2	5	23	6.337
# **Observations**			29 923 856			

Notes: An observation is an export flow at the firm, nc8 product, destination, year level.

Table 11: Correlation with firms' characteristics (restricted sample)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: estimated quality					
	No fixed effects		Dest, prod, year FE		Dest×prod×year FE	
log(wage)	0.089***	0.0069	0.32***	0.26***	0.36***	0.30***
	(0.0055)	(0.0057)	(0.0094)	(0.0084)	(0.011)	(0.0093)
log(employment)		-0.0017		0.017***		0.024***
		(0.0047)		(0.0048)		(0.0054)
log(capital)		0.081***		0.086***		0.098***
		(0.0033)		(0.0033)		(0.0036)
N	12 199 481	12 025 376	12 199 462	12 025 354	12 111 995	11 927 812

Notes: The variable log(*wage*) is obtained by taking the logarithm of the total wage bill divided by the number of employees. Specifications (1), (3) and (5) have a non-reported constant. Categories 'Mineral products' and 'Stone, Glass' are excluded from the regressions. Standard errors in parentheses are clustered at the firm-year level. *** $p < 0.1$, *** $p < 0.01$, *** $p < 0.01$

Table 12: Length of quality ladders and vertical differentiation (restricted sample)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: quality ladders					
	All markets		More than 5 firms		More than 20 firms	
Khandelwal (2010)'s ladders	0.013	0.016	0.22*	0.23*	0.41**	0.40**
	(0.056)	(0.056)	(0.091)	(0.091)	(0.14)	(0.14)
N	1 336 449	1 336 356	494 846	494 585	125 673	125 483
Sutton (2001)'s measure	2.60*	2.74*	3.43*	3.66**	6.34**	6.48**
	(1.21)	(1.22)	(1.34)	(1.34)	(2.41)	(2.39)
N	1 446 192	1 446 114	530 662	530 433	132 619	132 447
Dest FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No
Dest×year FE	No	Yes	No	Yes	No	Yes

Notes: Each coefficient in the table comes from separate regressions. Khandelwal (2010)'s measure is averaged from 10-digit product categories to 6-digit categories. Sutton (2001)'s measure is converted from ISIC rev.2 to 6 digit product classification. Categories 'Mineral products' and 'Stone, Glass' are excluded from the regressions. Standard errors in parentheses are clustered at the 6-digit product level. *** $p < 0.1$, *** $p < 0.01$, *** $p < 0.01$

Table 13: Correlation between prices and quality (restricted sample)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: log price					
	All markets		More than 5 firms		More than 20 firms	
Quality	0.031***	0.031***	0.026***	0.029***	0.023***	0.027***
	(0.00050)	(0.00025)	(0.00044)	(0.00027)	(0.00062)	(0.00036)
Quality × quality lad.	0.024***	0.019***	0.026***	0.020***	0.027***	0.023***
	(0.00038)	(0.00020)	(0.00021)	(0.00020)	(0.00028)	(0.00027)
Firm×Prod×year FE	No	Yes	No	Yes	No	Yes
N	18 239 671	12 732 203	14 686 306	10 774 182	9 314 356	7 045 312

Notes: Quality ladder is the difference between the 95th and 5th percentiles of the quality distribution within a market, normalized to have a mean of zero and a variance of one. Each regression includes product×dest×year fixed effects. Categories 'Mineral products' and 'Stone, Glass' are excluded from the regressions. Standard errors in parentheses are clustered at the product×dest×year level. *** $p < 0.1$, *** $p < 0.01$, *** $p < 0.01$

Table 14: Quality and extensive margins (restricted sample)

	(1)	(2)	(3)	(4)
Dependent variable:	*estimated quality*		*log price*	
log(# destinations)	0.58***	0.48***	0.0062***	0.0063***
	(0.0038)	(0.0042)	(0.00078)	(0.00055)
log(# products)	0.34***	0.31***	-0.0026***	-0.0014**
	(0.0031)	(0.0033)	(0.00071)	(0.00048)
Firm-dest-prod FE	Yes	No	Yes	No
First difference	No	Yes	No	Yes
N	12 732 203	7 838 504	12 732 203	7 838 504

Notes: Each coefficient is obtained from a separate regression. Each regression includes product×dest×year fixed effects. Categories 'Mineral products' and 'Stone, Glass' are excluded from the regressions. Standard errors in parentheses are clustered at the firm×year level. *** $p < 0.1$, *** $p < 0.01$, *** $p < 0.01$