A new Method for Quality Estimation using Trade Data: An Application to French firms*

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Abstract

This paper presents a novel instrumental variable strategy to estimate time-varying product quality at the micro level. Our method implies the estimation of firm-level demand functions. To deal with the endogeneity of prices, we construct a new firm-specific instrument, based on variations in exchange rates combined with firm-specific import shares. By shifting a firm's costs, this instrument generates firm-specific price variations independent from demand shocks. Our approach delivers consistent estimates of the price elasticity of demand from a limited number of assumptions. Higher quality is then assigned to products with higher sales conditional on prices. We implement our method on French customs data and we assess its reliability through correlations with alternative measures of quality. We use our estimates to measure the quality response of French firms to low-wage competition on foreign markets. This important question requires time-varying quality and thus can not be addressed with existing quality estimations. Using import penetration rates as a measure of competition, our results suggest that firms upgrade quality when facing increased low-wage competition.

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1 Introduction

The quality produced by firms has deep implications for aggregate outcomes in international trade. A recent literature has emphasized the key role of quality in shaping the patterns of trade.[1] The analysis of firm-level quality has also delivered new insights into the impact of globalization on inequalities.[2] The importance of these findings calls for a thorough understanding of quality determinants at the firm-level. However, the main challenge raised by this research agenda is that quality is unobserved.

In this paper, we propose a new empirical methodology to estimate time-varying product quality at the firm-level. Our method is robust to unobserved product characteristics. It requires information on a firm's output prices and sales as well as on its imports by country. The fact that our strategy identifies time-varying quality makes it suitable to analyze the way firms adjust their quality in response to changes in their economic environment. We implement our method on French customs data as it has been extensively used to analyze firm-level quality. We assess the reliability of our estimation by correlating the estimated quality of exports to other characteristics of the firm, including alternative measures of quality. Then, we take advantage of our measure to look at the within-firm quality response to low-cost competition on foreign markets. This important question requires a time-varying quality measure and cannot be addressed without our method.

The paper's main contributions can be summarized as follows. First, to motivate our estimation, we propose a simple system of demand for a vertically differentiated good. The demand system features nested CES preference, each nest being specific to a quality level. Secondly, we present an new firm-specific instrument for prices which allows us to consistently estimate demand functions at the firm-level. This instrument is robust to time varying quality and unobserved product characteristics. From the demand function, we are able to estimate the quality of French exports at the firm-product-destination-year level. Thirdly, using our estimates, we show that prices, the most conventional proxy for quality, are significantly more informative on quality in vertically differentiated sectors than in homogeneous sectors. Finally, we identify the quality response of French exports to low-cost competition on foreign markets. We find evidence that firms upgrade their quality when competition increases.

The methodology developed in this paper is motivated by the observation that leading approaches to estimate quality at the firm-level require information on product characteristics.[3].

[1]Quality has shed new line on the pattern of trade at the country-level (Schott 2004; Hallak 2006; Feenstra and Romalis 2012; Hallak and Schott 2011) as well as at the firm-level (Crozet et al. 2012; Gervais 2011; Manova and Zhang 2012).

[2]Recent contributions on firm-level quality, trade and inequality include Faber (2012), Brambilla et al. (2012) and Verhoogen (2008).

[3]Influential estimations of demand systems with vertically differentiated goods and observed product charac-

Unfortunately, such information is absent from most nationally-representative firm-level datasets. Consequently, existing literature has heavily relied on prices as a quality measure. This proxy is conceptually problematic because prices are polluted by differences in production costs.[4] Recent advances on the estimation of quality have been achieved by Gervais (2011) and Roberts et al. (2012). These works estimate firm-level demand fundamentals in frameworks where information on product characteristics is very limited. However, they obtain identification at a cost: quality is assumed constant over time, within the firm. By contrast, our approach is robust to both unobserved product characteristics and time-varying quality. [5]

Our work proceeds in several steps. First, we present our estimation. We reveal quality from the demand side. Namely, higher quality is assigned to products with higher sales conditional on prices. Our identification of quality therefore implies the estimation of demand functions at the firm-product level. We derive the expression of these demand functions from a simple model of demand for quality. The model features nested CES preferences, each nest being specific to a quality level. The main challenge we face to estimate demand functions is to deal with the endogeneity of prices. Prices are likely to be correlated to demand shocks, e.g., because quality is costly to produce.[6] To address this problem, 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 on 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.[7] Quality is then identified from the residual variation of demand, once price variations have been controlled for.

The strategy which consists in backing out quality from the estimation of a demand system is present throughout the literature. Our methodological contribution is in the way we deal with the endogeneity of prices. Similarly to us, Hallak and Schott (2011) and Khandelwal (2010) rely on an instrumental variable approach to identify quality at the country-product level using trade data. To be applied at the firm-product level, their methods require an instruments for

teristics include, e.g., Berry et al. (1995), Nevo (2000) and Handbury (2012)

[4]At the country-product level, Khandelwal (2010) shows that the ability of prices to proxy quality is particularly low for homogeneous goods. We get a similar result at the firm-level.

[5]To the best of our knowledge, Khandelwal et al. (forthcoming) propose the only time-varying measure of product quality at the firm-level, with unobserved product characteristics. However, their measure, unlike ours, is not estimated. We detail this point below, when presenting our methodology.

[6]See, e.g., Hallak and Sivadasan (2011), Johnson (2012) and Kugler and Verhoogen (2012) for trade models where quality is costly and endogenous at the firm-level.

[7]The use of exchange rates as an instrument for prices connects our estimation to Berman et al. (2012) and Amiti et al. (forthcoming). 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.

prices which varies across firms. We provide such an instrument. At the firm-level, Gervais (2011) and Roberts et al. (2012) also estimate quality 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. Also at the firm-level, Khandelwal et al. (forthcoming) 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 were obtained from country-level data. By opposition, we estimate price elasticity from the same data that we use to construct quality estimates.

As a second step, we implement our procedure using French customs data spanning from 1995 to 2010. On top of quality, our instrumental variable approach delivers a series of by-products which we use to assess its reliability. 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. Another output of the estimation is the price elasticity of demand. In order to evaluate the ability of our instrument to correct for the endogeneity of prices, we estimate this elasticity both via ordinary least squares and two stages least squares. Our instrumental variable procedure affects the estimates of price-elasticities consistently with a correction of a simultaneity 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 1.8 to 2.4, depending on the specification. In order to further assess the reasonableness of our price elasticity estimates, we rely on cross-industry comparisons. In line with evidence at the country-product level, we find that demand is significantly more elastic in more homogeneous sectors.[8]

Then we investigate the properties of our quality estimates by running correlations with existing measures of quality at the firm-level. A natural benchmark is provided by Crozet et al. (2012). This study uses one of the very few "direct" measure of firm-specific quality present in the literature. More specifically, Crozet et al. (2012) observe 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. Prices, the most popular proxy for quality in the literature, are another natural benchmark with which to compare our quality estimates. We find that prices are positively and significantly correlated to quality. This is true across firms as well as over time within a firm. However, this correlation is significantly smaller for more homogeneous sectors. Using Sutton (2001)'s sectoral measure of vertical differentiation, we find that for "mineral products", the least vertically differentiated

[8] See Broda and Weinstein (2006).

product category, prices are approximately 3 times less elastic to quality than for "chemicals and allied industries", the most differentiated product category. This means that prices are informative on quality, but less so in more homogeneous sectors.

Finally, to illustrate the scope of our method, we employ our quality estimates to analyze the way firms respond to low-cost competition in foreign market. The recent increase in the participation of low-wage countries in international trade has had a large impact on manufacturing industries in developed economies. For instance, Autor et al. (2013) show how manufacturing workers in the United States have been hurt by the increasing penetration of Chinese goods on the american market. Relatedly, Khandelwal (2010) provides evidence that the impact of low-wage competition has been significantly larger in industries with shorter quality ladders. Closer to our question, Martin and Méjean (2011) show that low-cost competition induces a reallocation of market shares towards higher quality firms which ultimately results in a rise of aggregate quality. By contrast, we look at the within-firm quality response to low-wage competition. This question requires a time-varying measure of quality and as such can not be addressed with existing firm-level quality estimations with trade data.

Our identification strategy consists in correlating the dynamics of low-cost competition in foreign markets with the dynamics of the product quality supplied by French firms to these markets. To this end, we first compute the penetration of low-wage countries at the country-product-year level using the trade dataset BACI. Then, for each destination market and each firm, we construct a measure of the low-cost competition faced by the firm in the rest of the world. This measure varies across firms within a market since firms serve different destinations. We identify the quality response to competition from the firm-specific dynamics in this rest-of-the-world measure of competition. This identification strategy assumes that there is a positive correlation in the quality of a good supplied by a firm across destinations. Intuitively, we assume that within the firm, the quality adjustment due to competition in one destination spills over the quality served to other destinations.

Using this identification strategy, our results suggest that low-cost competition induces quality upgrading within the firm. Interestingly the response of quality takes time to occur. More specifically, the quality of a firm raises by 1.2% four years after a 10 percentage point increase of the low-wage countries' penetration. We find no significant response before four years. It suggests that upgrading quality requires slow adjustments within the firm. In addition, we find that quality upgrading is more pronounced in more vertically differentiated industries. These results contribute to the literature on the relationship between firm-level quality and trade exposure. While existing studies mostly focus on firms from developing countries (see, e.g., Verhoogen 2008; Brambilla et al. 2012; Khandelwal et al. forthcoming), our results suggest a new channel through which firms from developed countries can mitigate the impact from low-wage competition.

This paper is structured as follows. In the next section, we derive a simple model of demand with vertically-differentiated goods. In section 3, we present our novel instrumental strategy, describe its validity and its positioning relative to existing methods. Section 4 applies our methodology and demonstrates its effectiveness. In section 5, we describe the quality estimates we obtain through correlations to alternative measures. In section 6, we investigate the impact of low-cost competition on within-firm quality adjustments. Finally, section 7 concludes.

2 An Empirical Model with Demand for Quality

In this section, we consider a simple demand structure for a vertically differentiated good. The model delivers an expression of the demand function at the firm-level in which quality is a component of the demand shifter. In the next section, we bring this demand function to the data.

2.1 Consumer Preferences

Let us consider a global economy composed of a collection of markets. Each market is populated with a mass of symmetric buyers and a mass of heterogeneous firms trading a differentiated good. Within a market, each firm produces a single variety of the good and has a monopoly on this variety. Varieties of a good are differentiated both horizontally and vertically [9].

Buyers combine varieties through a nested CES aggregator. At the lower level, buyers associate varieties horizontally within each quality nest. At the upper level, buyers bundle varieties along the quality ladder. The preference of a representative buyer is:

$$\begin{cases} \tilde{X}_{m,t}(q) &= \left[\int_{\Omega_{m,t}(q)} x_{v,t}^{\frac{\sigma-1}{\sigma}} \, dv\right]^{\frac{\sigma}{\sigma-1}} \\ X_{m,t} &= \left[\int (q\tilde{X}_{m,t}(q))^{\frac{\rho-1}{\rho}} \, dq\right]^{\frac{\rho}{\rho-1}} \end{cases} \tag{1}$$

With, $X_{m,t}$, $\tilde{X}_{m,t}(q)$ and $x_{v,t}$ respectively total consumption, consumption of quality q and consumption of variety v by the representative buyer in market m at date t [10]. $\Omega_{m,t}(q)$ is the set of varieties with quality q supplied to market m, at date t. σ and ρ are respectively the elasticity of substitution across varieties within a nest and between nests. As is standard, we assume $\sigma > 1$

[9] In our empirical application, we define a "variety" as a firm-country-product combination and a "market" as country-product combination.

[10] Remark that $x_{v,t}$ is not indexed by m. This is because we define a "variety" v as being specific to a market m.

to ensure that mark-ups are finite under monopolistic competition. We also make the natural assumption that varieties are closer substitutes within a quality nest than across nests: $\sigma \geq \rho$.

In equation (1), quality is a utility shifter. As such, quality is an index containing any intangible (e.g. reputation, quality of the customer service, brand name) and tangible characteristic of a variety that is observed by consumers. It is a measure of the overall appeal of a variety to a consumer. [11]

The use of Dixit-Stiglitz preferences is very standard in all leading heterogeneous trade models with vertical differentiation.[12] The novelty of our demand system lies in its quality-nested structure.[13] With CES preferences, the absence of quality nests implies that two varieties are equally substitutable within qualities and between qualities. If this unrealistic property might not be an issue in some applications, it shows particularly undesirable in the present paper. In fact, we are interested in identifying the impact of the competition from low-wage countries on firms' demand. As low-cost firms are most likely low quality firms, it is possible that their entry impacts more strongly low quality incumbents. Our demand system allows for this possibility.[14][15]

2.2 Firms' Demand and Quality as a Demand Shifter

In market m, at date t, consumers allocate their total expenditure, $E_{m,t}$, across varieties, in order to maximize their utility (1). The aggregate demand function faced by a variety v at date t is

$$r_{v,t} = {p^*_{v,t}}^{1-\sigma} q_{v,t}^{\rho-1} \tilde{P}_{m,t}(q_{v,t})^{\sigma-\rho} P_{m,t}^{\rho-1} E_{m,t} \tag{2}$$

With $r_{v,t}$ the sales of variety v . $p^*_{v,t}$ is the price of variety v faced by consumers of market m. Namely, $p^*_{v,t}$ is the CIF (Cost Insurance Freight) price labeled in market m's currency. $q_{v,t}$ is the quality of variety v. $\tilde{P}_{m,t}(q)$ is the quality q-specific price index, in market m, at date t. The

[11] We adopt a broad definition of quality, in line with the literature on quality and trade. Some contributions have adopted a more conservative terminology to refer to the same economic concept. For instance, Roberts et al. (2012) refer to the variety-specific utility shifter as a "demand index" when Foster et al. (2008) rather opt for "demand fundamental".

[12] see, e.g.,Verhoogen 2008; Baldwin and Harrigan 2011; Kugler and Verhoogen 2012; Johnson 2012; Crozet et al. 2012. By contrast, some contributions (e.g., Khandelwal 2010; Roberts et al. 2012) assume logit demand systems. Under mild conditions, CES and logit preferences deliver similar aggregate demand curves (see Anderson et al. 1987).

[13] If some trade and quality papers may use a nested demand structure (Khandelwal 2010), a nest is defined as a good, not a quality level.

[14] The entry of new competitors in a specific quality-nest q shifts down all firms' demand curve. However, the shift is larger for incumbent firms in nest q as they are closer substitutes to new varieties.

[15] The nested structure of our demand system also has implications for the quality response of firms to low-quality competition. Since nests act as a hedge against competition shocks in other nests, firms might want to adjust the entry of new low-quality competitors by upgrading quality in order to escape most affected nests. Section A formalizes that intuition. Section 6 provides empirical evidence supporting that prediction.

dependence of $\tilde{P}_{m,t}(q)$ on q, m and t stands for the fact that the density of competitors might differ along the quality ladder as well as across markets and over time. $P_{m,t}$ is the aggregate price index [16].

We assume that exporting from home country H (home country is "France" in the application) involves iceberg trade costs common to all firms serving a market. So CIF and FOB are linked be following relationship:

$$p^*_{vt} = e^{-1}_{mt}\tau_{mt}p_{vt} \tag{3}$$

With e_{dt} the direct nominal exchange rate from home currency to destination d's currency (home currency is Euro in the application), τ_{pdt} the iceberg trade cost ($\tau_{pdt} \geq 1$) and p_{fpdt} the FOB price in home currency. Plugging (3) and log-linearizing, we can re-express (2) as follows:

$$\log r_{vt} = (1-\sigma)\log p_{vt} + \lambda_{vt} + \mu_{mt} \tag{4}$$

$$\text{with} \quad \begin{cases} \lambda_{vt} \equiv (\rho-1)\log q_{vt} + (\sigma-\rho)\log \tilde{P}_{mt}(q_{vt}) \\ \mu_{mt} \equiv \log\left(\frac{\tau_{Hdt}}{e_{Hdt}}\right)^{1-\sigma} + (\rho-1)\log P_{mt} + \log E_{mt} \end{cases}$$

Equation (4) is the one we bring to the data. One can see from (4) that the demand shifter of a firm contains firm specific and market specific arguments. Since the latter are not informative on quality at the firm level, the estimation developed in this paper identifies $\lambda_{v,t}$, the firm-specific part of the demand shifter. As $\lambda_{v,t}$ is the demand shifter of a firm, cleaned out from market-level components, one should think of it as a demand shifter deviated from the average demand shifter on a market. It follows that $\lambda_{v,t}$ will not be suited to analyze the aggregate quality of a market.

$\lambda_{v,t}$ is a function of quality. Holding $\tilde{P}_{m,t}$, the derivative of $\lambda_{v,t}$ with respect to $\log q_{v,t}$ is $(\rho-1)$. The larger ρ, the smaller the love for variety of consumers along the quality ladder, the more sensitive consumers are to quality when they allocate their expenditure across qualities. In the limit case $\rho = \infty$, only the top best quality variety is demanded. ρ can therefore be seen as consumers' valuation for quality. The fact that this valuation is finite explains that low qualities

[16] Quality-specific and aggregate price indices verify:

$$\tilde{P}_{m,t}(q) = \left(\int_{\Omega_{m,t}(q)} {p^*_{v,t}}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} dv$$

$$P_{m,t} = \left[\int \left(\frac{\tilde{P}_{m,t}(q)}{q}\right)^{1-\rho}\right]^{\frac{1}{1-\rho}}$$

are ever consumed. As in Khandelwal (2010), our identification does not allow us to separate consumers' valuation for quality from quality itself. In other words, we will measure quality in unit of sales rather that in units of utility.

$\lambda_{v,t}$ is not only a function of quality. It also depends on the quality specific price index $\tilde{P}_{m,t}(q_{v,t})$. This price index can vary along the quality ladder within a market. As such, $\tilde{P}_{m,t}(q_{v,t})$ can act as a confounding factor when it comes to using $\lambda_{v,t}$ to rank firms in quality.[17] Suppose for instance that competition is tougher in the upper part of the quality ladder ($\tilde{P}_{m,t}(q)$ is decreasing in q). In that case, high quality firms enjoy a larger demand (conditional on price) because their products are more appealing. But this larger demand is dampened by higher competition. In that case, λ could be a decreasing function of quality.

In appendix A, we propose a simple model with endogenous quality where this competition effect does not dominate and $\lambda_{v,t}$ should be increasing with q. The idea behind this intuition is that if firms optimally choose their quality and if quality is costly- as assumed in models with endogenous quality- then firms need to have a positive return to quality ($\lambda_{v,t}(q)$ increasing in q) to find it profitable to invest in quality.[18] It follows that $\lambda_{v,t}$ can be used to rank firms in quality within a market.

In this section we have derived the expression of a variety's demand function and made explicit its dependence on quality. Next section proposes an method to identify these demand functions.

3 Quality Estimation Strategy

In this section, we describe the novel estimation strategy we implement to identify the quality of exports at the firm-product-destination-year level, using customs data. Identification of quality is achieved by estimating demand equation (4). The typical challenge of demand identification lies in the fact that prices are endogenous to demand shocks. In order to deal with price endogeneity, we present a novel instrument, obtained by interacting firm-specific importing shares with real exchange rates. Our instrument is appealing as it remains valid in the presence of time-varying

[17] Existing papers on quality and trade implicitly assume the intensity of competition to be constant along the quality ladder. It is clear in models with CES demand systems: existing contributions do not have quality nests which implies that competition is summarized by the aggregate price index which is common to all firms, irrespective of their quality. It is also the case in papers with nested logit preferences, for the reason that nests are not along the quality ladder. It follows that existing estimations of quality are also polluted with competition variations along the quality ladder. Our paper makes this pollution explicits and carefully discusses its implications.

[18] Let us illustrate this point through a simple example. Consider two firms, A and B. Firm A has a larger λ than firm B. If quality is costly and endogenous and firms maximize their profits, then it has to be that A has a larger quality than B, otherwise firm B would make more sales at a lower average cost by supplying the same quality as A.

(unobserved) quality. As such, our demand estimation strategy has a broader scope of application than most existing ones.[19]

The high dimensionality of the dataset employed here requires some definitions. Hereafter, index f will identify a firm, p a eight-digit product category, d a destination country, and t a year. A 'market' will be defined as a destination × product category × year combination and a 'variety' as a firm × product category × destination. Re-written following the dimensions of our data, equation (4) is

$$\log r_{fpdt} = (1 - \sigma) \log p_{fpdt} + \lambda_{fpdt} + \mu_{pdt} \tag{5}$$

In equation (5), only r_{fpdt} and p_{fpdt} are observable to the econometrician. Our strategy identifies the price-elasticity σ, a market fixed effect μ_{pdt} and our parameter of interest: the variety-specific demand shifter λ_{fpdt}. Prices are presumably correlated with the demand shifter of the firm, λ_{fpdt}, through endogenous quality choices, or any internalization of demand shocks by the firm. Next subsections respectively present and discuss our instrumental strategy to fix this endogeneity issue.

3.1 Dealing with Price Endogeneity

In our setup, the endogeneity of prices comes from two mechanisms. First of all, we face a well-known simultaneity problem as prices are likely to be correlated with demand shocks. This might be due to the strategic behaviors of firms (i.e. firms adjust their mark-ups to demand shocks); but also to the presence of vertical differentiation within a product category. In the latter case, correlation between the price of a product and its level of demand would come from high quality firms passing on the cost of quality to consumers. This endogeneity channel leads ordinary least squares to underestimate the price-elasticity of demand, σ.

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 quantity shipped. The use of this proxy may generate an attenuation bias due to the measurement error contained in the price variable.[20]

[19] We review existing firm-level demand estimations in section 3.1.

[20] 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.

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.[21] As a consequence, these instruments are not usable in our context. Indeed, trade data contain no product characteristic, except for the category in the product classification. 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.

Methods for demand estimation with trade data exist at the country-level. Khandelwal (2010) and Hallak and Schott (2011) use IV 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., quality is costly).

Literature on demand estimation with trade data is scarcer at the firm-level. Roberts et al. (2012) and Gervais (2011) 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 OLS estimate of σ is biased downward. The assumption that product quality is time-invariant is not sustainable in the present paper as our goal is precisely to identify within-firm quality variations induced by low-wage countries competition. Khandelwal et al. (forthcoming) 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

[21] 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 homogenous products or use barcode-level data, which rule out the possibility of unobserved quality differences.

and the macro level (see, e.g., Imbs and Méjean (2008) or Chetty (2012)) and so generate biases in estimated firm-level quality.

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

A Novel 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. Exporters which do not import do not identify our parameters. We use real exchange rates 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. Appendix A formalizes this mechanism. 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 assumptions. 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:

$$\overline{RER}_{ft} = \sum_{s} \omega_{0sf} \times \log(\text{rer}_{st}) \tag{6}$$

where ω_{0sf} is the share of goods imported by firm f, from source country s, at the initial date of the sample[22], and rer_{st} is the real exchange rate from a firm's own country (i.e. 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:

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

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

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The ability of this instrument to predict export prices might be reduced for firms that imports and exports goods from the same destination. [23] Consider for instance a French firm importing from and exporting to the United States. An appreciation of the dollar should have little impact on the price of its input: such a firm should be able to implement hedging strategies out of its sales to the US to absorb exchange rate shocks. Consequently, we create a second instrument taking into account the degree of potential hedging of a firm. The idea is to interact importing and exporting weights for a same country. Formally, the second instrument is:

$$\overline{RER}^{h}_{ft} = \sum_{s} \omega_{0sf} \times \omega^{\text{exp}}_{0sf} \times \log(\text{rer}_{st}) \tag{7}$$

where $\omega^{\text{exp}}_{0sf}$ is the exporting weight of a firm toward destination s. We expect the pass-through from the RER on imports to export prices to be decreasing with $\overline{RER}^{h}_{ft}$. The inclusion of this second instrument will improve the strength of our first stage and therefore generate more accurately estimated exogenous price variations.

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. 2012). 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. (forthcoming) 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. Moreover, we look at exchange rate movements on the import side, trying to control for exchange rate movements on the export size. Their focus is on the exchange rate on exports.

[23] We thank Amit Khandelwal for pointing out to us this mechanism.

3.2 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 import higher quality inputs (In appendix A, we derive a model in which the spatial structure of a firm's imports depends on the quality it produces). So we expect the instrument to be positively correlated to quality in the cross-section of firms. This would induce the price elasticity to be biased toward zero. To fix this problem, we add variety-specific fixed effects (as defined above, a variety is a firm $\times$ product category $\times$ destination combination) to our demand estimation. As a result, identification is in the time series of a variety. Since the instrument is constructed using initial 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 firms' 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. Since we assume that price elasticity is common across firms, we also implicitly assume that the impact of a nominal exchange rate shock on a firm's demand curve is the same to all firms. So the impact of exchange rates on the demand shifter will be absorbed by market fixed effects. Because firms certainly face heterogeneous demand elasticities in practice, we provide several robustness checks in the appendix in order to further demonstrate the innocuity of this problem.. We proceed by excluding products sold by a firm that contemporaneously import from and export to a market (see appendix D, table 16). Price elasticity estimates exhibit little sensitivity to sample variations. This is suggestive that the 'competitiveness' mechanism is unlikely to affect our results.

A last potential threat to the identification could come from the fact that exchange rate variations directly cause quality adjustments.[24] Bastos et al. (2012) show that an exchange rate shock may induce a firm to upgrade its quality if it improves its competitiveness in rich destination markets. In appendix A, we propose a model which predicts a symmetric effect on the import side. In the model, 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.

[24] We thank Juan Carlos Hallak and Maria Bas for pointing out to us these potential threat to the identification.

There is no reason to think that quality changes resulting from exchange rates variations are correlated with the instrument in a systematic way. A priori, 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 sign of the bias on price-elasticity, if any, 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:

$$\overline{gpdc}_{ft}^{\text{exp}} = \sum_s \omega_{sft}^{\text{exp}} \times \log(\text{gdpc}_{st}) \tag{8}$$

$$\overline{gpdc}_{ft}^{\text{imp}} = \sum_s \omega_{sft}^{\text{imp}} \times \log(\text{gdpc}_{st}) \tag{9}$$

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.[25] In the mechanism described above, exchange rates are suspected to affect quality only through an impact on a firm's spatial structure of imports. Controlling for that structure of exports thus implies that the instrument is orthogonal to the demand residual. Model A provides a theoretical foundation to these controls.

Consistently with above discussion, our preferred econometric specification is:

$$\begin{cases} \log r_{fpdt} = (1-\sigma)\log p_{fpdt} + \alpha_2 \overline{gpdc}_{ft}^{\text{exp}} + \beta_2 \overline{gpdc}_{ft}^{\text{imp}} + \delta_{fpd}^{(2)} + \mu_{pdt}^{(2)} + \varepsilon_{fpdt}^{(2)} \\ \log p_{fpdt} = \gamma_1 \overline{RER}_{ft} + \gamma_2 \overline{RER}_{ft}^{h} + \alpha_1 \overline{gpdc}_{ft}^{\text{exp}} + \beta_1 \overline{gpdc}_{ft}^{\text{imp}} + \delta_{fpd}^{(1)} + \mu_{pdt}^{(1)} + \varepsilon_{fpdt}^{(1)} \end{cases} \tag{10}$$

With $\delta^{(i)}$, $i = 1,2$ and $\mu^{(i)}$, $i = 1,2$ respectively flow and market fixed effects. $\varepsilon^{(i)}$, $i = 1,2$ are residual terms. And the identifying assumption is:

$$\mathbb{E}\left[\begin{pmatrix} \overline{RER} \\ \overline{RER}^{h} \end{pmatrix} .\varepsilon^{(2)}\right] = 0$$

Namely, conditional on controls, $\overline{gpdc}^{\text{imp}}$ and $\overline{gpdc}^{\text{exp}}$, and fixed effects, demand shocks are uncorrelated to instruments.

In system (10), demand equation is identical to structural demand equation (5) where the

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

flow-specific demand shifter, λ_{fpdt}, is identified by:

$$\lambda_{fpdt} = \alpha_2 \overline{gpdc}_{ft}^{\text{exp}} + \beta_2 \overline{gpdc}_{ft}^{\text{imp}} + \delta_{fpd}^{(2)} + \varepsilon_{fpdt}^{(2)} \tag{11}$$

We demonstrate the effectiveness of our method in section 4.3.

4 Data and Demand Estimation Results

Previous section has described the estimation of quality. We now apply this procedure to French exporters using French 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 systematically larger, in absolute values, than corresponding OLS estimates. This is strongly suggestive that the use of our IV estimation corrects endogeneity biases described in section 3.1. Finally, we estimate quality levels by applying our methodology separately to different types of goods. We document the relevancy of our quality estimates through correlations with firm-level characteristics and existing measures of quality.

4.1 Data

We exploit firm-level trade data from the French customs. These data provide a comprehensive record of the yearly values and quantities exported and imported by French firms from 1995 to 2010. Trade flows are disaggregated at the firm, country and eight-digit product category of the combined nomenclature (CN).[26] Imports and exports are reported separately.

Information on quantities in trade data is known to be noisy. Because these noisy quantities are used to compute unit values, and could generate spurious correlations between quantities and prices, the data are cleaned 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.[27] 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.

[26] 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 affect our study since, this same year, the total values of flows contained in the dataset represented roughly 98% of the aggregated estimates of French international trade.

[27] Appendix B provides the details of the cleaning procedure.

there are really two samples: exporter-importer and exporter. Exporter-importer is sometimes reduced to 1995 importers such that flow and market fixed effects are identified.

Size of the Dataset After this cleaning procedure, the size of the dataset remains large, with more than 3 millions flows recorded every year. Table 1 displays the number of observations , varieties, and firms present in the exporting and importing tables of the dataset. 1995 importers are firms for which our instrument is constructed. Last column therefore gives us the actual size of the sample used to implement the estimation. We are left with approximately 45% of total observations, but since 1995 importers are large exports, their exports stand for almost 70% of the sample total.

Table 1: Size of the dataset

	Exports of Exporters	**Imports of Importers**	**Exports of Importers**	**Exports of 1995 Importers**
# **Observations**	29,102,408	37,804,366	25,583,171	13,257,803
# **Varieties**	5,144,897	10,108,471	4,074,342	1,799,738
# **Firms**	419,624	404,344	167,692	68,255
Share of Total Exports	100%	-	98%	67.5%

Notes: An observation is a trade flow at the firm, nc8 product, destination, year level. First column (respectively second column) contains the number of export (import) flows in the dataset. Third column reports the number of exporting flows for which importing flows are also reported for the same firm, at the same year. Fourth column reports the number of exporting flows for which importing flows are also reported for the same firm in 1995. A variety is a firm-product pair.

The estimation of demand functions requires a lot of variations in the data. First of all, due to the presence of market fixed effects, we need the instrument to vary across firms exporting to a given market. To get that, the set of source countries must differ across suppliers of a market. Secondly, because flow-specific and market-specific fixed effects will be used in the estimated equations, we need firms to serve a given product-destination for many years and product-destinations to be served by many firms simultaneously. Table 2 provides information about the distribution of the number of observations along different dimensions of the data. In this table, we provide statistics for the exports of the set of firms used to identify demand equations: firms being simultaneously importers in 1995 and exporters.[28] From table 2, one can see that the median importing-exporting firm sells in four different product category, to three different destinations, and imports from four different countries. The median flow (a firm-product-destination combination) is present for three years in the sample which means that flow

[28]In section 6, where we look at the effect of low-wage countries' competition, we use the entire set of exporters in our dataset. Similar statistics about this different set of firms can be found in table 15 of appendix C

fixed effects are identified for more than half the observations. Symmetrically, the median market is served by two firms so the market fixed effect is identified for at least half the sample. The last row is certainly the most important as it reports the number of 'identifying observations', i.e. the number of observations for which both the market and the flow fixed effect are identified. It appears that the price-elasticity is effectively estimated from close to 10 millions observations.

Table 2: Descriptive Statistics for the Exports of 1995 Importers

		p5	p25	p50	p75	p95	Mean
# **Products**	*by firm-year*	1	1	3	9	29	7.4
# **Destinations**	*by firm-year*	1	1	4	9	36	9.7
# **Source countries**	*by firm-year*	1	2	4	7	15	5.3
# **Products**	*by firm-country-year*	1	1	1	3	10	3.3
# **Destinations**	*by firm-product-year*	1	1	1	2	9	2.5
# **Years**	*by flow*	1	1	3	7	14	4.8
# **Flows**	*by market*	1	1	2	4	15	4.2
# **Identifying Observations**							**9,336,602**

Notes: These statistics are from firms being exporters and importers simultaneously in our sample. A 'flow' is a combination of a firm, a product and a destination. A 'market' is a combination of a product, a destination and a year.An 'Identifying Observation' is a firm-product-destination-year combination which belongs to a multiple-year flow and a multiple-firm market.

Descriptive Statistics on the Instrument The instrument crosses two informational sources: import shares and real exchange rates. Figure 1 reports the 1995-2010 evolution of real exchange rates for the top 5 countries in terms of total French imports. After 1999, Real-exchange-rate movements of countries in Euro zone after 1999 are due solely to different rates of inflation.

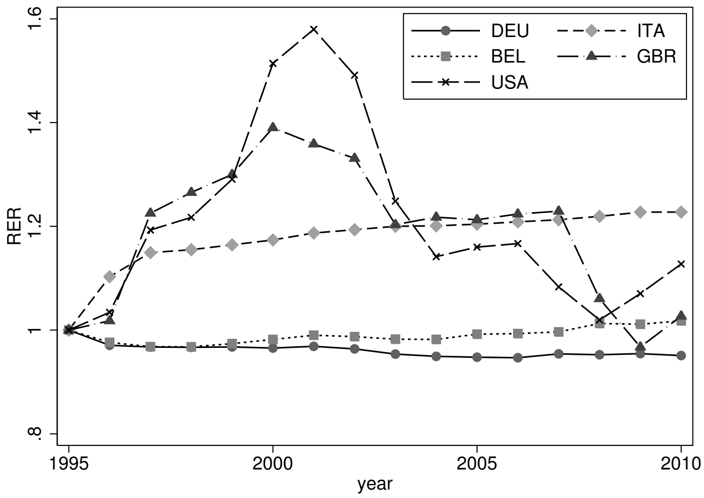
The instruments are constructed from 1995 import shares and intend to proxy a firm's exchange rate shocks over the period. One concern is that if import shares vary a lot over time, then the instrument would be a bad proxy for real exchange rate shocks occurring towards the end of the period. This might generate a weak instrument issue. In table 3 we report how import share autocorrelate over time within a firm. Even though the correlation of import shares at date t with 1995 import shares, they remain high and strongly significant. This is convincing that the instrument should not lose too much statistical power over time.

Table 3: Persistence of Import Shares over Time

Year t	**Correlation Import Shares** $(\omega_{fs1995}, \omega_{fst})$	**N**
1995	1.000	185,277
1996	0.850	120,282
1997	0.795	105,671
1998	0.761	97,060
1999	0.717	89,930
2000	0.691	83,164
2001	0.676	75,518
2002	0.658	69,734
2003	0.643	64,937
2004	0.630	61,449
2005	0.611	57,496
2006	0.604	54,418
2007	0.589	51,651
2008	0.585	49,079
2009	0.577	45,568
2010	0.563	44,044

Notes: This table reports the auto-correlation of firm-country import shares over time. We drop observations for non-exporters. All correlations are significant at 1%

Figure 1: RER 1995-2010-Top Source Countries



Notes: Real exchange rates are calculated as $e_{Euro,st} \times \frac{\text{CPI}_{st}}{\text{CPI}_{France,t}}$ 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 due solely to different inflation rates. 1995 real exchange rates are normalized to one.

4.2 Estimation procedure

The validity of the identification strategy requires to take into account market-specific effects, as well as flow-specific effects, in order to make the identification within-firm, within-market. This implies to estimate two large sets of fixed effects along these two dimensions. Estimation of linear equations with two sets of high-dimensional fixed effects and an unbalanced panel is cumbersome. Indeed, because the panel is unbalanced along these two dimensions, the two sets of fixed effects are not orthogonal. Consequently, our variables need to be simultaneously projected on these two sets of fixed effects, and we cannot rely on successive projections. In order to do so, we rely on the algorithm developed in Guimaraes and Portugal (2010). This algorithm aims to demean the variables of interest along the two sets of fixed effects. Parameters of interest are then estimated using demeaned variables.

The estimation procedure is carried out in two stages: a first stage regresses the logarithm of the export prices on the firm-specific weighted exchange rate, and the sets of fixed effects. In some specifications, we will introduce the average gdp per capita of destinations and source countries as controls. Moreover, we will also run separate specifications where we introduce the second instrument, taking into account the degree of hedging.[29] In order to predict variations in the logarithm of export sales, the second stage uses price predictions as an explanatory variable, as well as the other exogenous variables used in the first stage. Therefore, the parameter on price measures the price-elasticity of demand. Standard errors are adjusted to take into account this two-stages procedure. Moreover, we cluster standard errors at the market level, in order to avoid misleading inference that could potentially come from correlated demand shocks between varieties on a market.

4.3 Pooled Industries Results

In order to describe the effectiveness of the instrumental strategy, we will first present results when estimating an unique price-elasticity. The first stage of the estimation procedure shows that the instruments employed are strong enough, and impact export prices in a way consistent with economic theory. Then, we report the results of the second stage. Instrumentation corrects estimated coefficients as expected which provides support for the relevancy of our instrumental variable strategy.

First stage To build the instrument, we theorized that (i) exchange rate variations on imports input prices and (ii) that input prices impact output prices. As a preliminary test to our instrumental strategy, we test the first part of this causal chain. To do this, we regress the unit value of imports over the real exchange rates. A price is defined at the most disaggregate level: it corresponds to a firm-source country-CN 8 product category and a year. Firm-source-product fixed effects are added to the regression. Results are reported in table 4. As expected, real exchange rates significantly and positively impact input prices.

Then we turn to the first stage per se. Table 5 shows that our instruments are strongly correlated with export prices, the endogenous variable. It presents the results of the first stage for four different specifications. Columns (1) and (2) only use the contemporaneous average exchange rate, $\overline{RER}_{ft}$, as a predictor of export prices. The difference between these two columns lies in the inclusion of the term capturing the potential quality adjustment following changes in GDP per capita from destination or source countries: $\overline{gpdc}_{ft}^{\text{exp}}$ and $\overline{gpdc}_{ft}^{\text{imp}}$. In columns (3) and (4) the specification is augmented with the second instrument that takes into account the degree of hedging, $\overline{RER}_{ft}^{h}$.

Three main results emerge from table 5. First of all, the sign of the instruments' coefficients is consistent with the theoretical predictions. An increase in the average exchange rate faced by the firm is positively correlated with the price of its exported output. As an average effect,

[29] The instrument strength will become a potential issue when reducing the number of observations by applying this estimation procedure separately to a number of industries.

Table 4: Pass-through from Exchange-rates to Import Prices

	log Import Price$_{fpst}$
log RER$_{st}$	0.3072***
	(58.98)
Flow Effects	YES
N	15,477,199
R-square	0.003

Notes: A flow is a Prod×Dest×Year combination. t statistics in parentheses. *** p<0.01

Table 5: First stage results

	log price export			
	(1)	(2)	(3)	(4)
$R\bar{E}R_{ft}$	0.087***	0.092***	0.11***	0.12***
	(0.005)	(0.005)	(0.005)	(0.005)
$R\bar{E}R^{h}_{ft}$			-0.31***	-0.32***
			(0.023)	(0.024)
$g\bar{d}pc^{\mathbf{exp}}_{ft}$		0.007***		0.007***
		(0.001)		(0.001)
$g\bar{p}dc^{\mathbf{imp}}_{ft}$		0.012***		0.012***
		(0.001)		(0.001)
N	9 336 602	9 124 226	9 336 602	9 124 226
partial F-stat	326.5	341.4	267.53	273.6

Notes: Dependent variable is the logarithm of the price of the exported good, at the firm×nc8×destination×year level. $R\bar{E}R_{ft}$ is the import-weighted exchange rate for a firm, based on its importing shares in the first year of the sample. $R\bar{E}R^{h}_{ft}$ is the import×export weighted exchange rate for a firm, based on its importing and exporting shares in the first year of the sample. $g\bar{d}pc^{\exp}_{ft}$ is the average GDP per capita of the destinations of the firm. $g\bar{d}pc^{\text{imp}}_{ft}$ is the average GDP per capita of the sources countries of the firm. Partial F-statistics are computed excluding the average GDPs per capita. Firm×Prod×Dest and Prod×Dest×Year fixed effects included in all regressions. Market-level clustered standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

we find an elasticity of 0.9 between imported exchange rates and output prices. Moreover, we see that our second instrument is also consistent with the theory. Firms whose exporting shares are correlated with importing sharesare less affected by exchange rate changes since; potentially because they are able to hedge these variations away. Secondly, the coefficients for the GDP per capita per variables are also consistent with theory. As predicted in Bastos et al. (2012), following an increase in the average GDP per capita of its destinations, a firm should upgrade its product, generating a positive impact on prices. Similarly, the average gdp per capita of source countries is positively correlated with output prices, suggesting a positive correlation between the quality of the output and the characteristics of the countries the firm imports goods from. One can notice that the introduction of these two terms does not affect the relationship between the instrument and output prices. As mentioned earlier, there is no reason to think that the cost shifter generated by exchange rates variations should induce systematic changes in the quality choices made by firms. Therefore, it is not surprising to see that these two controls do not affect the strength of the instruments. Finally, we also observe that our set of instruments display a strong correlation with exported prices. With partial F-statistics ranging from 267 to 341, weak instruments are not an issue here.

Second stage After checking the validity of the first step, we use prices predicted by our set of instruments as an exogenous variable in the demand equation. We estimate the demand equation using the four different specifications displayed in table 5. Moreover, in order to assess the effectiveness of our instrumental strategy, we compare our result to a specification using OLS, that does not address the endogeneity problem. Results are displayed in table 6. We number columns so that second stage specifications have the same summer as corresponding first stage specification in table 5. In addition, column (0) presents the results of the OLS specification.

This table demonstrates the effectiveness of our instrumental strategy. The coefficient for the OLS regression in column (0) is biased due to simultaneity and measurement errors problems. Whereas measurement errors drive the estimate toward zero, the simultaneity problem generates a positive bias on the estimation of the elasticity. These predictions are confirmed with a positive coefficient of 0.18 for the OLS specification. By contrast, when using our sets of instrumental variables, the estimates for the price coefficient is lower, ranging from -0.82 to -1.38. This implies estimates of the price-elasticity of demand ($-\hat{\sigma}$) ranging from -1.82 to -2.38. that are consistent with the recent findings in the literature.[30]. Moreover, we can see that the coefficients on the variables $g\bar{p}dc_{ft}^{\text{expp}}$, $g\bar{p}dc_{ft}^{\text{imp}}$ are also consistent with the theory, since they reveal that products sourced and supplied to richer countries are of better quality (i.e. they are more demanded,

[30] 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. Some recent studies estimate firm-level price-elasticites for several industries. Foster et al. (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 (2011) a median of -2.11 with 504 products.

Table 6: Second stage results

	Log Export Sales				
	(0)	(1)	(2)	(3)	(4)
	OLS	IV	IV	IV	IV
Log price $(1-\hat{\sigma})$	**0.18*****	**-1.38*****	**-1.35*****	**-0.86*****	**-0.82*****
	(0.002)	(0.20)	(0.18)	(0.14)	(0.13)
$\overline{gpdc}_{ft}^{\mathbf{exp}}$			0.15***		0.15***
			(0.003)		(0.003)
$\overline{gpdc}_{ft}^{\mathbf{imp}}$			0.027***		0.021***
			(0.003)		(0.002)
Instrument	.	Single	Single	Hedg.	Hedg.
N	13 938 430	9 336 602	9 124 226	9 336 602	9 124 226

Notes: Dependent variable is the logarithm of export sales, at the firm×nc8×destination×year level. Log price is the prediction from the first stage. $\overline{gdpc}_{ft}^{\text{exp}}$ is the average GDP per capita of the destinations of the firm. $\overline{gdpc}_{ft}^{\text{imp}}$ is the average GDP per capita of the sources countries of the firm. Firm×Prod×Dest and Prod×Dest×Year fixed effects included in all regressions. Market-level clustered standard errors in parentheses, adjusted for the two stages estimation procedure. *** p<0.01

conditional on price). Finally, it is noteworthy that the estimates are quite consistent across specifications, even tough the specifications with two instruments seem to generate slightly bigger coefficients.[31]

Estimating a single coefficient for all industries shows that instrumenting affects estimates in a direction consistent with a correction of the simultaneouty bias in demand equations. However, in order to infer quality measures from these demand equations, we separately apply this method to different product categories.

4.4 Demand Estimation by Industry

In this section, we describe the results obtained by replicating the instrumentation strategy separately for fifteen product category.[32]. We use the set of instruments displayed in column

[31] This phenomenon could be related at a first sight to a weak instrument bias: while single-instrument IV regression are median-unbiased in the case of weak instruments, this is not true for specifications with more than one instrument (as in (3) and (4)). Therefore, those specifications could be affected by IV bias from weak instrument. However, this possibility is ruled out by the strength of our instruments in all specifications.

[32] Unfortunately, when estimating at a more disaggregated level of the product classification, the number of observations per product category decreases and our instruments become weak in an important subset of product categories.

(4) of table 5. As a way to make our first stage as strong as possible, this specification includes the instrument taking into account the degree of hedging as well as both gdp per capita control variables.

Product-specific price-elasticity estimates The results of this procedure are displayed in table 7. For each product category, we report the IV and OLS estimates of the price-elasticities of demand, as well as the F-statistics of the first stage of the instrumental variable procedure.

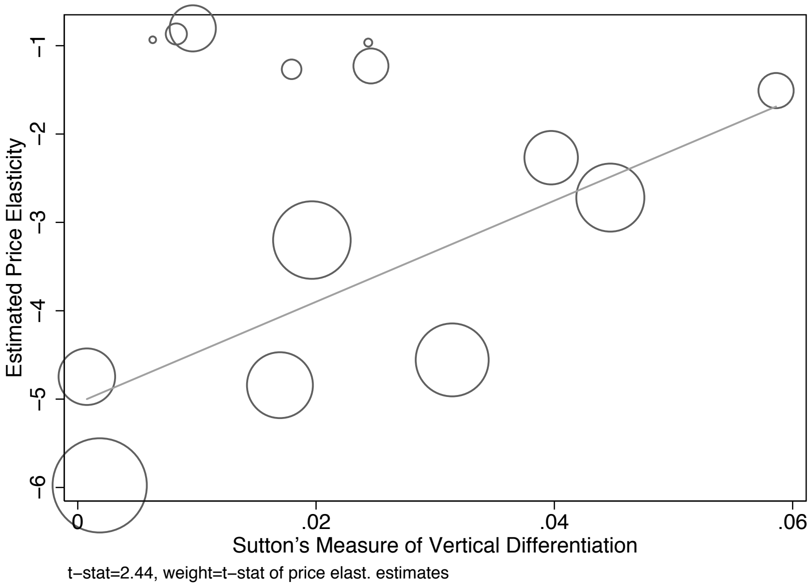
Table 7: Price-elasticity estimates ($-\sigma$) for different product categories

Product categories	**OLS**		**IV**		
	Coef	SE	Coef	SE	F-stat
Animal Products	-0.83	(0.015)	**13.3**	(20.3)	1.17
Textiles	-0.69	(0.004)	**-0.80*** **	(0.14)	331.9
Metals	-0.81	(0.006)	**-0.87***	(0.46)	22.3
Vegetable Products	-0.81	(0.011)	**-0.93**	(2.27)	1.91
Foodstuffs	-0.95	(0.007)	**-0.97**	(0.81)	11.8
Machinery, Electrical	-0.85	(0.004)	**-1.23*** **	(0.29)	40.8
Wood, Wood products	-0.79	(0.007)	**-1.27**	(1.08)	2.93
Chemicals and Allied	-0.90	(0.006)	**-1.51*** **	(0.63)	12.9
Plastics, Rubbers	-0.86	(0.008)	**-2.27*** **	(0.68)	12.6
Miscellaneous	-0.76	(0.005)	**-2.72*** **	(0.57)	9.75
Transportation	-0.71	(0.012)	**-3.20*** **	(0.56)	23.85
Stone, Glass	-0.82	(0.009)	**-4.55*** **	(1.03)	4.93
Mineral Products	-0.81	(0.022)	**-4.75*** **	(1.80)	2.30
Footwear, Headgear	-0.72	(0.013)	**-4.84*** **	(1.36)	3.6
Raw Hides, Skins, Leather...	-0.77	(0.010)	**-5.98*** **	(0.86)	8.08

Notes: Each row corresponds to a product category for which the demand equation is estimated. The IV specifications use the average exchange rates as instruments $\overline{RER}_{ft}$, in addition to the hedging term, $\overline{RER}^h_{ft}$, and the two gdp per capita controls, $\overline{gpdc}^{\text{exp}}_{ft}$ and $\overline{gpdc}^{\text{imp}}_{ft}$. Last column provides the value of the partial F-statistic of the first stage of the 2SLS procedure. Firm×Prod×Dest and Prod×Dest×Year fixed effects are included in all regressions. Standard errors are clustered at the market level. * p<0.1, ** p<0.05, *** p<0.01

We can see from table 7 that, for almost all industries, the IV coefficient is higher in absolute values than the OLS coefficients. This is consistent with our instrument correcting with the simultaneity bias that links quality and prices in demand equation. While the OLS estimates seem strongly driven by measurement errors, our IV estimates are all negative, and in a range consistent with the existing literature in Industrial Organization. As an outlier, the first product category, related to Animal Products records a very large and positive elasticity, that is due to a large imprecision of this parameter. Because of this, we will exclude this product category for the rest of the paper. Overall our estimates range from -0.80 to -5.98 for vertically-differentiated goods, Foster et al. (2008) estimate price-elasticities from -0.52 to -5.93 for eleven homogenous goods. More generally, we can see that our procedure performs poorly in industries that primarily rely on natural resources: Indeed, low F-stat are recorded for Animal, Vegetable, Mineral and Wood Products. This is consistent with our identification strategy since it is likely that these industries mainly rely on domestic inputs and therefore, won't be affected by exchange rates variations.

Figure 2: Price Elasticity Versus Vertical Differentiation



Notes: Each circle corresponds to a product category, i.e. a 1-digit position of the HS classification. The size of a circle is proportional to the absolute value of the t-statistics on $1-\sigma$. The x-axis is Sutton (2001)'s measure of vertical differentiation, i.e. the share of R&D and advertising expenditures in a sector's total sales. It is computed at the ISIC 4-digit rev. 2 level, by Kugler and Verhoogen (2012), using US data. To compute it at the product category level, we average Sutton's measure over the different ISIC 4-digit rev. 2 a product category belongs to, and we weight by total exports over the period. The y-axis is equal to estimated price-elasticity. The line is the predicted value of a weighted OLS regression of price-elasticity over Sutton's measure. Weights are the absolute value of the t-statistics on $1-\sigma$. "Animal Products" excluded from the regression. The relationship is not significant when it is included.

As a way to assess the reasonableness our price elasticity estimates, we correlate them to Sutton (2001)'s measure of vertical differentiation. Our expectation is that in vertically differentiated sectors, consumers are more sensitive to quality and less to prices. As shown by figure 2, the demand faced by exporters of vertically differentiated products is significantly more elastic. This is consistent our prediction.

5 Analysis of Estimated Quality

Once demand functions have been estimated, we simply pick up quality using (11). As a first way to describe our estimates of quality, in table 8 we provide a decomposition along several dimensions. Here, it is important to remember that this 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. One can see from table 8 that the dispersion of quality is well predicted by variety-specific effects. Indeed, half of this quality dispersion is captured by time-invariant variety-specific effects, and two thirds 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. We will rely on this evidence that quality choices are made at the variety level, when identifying quality upgrading in a destination from competition shocks in other destinations served by a variety.

Table 8: Variance Decomposition of the quality measure

	Quality λ_{fpdt}			
Firm FE	✓			
Firm×Prod FE		✓		
Firm×Year FE			✓	
Firm×Prod×Year FE				✓
R^2	0.17	0.51	0.23	0.69

Notes: Each column describes the regression of our quality measure from table 7 on a different set of fixed effects.

We can see that there is still a wide variation across destinations. Controlling for Firm×Prod×Year FE, we can predict 69 percents of the variation of our quality measure. Moreover, half of the variation between firms are captured by firm×product fixed effects.

5.1 A consistency test: Estimated versus Expert Assessed Quality

In order to assess the relevancy of our measure, we relate it to the only objective quality measure that we are aware of 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.

We correlate These expert assessed ratings to our revealed measure quality for Champagne exports.[33] The quality of Champagne is described by a number of stars, one being the lowest quality, and five the highest. We nonparametrically regress our measure of quality for Champagne producers to their respective assigned quality. Results are presented in table 9.

Table 9: Estimated Versus Expert Assessed Quality of Champagne Exports

	Quality λ_{fpdt}
2 Stars	0.060***
	(0.006)
3 Stars	0.112***
	(0.006)
4 Stars	1.245***
	(0.005)
5 Stars	1.421***
	(0.007)
N	31,116
R-squared	0.136

Notes: Dependent variable is estimated quality λ_{fpdt}. We match Champagne producers with the ratings used in Crozet et al. (2012), initially coming from Juhlin (2008). A larger number of star means a higher expert assessed quality. We drop non-Champagne exports of Champagne producers. Robust standard errors in parentheses. *** $p < 0.01$

We can see from table 9 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 reassuring about the

[33]We thank the authors for sharing their data

relevancy of our estimated measure of quality.

5.2 Correlation with firm-level variables

In order to further improve our understanding of the characteristics of our quality measure, we relate its estimated value to firms' characteristics. We merge our estimated qualities with firm-level data from France. 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.[34] Therefore, we are able to inspect how our quality measure is able to explain firm characteristics such as prices or average wages. Table 10 inspects these correlations using the number of employees of the firm, its average wage, and our estimates of quality.

Table 10: Estimated Quality and Firm characteristics

	Log average wage			
	(5)	(6)	(7)	(8)
Est. quality	0.008***	0.009***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
log(employment)		-0.010***		-0.010***
		(0.004)		(0.004)
log(export price)			0.032***	0.032***
			(0.003)	(0.003)
N	13 468 383	13 468 383	13 468 383	13 468 383

The results displayed in table 10 are reassuring about the relevancy of our measure. First of all, we can see in panel B that our estimated measure of quality is again a predictor of the wages paid by the firm. Interestingly once estimated quality is controlled for, the sign of the wage-size correlation is significantly negative. Without controlling for quality, the literature finds a positive relationship between size and wages (see Verhoogen (2008)). The theoretically explanation is that (i) wages contain information on workers'quality and (ii) firms employing higher quality workers are larger. In these theories, the positive relationship may be turned to negative as soon as firms are assumed vertically homogeneous. Therefore, we interpret the fact that the we get a negative coefficient on employees as a signal that estimated quality is a good control for workers'quality.

[34]This dataset has been widely used in the literature (see Eaton et al. (2011) or Berman et al. (2012) for instance).

5.3 How well do Prices proxy for Quality?

As a last way to analyze the properties of our measure of quality, we look at the relationship between estimated quality and export prices. This is an important point since prices have been extensively used in the literature as a proxy for quality. The problem is that prices are supposedly also a function of a firm's production cost. Therefore in sector with little vertical differentiation, prices should poorly capture differences in demand fundamentals, whether across firms or over time. To test this intuition, we regress (log) prices over estimated quality and we allow the slope of the relationship to depend on Sutton's measure of vertical differentiation.

Table 11: Relationship between Prices and Quality across Sectors

	log $Export\ Price_{fpdt}$ (1)	(2)
Quality λ_{fpdt}	0.033***	0.025***
	(0.000)	(0.001)
Quality$_{fpdt}$ × **Sutton**$_p$	1.260***	1.048***
	(0.005)	(0.018)
Market Effects	YES	YES
Flow Effects	NO	YES
N	13 542 905	13 542 905
R-squared	0.845	0.983

Notes: Dependent variable is the logarithm of exports unit value at the firm×nc8×destination×year level. 'Sutton' is the share of advertising and R&D expenditures in a US sector's sales. It is computed at the 4 digit level of ISIC-rev 4 classification by Kugler and Verhoogen (2012). A flow is a firm×nc8×destination combination. A market is a nc8×destination×year combination. Market-level clustered standard errors in parentheses. *** $p < 0.01$

Results for this exercise are reported in table 11. First finding is that there is a positive relationship between estimated quality and prices in all sector. However, the slope of that relationship is significantly steeper in more vertically differentiated industries, consistently with the intuition presented above. This is true whether we look in the cross-section of a market (column (1)) or in the dynamics of a flow (column (2)). To get a sense of the magnitude of the differences in slope across sectors, let us compare the quality-elasticity of prices between "mineral products" and "chemical and allied", respectively the least and the most vertically differentiated product categories. In "mineral products", the quality-elasticity of prices is approximately 0.035 when it is about 0.11 in "chemical and allied". This means that prices are three time less informative on quality for "mineral products" than for "chemical and allied".

6 The Quality Response to Low-Wage Countries' Competition

In this section, we exploit our measure of quality to document the quality response of French firms to low-cost competition. We start by describing this identification strategy in the next section, and then display the results of the estimation.

6.1 Identification strategy

Following Bernard et al. (2009), we define low-wage countries'competition (LWC) as the share of imports from countries with a GDP per capita inferior to 5% of French GDP per capita. More specifically, LWC is constructed from bilateral trade dataset BACI, according to following formula:

$$LWC_{pdt} = \frac{I_{idt}^{\text{low}}}{I_{idt}}, \tag{12}$$

Where I_{idt}^{low} is country d's imports of 6-digit HS product i from low-wage countries at date t. Respectively, I_{idt} is country d's total imports of product i at date t. In equation (12), p is an 8-digit CN product position which belongs to 6-digit HS category i.[35]

A natural way to identify the within-firm quality response to LWC would be to regress the dynamics of the quality measure, λ_{fpdt}, over the dynamics of LWC_{pdt}. Since LWC does not vary across firms within a market, this approach would amount to looking at the impact of LWC over the mean quality of exports in a market. The problem is that our measure of quality is defined relatively to the average quality in a market. So its market-level mean is normalized to zero and is constant over time. As a consequence, identification requires variation in low-cost competition across firms, within a market.

In order to generate such variation, we make use of the information on multi-destinations exporters. Within a market, firms differ in the other markets they serve simultaneously. Therefore, for any given market, we can construct a measure of the competition faced by a firm-product variety in the rest of the world. Let LWC_{fpdt}^{ROW} be that measure and let t_{0fp} be the first year when fvariety fp is observed in the sample. LWC_{fpdt}^{ROW} verifies:

$$LWC_{fpdt}^{ROW} = \frac{\sum_{d' \in \mathcal{D}_{0fp}, d' \neq d} r_{0fpd'} \times LWC_{pd't}}{\sum_{d' \in \mathcal{D}_{0fp}, d' \neq d} r_{0fpd'}}$$

[35] Documentation about BACI can be found in Gaulier and Zignago (2010)

With $\mathcal{D}_{0fp}$ the product-specific set of destinations of a variety $f-p$ at date t_{0fp}. r_{0fpd} is the sales of variety fp in destination d, at initial date t_{0fp}.

In the cross-section of a market, a variety with a higher LWC^{ROW} faces a fiercer low-wage competition in the rest of the world. Our identification strategy consists in correlating the dynamics of LWC^{ROW}_{fpdt} with the dynamics of λ_{fpdt}. Since competition shocks we exploit occur in a market different from the quality adjustments we intend to identify, our identifying assumption is that quality variations are correlated across destinations within a variety. In the extreme case where a variety is served with a same quality in all destinations, our strategy would capture the exact impact of a local competition shock on local quality. In general, the effect we estimate will be discounted for the fact that qualities do not perfectly co-move across destinations.

Our econometric specification is:

$$\lambda_{fpdt} = \sum_{\tau=0}^{5} \beta_\tau LWC^{ROW}_{fpd,t-\tau} + FE_{fpd} + FE_{pdt} + u_{fpdt} \tag{13}$$

With FE_{fpd} a set of flow fixed effects and FE_{pdt} a set of market fixed effects. Model (13) identifies the effect of competition on quality, up to a five years lag. FE_{pdt} controls for the fact that competition in the rest of the world could be correlated to local competition shocks. Flow fixed effect FE_{fpd} controls for the average quality of a flow over the period. Flow fixed effects are included because in the cross-section of a market, quality might be correlated to LWC^{ROW}_{fidt} through the self-selection of firms into export markets over quality. For instance, high quality firms might self-select into markets with stronger low-wage competition. The inclusion of flow-fixed places the estimation in the dynamics of a trade flow. As we use initial export shares to construct LWC^{ROW}, its dynamics is not driven by some (endogenous) reallocation of exports.

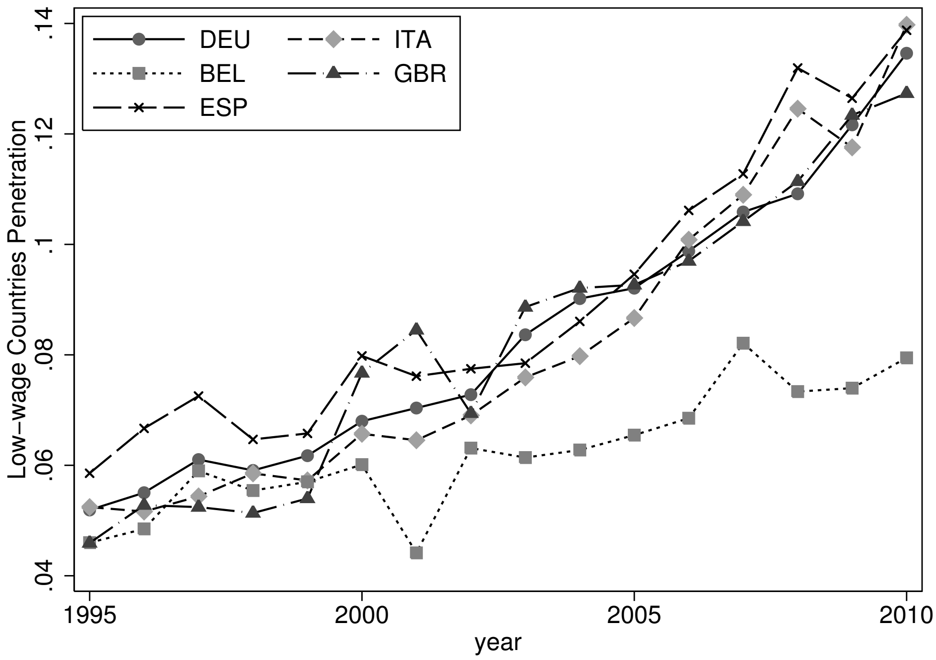
Given our fixed effect specification, our identifying assumption is that the relative dynamics of LWC^{ROW} across firm-product-destination flows, within a product-destination market are exogenous to relative quality shocks. Next subsection presents our results.

6.2 Results

In this subsection, we show the results obtained by estimating variants equation (13). Specifications will differ in the dependent variable we consider as well as in the number of lags we estimate.

Before turning to the core results, we report some descriptive elements on low-wage competition. In figure 3, we plot the penetration of low-wage countries by year in the top five largest destination markets for French exporters. Unsurprisingly, the penetration has increased steadily over the period and consistently across destinations. Our identification will come from the difference in the dynamics across countries.

Figure 3: Low-wage Countries' Penetration 1995-2010-Top Source Countries



Results from our main specification are reported in table 12. To obtain table 12, we have run specification (13) first by including each lag of rest-of-the-world competition separately and then by including all lags together. In order to make regressions comparable, we use a same sample of firms for which we observe at least five lags of quality. Overall, 12 suggests little quality upgrading. Only LWC_{t-4}^{ROW} is significant at 10%, when included alone. Coefficient 0.1738 associated to LWC_{t-4}^{ROW} means that after 4 years, a 10 percentage point increase in the rest-of-the-world low-cost penetration causes the firm to quality to increase by 2%. We think of the fact that the effect of competition takes time to occur as being indicative of the fact that we are indeed capturing some quality upgrading. Indeed, our measure of quality is revealed from the demand faced by a firm. No matter the way the firm produces higher quality, it seems reasonable to think that it takes time to result into larger sales.

In order to gain confidence into the fact that the effect we capture in table 12 is indeed a quality upgrading response to competition, we now interact our measure of competition we a sectoral measure of the vertical differentiation. Our prediction is that the effect of competition should be larger for more vertically differentiated sectors as firms from homogeneous sectors can

Table 12: Rest-of-the-world low-wage Competition and Quality Upgrading.

	Dep. variable: Quality $\lambda_{f,p,d,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LWC_t^{ROW}	0.0296						0.0409
	(0.35)						(0.49)
LWC_{t-1}^{ROW}		-0.0690					-0.0868
		(-0.81)					(-1.02)
LWC_{t-2}^{ROW}			0.0654				0.0585
			(0.75)				(0.67)
LWC_{t-3}^{ROW}				0.1232			0.0922
				(1.34)			(1.01)
LWC_{t-4}^{ROW}					0.1738*		0.1432
					(1.84)		(1.52)
LWC_{t-5}^{ROW}						0.1298	0.1023
						(1.39)	(1.09)
Observations	911,601	911,601	911,601	911,601	911,601	911,601	911,601
R^2	0.934	0.934	0.934	0.934	0.934	0.934	0.934

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

not adjust their quality. This prediction is confirmed in table 13. More specifically, we see that for that the interaction term is significant for the third and fourth lag. This confirms the fact that the effect we identified in 12 is driven by firms from vertically differentiated sectors. This is reassuring that we are actually capturing a quality response.

As a robustness check, we re-run specification (13) by taking prices, instead of quality, as a dependent variable. The results are reported in table 14. This robustness test is motivated by the assumption that quality is costly to produce. [36]. Therefore, a quality upgrading should also show up through increased prices. This is the message from table 14. In addition, we can notice that if the response on prices takes time, it occurs sooner the quality response in table 12. Combined, these results suggest that the quality upgrading operated by firms takes time to translate into larger sales (conditional on prices).

All in all, these results are very suggestive that firms upgrade their quality when the penetration of low-wage countries go up.

[36]See, e.g., Hallak and Sivadasan (2011), Johnson (2012) and Kugler and Verhoogen (2012) for trade models where quality is costly and endogenous at the firm-level.

Table 13: Is Quality Upgrading more Significant in more Vertically Differentiated Sectors?

	Dep. variable: Quality $\lambda_{f,p,d,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LWC_{t}^{ROW}	0.0006						-0.0004
	(0.00)						(-0.00)
$LWC_{t}^{ROW}\times$ Sutton	1.8691						2.4517
	(0.47)						(0.62)
LWC_{t-1}^{ROW}		-0.0276					-0.0191
		(-0.19)					(-0.13)
$LWC_{t-1}^{ROW}\times$ Sutton		-2.9749					-3.6405
		(-0.75)					(-0.91)
LWC_{t-2}^{ROW}			-0.0144				0.0254
			(-0.10)				(0.17)
$LWC_{t-2}^{ROW}\times$ Sutton			-0.7124				-2.4117
			(-0.17)				(-0.55)
LWC_{t-3}^{ROW}				-0.1583			-0.1474
				(-1.07)			(-1.00)
$LWC_{t-3}^{ROW}\times$ Sutton				9.3622**			8.5479**
				(2.33)			(2.08)
LWC_{t-4}^{ROW}					-0.1186		-0.1187
					(-0.76)		(-0.75)
$LWC_{t-4}^{ROW}\times$ Sutton					9.5673**		8.8398**
					(2.27)		(2.01)
LWC_{t-5}^{ROW}						0.1297	0.1811
						(0.87)	(1.20)
$LWC_{t-5}^{ROW}\times$ Sutton						-1.3316	-4.3254
						(-0.32)	(-1.03)
Observations	728394	728394	728394	728394	728394	728394	728394
R^2	0.939	0.939	0.939	0.939	0.939	0.939	0.939

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

7 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 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

Table 14: How Do Prices Adjust to Competition?

	Dep. variable: log export prices						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LWC_t^{ROW}	0.0060						0.0042
	(0.32)						(0.22)
LWC_{t-1}^{ROW}		0.0240					0.0169
		(1.27)					(0.90)
LWC_{t-2}^{ROW}			0.0461**				0.0359*
			(2.33)				(1.82)
LWC_{t-3}^{ROW}				0.0532***			0.0375*
				(2.61)			(1.84)
LWC_{t-4}^{ROW}					0.0688***		0.0514**
					(3.33)		(2.47)
LWC_{t-5}^{ROW}						0.0726***	0.0624***
						(3.42)	(2.93)
Observations	911601	911601	911601	911601	911601	911601	911601
R^2	0.992	0.992	0.992	0.992	0.992	0.992	0.992

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

quality at the firm-level. Our strategy is robust to unobserved vertical differentiation. It only requires firm-product information on prices, sales and imports by country.

We identify quality by estimating a demand function at the firm-product level. Quality is obtained as a residual of demand, once prices have been controlled for. In order to deal with the endogeneity of prices in the demand function, we construct a new firm-specific instrument. This instrument interacts variations in exchange rates with firm-specific importing shares. We implement our estimation on French customs data and get a number of elements supporting the reliability of our approach.

As a first application to our method, we compare (export) prices, a widely used proxy for quality, with our export quality estimates. We find a positive and significant relationship between quality and prices, however, this relationship is weaker in more homogeneous sectors. These results hold in the cross-section as well as in the dynamics of a firm. Our findings calls for a cautious use of prices to measure quality.

Finally, we use estimated quality, along with information on low-wage countries penetration rates to identify the quality response of firms' exports to low-wage countries' competition. Our results suggest that firms upgrade their quality when competition intensifies. This result is important for policy analysis as it reveals a new channel through which exporting firms can mitigate the effect of low-wage competition.

References

Mary Amiti, Oleg Itskhoki, and Jozef Konings. Importers, exporters, and exchange rate disconnect. Technical report, forthcoming.

Simon P Anderson, André De Palma, and Jacques-Francois Thisse. The ces is a discrete choice model? *Economics Letters*, 24(2):139–140, 1987.

David H Autor, David Dorn, and Gordon H Hanson. The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 2013.

Richard Baldwin and James Harrigan. Zeros, quality, and space: Trade theory and trade evidence. *American Economic Journal: Microeconomics*, 3(2):60–88, 2011.

Paulo Bastos, Joana Silva, and Eric Verhoogen. Export destinations and input prices: Evidence from portugal. 2012.

Nicolas Berman, Philippe Martin, and Thierry Mayer. How do different exporters react to exchange rate changes? *The Quarterly Journal of Economics*, 127(1):437–492, 2012.

Andrew B Bernard, J Bradford Jensen, and Peter K Schott. Importers, exporters and multinationals: a portrait of firms in the us that trade goods. In *Producer Dynamics: New Evidence from Micro Data*, pages 513–552. University of Chicago Press, 2009.

Steven Berry, James Levinsohn, and Ariel Pakes. Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, pages 841–890, 1995.

Irene Brambilla, Daniel Lederman, and Guido Porto. Exports, export destinations, and skills. *The American Economic Review*, 102(7):3406–38, 2012.

Christian Broda and David E Weinstein. Globalization and the gains from variety. *The Quarterly Journal of Economics*, 121(2):541–585, 2006.

Christian Broda and David E Weinstein. Product creation and destruction: Evidence and price implications. *The American economic review*, 100(3):691–723, 2010.

Raj Chetty. Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply. *Econometrica*, 80(3):969–1018, 2012.

Matthieu Crozet, Keith Head, and Thierry Mayer. Quality sorting and trade: Firm-level evidence for french wine. *The Review of Economic Studies*, 79(2):609–644, 2012.

Jean-Pierre Dubé. Multiple discreteness and product differentiation: Demand for carbonated soft drinks. *Marketing Science*, 23(1):66–81, 2004.

Jonathan Eaton, Samuel Kortum, and Francis Kramarz. An anatomy of international trade: Evidence from french firms. *Econometrica*, 79(5):1453–1498, 2011.

B. Faber. Trade liberalization, the price of quality, and inequality: Evidence from mexican store prices. 2012.

Robert C Feenstra. New product varieties and the measurement of international prices. *The American Economic Review*, pages 157–177, 1994.

Robert C Feenstra and John Romalis. International prices and endogenous quality. Technical report, National Bureau of Economic Research, 2012.

Lucia Foster, John Haltiwanger, and Chad Syverson. Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, 98(1):394–425, 2008.

Guillaume Gaulier and Soledad Zignago. Baci: International trade database at the product-level (the 1994-2007 version). 2010.

A. Gervais. Product quality and firm heterogeneity in international trade. *University of Notre Dame Unpublished Manuscript*, 2011.

Paulo Guimaraes and Pedro Portugal. A simple feasible procedure to fit models with high-dimensional fixed effects. *Stata Journal*, 10(4):628, 2010.

J.C. Hallak and P.K. Schott. Estimating cross-country differences in product quality. *The Quarterly Journal of Economics*, 126(1):417–474, 2011.

Juan Carlos Hallak. Product quality and the direction of trade. *Journal of International Economics*, 68(1):238–265, 2006.

Juan Carlos Hallak and Jagadeesh Sivadasan. Firms' exporting behavior under quality constraints. 2011.

J. Handbury. Are poor cities cheap for everyone? non-homotheticity and the cost of living across us cities. 2012.

Jerry A Hausman. Valuation of new goods under perfect and imperfect competition. In *The economics of new goods*, pages 207–248. University of Chicago Press, 1996.

Jean Imbs and Isabelle Méjean. Elasticity optimism. 2008.

Robert C Johnson. Trade and prices with heterogeneous firms. *Journal of International Economics*, 86(1):43–56, 2012.

R. Juhlin. *Champagne Guide*. Richard Juhlin Publishing AB, 2008.

A. Khandelwal. The long and short (of) quality ladders. *The Review of Economic Studies*, 77 (4):1450–1476, 2010.

A.K. Khandelwal, P.K. Schott, and S.J. Wei. Trade liberalization and embedded institutional reform: Evidence from chinese exporters. *American Economic Review*, forthcoming.

M. Kugler and E. Verhoogen. Prices, plant size, and product quality. *The Review of Economic Studies*, 79(1):307–339, 2012.

Kalina Manova and Zhiwei Zhang. Export prices across firms and destinations. *The Quarterly Journal of Economics*, 127(1):379–436, 2012.

J. Martin and I. Méjean. Low-wage countries' competition, reallocation across firms and the quality content of exports. 2011.

Aviv Nevo. Mergers with differentiated products: The case of the ready-to-eat cereal industry. *The RAND Journal of Economics*, pages 395–421, 2000.

Justin R Pierce and Peter K Schott. Concording us harmonized system codes over time. *Journal of Official Statistics*, 28(1):53–68, 2012.

M.J. Roberts, D.Y. Xu, X. Fan, and S. Zhang. A structural model of demand, cost, and export market selection for chinese footwear producers. *NBER*, 2012.

Peter K Schott. Across-product versus within-product specialization in international trade. *The Quarterly Journal of Economics*, 119(2):647–678, 2004.

John Sutton. *Technology and market structure: theory and history*. The MIT Press, 2001.

Eric A Verhoogen. Trade, quality upgrading, and wage inequality in the mexican manufacturing sector. *The Quarterly Journal of Economics*, 123(2):489–530, 2008.

A A Simple Model of Endogenous Quality with Imported Inputs

In the section, we develop a partial equilibrium model with heterogeneous firms, endogenous quality, and imported inputs. The model builds upon the first variant of Kugler and Verhoogen (2012)'s model: quality only impacts variable production costs, not fixed costs. We extend the original model by assuming that production is obtained by combining a set of imported inputs rather than just a single input. The main purpose of this simple model is to ground theoretically the validity of our instrument for prices. The model formalizes the relationship between the RER's faced by a firm on its imports and its export price and hence validates the rank condition. As to the exogeneity of the instrument, the model predicts that importing shares are endogenous to quality and thus suggests that importing shares should be set constant in the instrument, which is what we do in the estimation. Moreover, the model delivers a mechanism through which quality could be endogenous to RER's on imports. This potential endogeneity of the instrument can be neutralized by controlling for a sufficient statistic also provided by the model.

In addition to its predictions on the validity of the instrument, the model delivers implications on other issues. First, we show that in the model, we can perfectly rank varieties in quality using λ. Second, on the quality response to low-cost competition, the model predicts that firms in the lower end of the quality ladder should upgrade their quality to escape competition from new entrants.

A.1 Technology

As in the model of demand developed in section 2, the unit of analysis is a variety of a differentiated final good [37]. A variety is produced by combining inputs from different sources. For each input, a firm must decide the quality and the number of physical units involved in the production of a variety. These decisions impact the volume and the quality of the output. This production process is thus described by two functions: one for physical production, another one for the production of quality.

The physical production function is:

$$x_{v,t} = \varphi^a_{v,t} \left(\sum_{s \in \mathcal{S}_v} \gamma_{v,s} [z_{s,v,t}]^{\frac{\kappa-1}{\kappa}} \right)^{\frac{\kappa}{\kappa-1}} \tag{14}$$

With $x_{v,t}$ the physical output and $z_{s,v,t}$ the quantity of input from source s involved in the production of variety v. κ is the elasticity of substitution across inputs. $\gamma_{v,s}$ is the weight of input

[37] In this model, a firm is a collection of independent production lines, each line producing a variety.

from s in the production of v ($\sum_{s\in\mathcal{S}_v}\gamma_{v,s}=1$). $\varphi_{v,t}$ is what Kugler and Verhoogen (2012) refer to as "capability". As it appears in (14), $\varphi_{v,t}$ is of the same nature as total factor productivity: it shifts up output conditional on inputs. However, unlike physical productivity, and as will be formalized below, capability also plays a role in the production of quality. Parameter a is simply the capability-elasticity of physical output. We assume $a > 0$.

$\mathcal{S}_v$ is the set of source countries of a firm. We take $\mathcal{S}_v$ as fixed and given. Our sense is that making $\mathcal{S}_v$ endogenous and varying (by assuming fixed export costs for instance) would not change the main qualitative insights of the model.

Inputs are vertically differentiated. Input quality determines output quality through following function:

$$q_{v,t} = \left[\frac{1}{2}\left(\varphi_{v,t}^{b}\right)^{\theta} + \frac{1}{2}\left(\min\left\{q_{I,s,v,t}\right\}_{s\in\mathcal{S}_v}\right)^{\theta}\right]^{\frac{1}{\theta}} \tag{15}$$

With $q_{v,t}$ output quality and $q_{I,s,v,t}$ input s quality. The production of quality is CES in capability and in the quality of imported inputs. The innovation with respect to Kugler and Verhoogen (2012) is that a firm must decide on the quality not of a single input but of many inputs. Here we assume that different input qualities combine through a Leontieff production function. This specification is convenient as it boils the quality choice of a firm down to picking a single quality throughout all its imports. A more flexible CES form would leave our main qualitative results unaltered [38].

We assume $\theta < 0$ so that input quality and capability are complementary. This means that the quality upgrading obtained from a marginal increase in the quality of inputs is larger for high capability firms/varieties. This structure leads high capability firms to produce higher quality goods. Parameter b simply drives the elasticity of quality production to capability: a higher b gives a larger incentive to higher φ firms to produce high quality goods. We assume $b > 0$.

The last technology assumption regards the price of inputs. In each country, the input is produced from labor under perfect competition and constant returns to scale. Unit labor requirements are a power function of input quality. As a result, the price of input from source s with quality q_I is:

$$p^*_{I,s,t}(q_I) = w_{s,t}q_I^{\beta_s} \tag{16}$$

$p^*_{I,s,t}(q_I)$ is the FOB (Free on board) price of input with quality q_I labelled in s's currency. $w_{s,t}$ is the unit wage rate in s. β_s is the elasticity of input price to quality in source s. One

[38] In next subsection, we discuss the fact that allowing for more substitutability across qualities plays in favor of the validity of our instrument. In that sense, the Leontieff specification is conservative.

should think of β_s as the relative price of high to low quality in country s. As evidenced by Schott (2004), rich countries have a comparative advantage in the production of high quality goods. In terms of the model, it means that β_s is larger for poor countries. The key implication of specification (16) is that the optimal spatial allocation of a firm's imports depends on a firm's quality: high quality firms import high quality inputs from low β (rich) countries.

Imports of inputs involves iceberg costs. The CIF cost of an input s with quality q_I, labelled in home currency (one should think of home as France, consistently with the empirical application) is:

$$p_{I,s,t}(q_I) = e_{H,s,t}\tau_{H,s,t}p^*_{I,s,t}(q_I)$$

With $e_{H,s,t}$ the direct nominal exchange rate between home and s and $\tau_{H,s,t}$ the iceberg trade cost between home and s ($\tau \geq 1$).

Next subsection solves the optimal price, import shares and quality of the firm and draws the implications for the validity of our instrument for prices.

A.2 Prices, Quality, Import Shares and RER's

The rank condition: RER and prices A variety v faces demand (2). We assume that competition is monopolistic so that firms charge a constant mark-up over their marginal cost:

$$p_{v,t} = \frac{\sigma_g}{\sigma_g - 1} mc_{v,t}$$

We obtain the expression of the marginal cost of a firm (conditional on output quality) as follows. First, we use the fact that, due to the Leontieff assumption, a firm imports a single input quality. So one can invert (15) to get input quality as a function of output quality. By plugging this relationship into (16), we get input prices as a function of output prices. Finally, minimizing the production cost of a firm subject to (14) gives

$$mc_{v,t}(q) = \varphi_{v,t}^{-a}\left(\sum_{\mathcal{S}_v}\gamma_{v,s}^{\kappa}\left[\tau_{H,s,t}e_{H,s,t}w_{s,t}\left(2q^{\theta} - \left(\varphi_v^b\right)^{\theta}\right)^{\frac{\beta_s}{\theta}}\right]^{1-\kappa}\right)^{\frac{1}{1-\kappa}} \tag{17}$$

The marginal cost of a firm is simply a CES index of CIF import prices. Equation (17) formalizes the idea that prices are endogenous to quality, hence the need to instrument prices when estimating demand functions. Thankfully, equation (17) also provides us with a candidate instrument for prices: RER's on imports, which in terms of the model we interpret as $e_{H,s,t}w_{s,t}$. Equation (17) says that $e_{H,s,t}w_{s,t}$ affects output prices and thus verifies the rank condition. To be a valid instrument, the average RER on imports should also be orthogonal to quality q. We verify this in next paragraph by analyzing optimal quality.

Exogeneity Condition: Import Shares Our instrument is an import weighted average RER at the firm level. In the estimation, we set weights constant as there is a concern that they are endogenous to a firm's quality. The present model formalizes this intuition and hence justifies the use of constant weights. The expression of optimal import weights, conditional on quality is

$$\omega_{s,v,t}(q) = \frac{\gamma_{v,s}^{\kappa}\left(e_{H,s,t}\tau_{H,s,t}w_s q^{\beta_s}\right)^{1-\kappa}}{\sum_{s'\in\mathcal{S}_v}\gamma_{v,s'}^{\kappa}\left(e_{H,s',t}\tau_{H,s',t}w_{s',t}q^{\beta_s'}\right)^{1-\kappa}}$$

where $\omega_{s,v,t}$ is the share of source s in imports from variety v.

This weight is a function of quality. To better understand the way a firm sets its weights, let us write the elasticity of a weight to quality:

$$\frac{\partial \log \omega_{s,v,t}(q)}{\partial \log q} = -\left(\beta_s - \sum_{\mathcal{S}_v}\beta_s\omega_{s,v,t}(q)\right) \tag{18}$$

Expression (18) has an intuitive interpretation. When a firm upgrades its quality, it reallocates its imports towards sources in which the relative cost of quality, β_s, is low, relative to the average cost in its source portfolio, $\sum_{\mathcal{S}_v}\beta_s\omega_{s,v,t}(q)$. It follows that high quality firms import from countries with low β (i.e. developed countries, according to Schott (2004)). If the RER of a source s is correlated to its β_s, as is very likely, then it follows that the average RER of a firm is correlated to its quality, through its import shares: high quality firms import from developed countries, which have strong currencies. It is therefore necessary to fix import weights, as we do in the estimation, to guarantee the exogeneity of the instrument.

Exogeneity Condition (continued): RER and quality The optimal quality of a firm maximizes profit function:

$$\pi_{v,t}(q) = \frac{1}{\sigma}p_{v,t}^{*}(q)^{1-\sigma_g}q_{v,t}^{\rho_g-1}\tilde{P}_{m,t}(q_{v,t})^{\sigma_g-\rho_g}P_{m,t}^{\rho_g-1}E_{m,t} \tag{19}$$

we assume that exporting involves iceberg costs, so the CIF price labelled in m's currency, $p^*_{v,t}(q)$, verifies

$$p^*_{v,t}(q) = e^{-1}_{H,m,t}\tau_{H,m,t}p_{v,t}(q)$$

It follows that the first order condition on quality is:

$$(\sigma - 1)\underbrace{\left[\frac{\sum_{\mathcal{S}_v}\beta_s\omega_{s,v,t}(q)}{1-\left(\frac{\varphi^b_{v,t}}{2q}\right)^\theta}\right]}_{\substack{\text{Quality-Elasticity}\\ \text{of marg. costs.}}} = \underbrace{(\rho - 1) + \frac{\partial \log \tilde{P}_{m,t}(q)}{\partial \log q}}_{\substack{\text{Quality-Elasticity of}\\ \text{the Demand Shifter } \exp(\lambda)}} \tag{20}$$

To choose their optimal quality, firms operate a quality-cost trade-off. From equation (20) it appears that the optimum is reached when a firm equalizes the quality-elasticity of its demand shifter to the quality-elasticity of its production costs.

Equation (20) implicitly defines optimal quality. It appear that optimal quality is a function of importing shares $\omega_{s,v,t}$. The rationale for that prediction hinges on the leontieff assumption on the quality of the basket of inputs. When a firm decides to upgrade its quality, it must increase the quality imported from its whole input basket. By how much the cost of its input basket goes up as a consequence depends on the import weighted average elasticity of input prices to quality: $\bar{\beta}_{v,t}(q) = \sum_{\mathcal{S}_v}\beta_s\omega_{s,v,t}(q)$.

Importing shares are also a function of RER's. This is very intuitive: firms minimize their production cost by importing from weak currency sources. Consequently, when a RER shock occurs, firms adjust their importing share which as a result impacts their perceived relative cost of quality $\bar{\beta}_{v,t}(q)$ and eventually leads the firm to adjust its quality.

To make this mechanism more practical, consider the example of a firm importing from a developing country with a high β, say China, and from a developed country with a low β, say the USA. If yuan appreciates, then the firm reallocates its imports towards the USA, it decreases the quality-elasticity of its production costs and so the firm upgrades its quality.

The crucial implication of this discussion is that quality is potentially endogenous to RER shocks [39]

[39] How does this result depend on the Leontieff assumption in the production of quality? Intuitively, it the firm could combine the quality of its inputs through a CES function with strictly positive elasticity of substitution, it could concentrate its imports of quality from a country with a low β, and import large physical amounts of low quality inputs from the rest of the world. Therefore, the cost of upgrading its quality would be driven by the β

. If this questions the validity of our instrument, note that the sign of the bias which would result from the relationship between RER and quality is unclear. To see this, let us consider previous example again. Here, the firm faces a positive cost shock (yuan appreciates) and simultaneously upgrades its quality. This suggests that the price elasticity obtained through our IV estimation is biased towards zero. Now take a symmetric situation where the dollar appreciates instead of the yuan. Then the firm reallocates its imports towards China and downgrades its quality. This case would rather suggest a price elasticity biased away from zero.

Equation (20) also predicts that conditional on $\bar{\beta}_{v,t}$, quality is exogenous to RER's. In terms of our estimation, this means that our instrument is valid once $\bar{\beta}_{v,t}$ is controlled for in the estimation. As we think of β_s as a measure of development of a country, a natural proxy for $\bar{\beta}_{v,t}$ is the import weighted average income per capita of a firm. In section 4, we show that our price elasticity estimates are robust to whether we control on not for $\bar{\beta}_{v,t}$. This consistent with the idea that the sign of the bias, if any, is not clear theoretically.

A.3 Other Implications of the Model

The Demand Shifter as a measure of Quality In section 2, we show that the demand shifter $\lambda_{v,t}$ is a measure of quality, polluted with a quality-specific demand shifter, $\tilde{P}_{m,t}(q)$. In this paragraph we show following proposition:

Proposition A.1 *If $\lambda_{v,t} > \lambda_{v',t}$, then $q_{v,t} > q_{v',t}$*

Proposition A.1 simply says that despite the presence of the quality price index, $\lambda_{v,t}$ can be used to rank varieties in quality, within a market. This is a crucial result regarding the scope of application of our measure of quality.

To demonstrate proposition A.1, let us consider two varieties A and B such that A has a larger demand shifter than B: $\lambda_A > \lambda_B$ (We drop time subscript in this paragraph). Assuming that firms maximize their profit implies:

$$\frac{\pi_B(q_A)}{\pi_B(q_B)} \leq 1 \tag{21}$$

From (20), it is straightforward to get:

of the source from which it imports quality, and not from its all input portfolio. It follows that the reallocation of its physical imports induced by a RER shock would have little impact on its choice of quality. The leontieff specification therefore is the most challenging for our instrument as it is the case where quality is the most endogenous to RER. In that sense it is a conservative assumption.

$$\frac{\pi_B(q_A)}{\pi_B(q_B)} = \frac{\exp(\lambda_A)}{\exp(\lambda_B)} \left(\frac{mc_B(q_A)}{mc_B(q_B)}\right)^{1-\sigma_g} \tag{22}$$

Plugging (22) into (21) and re-arranging gives

$$\left(\frac{mc_B(q_A)}{mc_B(q_B)}\right)^{1-\sigma_g} \leq \frac{\exp(\lambda_B)}{\exp(\lambda_A)} < 1$$

Where second inequality is an assumption of the proof.

Using the fact that $mc_B(q)$ is strictly increasing and that $\sigma_g > 1$ we get

$$q_A > q_B$$

which concludes the proof.

Low-Quality Competition and Quality Upgrading In our empirical application, we are interested in the within-firm effect of low-cost competition on quality. In this paragraph, we show that our model of the firm has predictions on this question. In terms of the model, one can think of low-cost competition as an entry of firms in the lower end of the quality ladder. The direct effect of this entry is a decrease of the low-quality price index, and, as result, an increase in the elasticity of the quality price index with quality, $\frac{\partial \log \tilde{P}_{m,t}(q)}{\partial \log q}$, in the lower end of the quality ladder. Put simply, the entry of low-quality competition makes competition relatively weaker in high-quality nests. This creates an incentive for firms to upgrade their quality in order to escape low-cost competition.

First order condition (20) formalizes this insight: $\frac{\partial \log \tilde{P}_{m,t}(q)}{\partial \log q}$ is a component of the return to quality. When it goes up, as is the case in the lower part of the quality ladder when low-quality competitors enter the market, incumbents optimal quality goes up [40].

[40] Here we run a partial equilibrium analysis. Since all incumbents face the shock in the price index schedule, they all face the same incentive to upgrade their quality. As a result, in general equilibrium, quality-specific price indices may react to the entry of new competitors indirectly, through the quality response of incumbents. Our intuition is that this general equilibrium effect should dampen, but not reverse the quality upgrading response of firms.

B Data Trimming

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). Because variations across prices are less subject to idiosyncratic variations than quantities, we clean the data, based on their computed prices, following three dimensions.

- Observations are dropped for prices for which variations across times differ from a factor five or more. Formally, observations are dropped if $\frac{p_{fpdt}}{p_{fpdt-1}} > 2$ or $\frac{p_{fpdt}}{p_{fpdt-1}} < \frac{1}{2}$
- Observations are dropped for prices which differ from a factor five or more from the mean across all destinations. Formally, observations are dropped if $\frac{p_{fpdt}}{p_{fp\bullet t}} > 2$ or $\frac{p_{fpdt}}{p_{fp\bullet t}} < \frac{1}{2}$
- 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.

Finally, for several observations, quantities are displayed in different units than weight. We convert these units in weight by regressing weights on units at the product$\times$year level. Therefore, we are able to back-up the weight equivalent of these units.

C Descriptive Statistics

Table 15: Descriptive Statistics for all exporters

		p5	p25	p50	p75	p95	Mean
# **Products**	*by firm-year pair*	1	1	2	5	21	5.7
# **Destinations**	*by firm-year pair*	1	1	2	4	18	4.5
# **Products**	*by firm-country-year comb.*	1	1	1	2	9	2.9
# **Destinations**	*by firm-product-year comb.*	1	1	1	2	8	2.3
# **Years**	*by flow*	1	1	3	6	13	4.3
# **Flows**	*by market*	1	1	2	4	20	5.7

Notes: A 'flow' is a combination of a firm, a product and a destination. A 'market' is a combination of a product, a destination and a year.

D Robustness checks

Table 16: Robustness checks

	Base	No hedging		Long diff.		No crisis
	(1)	(2)	(3)	(4)	(5)	(6)
First stage:						
$R\bar{E}R_{ft}$	0.092***	0.083***	0.089***	0.071***	0.099***	0.083***
	(0.005)	(0.012)	(0.008)	(0.007)	(0.008)	(0.006)
$g\bar{d}pc_{ft}^{\mathbf{exp}}$	0.007***	0.009***	0.010***	0.004***	0.008***	0.006***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
$g\bar{p}dc_{ft}^{\mathbf{imp}}$	0.012***	0.006***	0.008***	0.008***	0.012***	0.011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Second Stage:						
Log(Price)	-1.35	-1.30	-1.67	-2.38	-1.93	-0.89
	(0.18)	(0.51)	(0.33)	(0.31)	(0.26)	(0.22)

Notes: Specification (1) is the baseline from column (3), table 5. Columns (2) and (3) dropped importers who export to the same country: specification (2) does it for a given year, specification (3) for any year in the sample. Specifications (4) and (5) respectively use 3 and 5 years differences instead of flow fixed effects. Finally, specification (6) drops years posteriors to 2007 to avoid the role played by the trade collapse phenomenon. All specifications use the gdp per capita controls in the second stage, even though the results are not displayed.

E List of Low-Wage Countries

Table 17: Low-Wage Countries

Angola	Djibouti	Lao People's Rep.	Rwanda
Armenia	East Timor	Lesotho	Senegal
Azerbaijan	Eritrea	Liberia	Sierra Leone
Bangladesh	Ethiopia	Madagascar	Solomon Islands
Benin	Gambia	Malawi	Sri Lanka
Bhutan	Georgia	Mali	Sudan
Bolivia	Ghana	Mauritania	Tajikistan
Burkina Faso	Guinea	Moldova, Rep. of	Tanzania, United Rep of
Burundi	GuineaBissau	Mongolia	Togo
Cambodia	Guyana	Mozambique	Turkmenistan
Cameroon	Haiti	Nepal	Uganda
Central African Republic	India	Nicaragua	Ukraine
Chad	Indonesia	Niger	Uzbekistan
China	Iraq	Nigeria	Viet Nam
Comoros	Kenya	Pakistan	Yemen
Congo	Kiribati	Papua New Guinea	Zambia
Ivory Coast	Kyrgyzstan	Philippines	Zimbabwe

Notes: A low-wage country is defined as a country which GDP per Capita in 2002 is inferior to 5% of the French one in 2002.