Corporate Financial Structure and Export Quality: Evidence from France[☆]

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Abstract

Does the corporate financial structure determine the ability of a firm to compete in foreign markets through quality? We investigate this question by estimating the perceived quality of individual French exporters' output within different destination markets. Once we control for firms' heterogeneity and reverse causality, we find that the ratio of exporters' debt over to total assets is negatively correlated with a theoretically grounded estimator of export quality. This result only holds for exporters with insufficient internal resources to finance current expenses. We argue that the negative impact of leverage on quality is consistent with models predicting that debt financing hampers the incentive to invest in quality upgrading. However, this distortion appears to affect only firms for which high leverage is not the outcome of a value-optimizing choice but rather a consequence of insufficient internal resources.

Keywords: Export, Output Quality, Leverage
JEL classification: C11, D22, F14,G36.

1. Introduction

Departing from the Modigliani and Miller (1958) theorem, a number of empirical papers question the irrelevance of corporate financial structure for real activities by showing that leverage, as a measure of debt financing, affects investment patterns and productivity growth within firms (e.g., Aivazian et al., 2005; Nucci et al., 2005;

[☆]The authors would like to thank Stefano Schiavo, Jaanika Merikull, Lucia Tajoli, and all the participants to the EACES workshop, the ITSG workshops and the LAREFI-Montesquieu Bordeaux IV workshop for their helpful comments and suggestions.

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Nunes et al., 2007; Coricelli et al., 2012). These findings from the financial literature are paralleled by evidence reported in studies on heterogeneous export performance across firms. Models of export behavior in which credit constraints prevent illiquid firms from seizing profitable export opportunities (Manova, 2008; Chaney, 2013) have motivated several analyses on the role of financial attributes in determining export entry and success in foreign markets (Greenaway et al., 2007; Bellone et al., 2010; Berman and Hricourt, 2010; Askenazy et al., 2011; Minetti and Zhu, 2011). Although the direction of causality between firms' export status and financial attributes is a matter of debate, the conclusions of these papers agree that exporters and non-exporters differ with respect to liquidity and financial structure.

Our paper extends this line of research by exploring a new finance-quality channel through which exporters' leverage affects quality heterogeneity across exported varieties. Our hypothesis stems from the predictions of models in the financial literature demonstrating that the recourse to debt financing may ultimately affect the costs and incentives to invest in quality-enhancing activities (Long and Malitz, 1985; Maksimovic and Titman, 1991). We base our empirical analysis on firm-level export and balance sheet data provided by the French Customs and French National Statistical Office (INSEE), respectively. The principal novelty of our study is the finding that leverage negatively affects the ability of some exporters to compete in foreign markets by affecting quality. These exporters have insufficient working capital to cover their operating costs and are hence 'illiquid' exporters. In light of corporate finance theory, we interpret this evidence as an indication that leverage has a differential impact on firms' real activities depending on whether debt financing is an optimizing choice (Jensen and Meckling, 1976) or a necessary substitute for insufficient internal resources (Myers and Majluf, 1984).

The primary methodological contribution of this paper is to apply to the empirical strategy introduced in Khandelwal (2010) to firm-level data to obtain a measure of export quality from the estimation of a discrete choice model of consumer demand (Berry, 1994). In the trade literature, variations in unit-values across different exported varieties of the same product have been interpreted as a sign of quality heterogeneity that explains why more expensive varieties are observed penetrating more competitive and distant markets, in contrast with the efficiency interpretation of the Melitz model (Bastos and Silva, 2010; Baldwin and Harrigan, 2011; Manova and Zhang, 2012). However, this strategy is not viable to study the impact of leverage on quality. Because corporate financial structure may affect both productivity-enhancing investments and output quality upgrades, its net effect on firm prices is ambiguous. The measure of export quality that we employ addresses this concern because it is based on the revealed choice of consumers among alternative varieties after controlling for differences in price. This measure also allows us to extend the investigation of output quality to multiple product categories, in contrast to product-specific indicators, such as the the wine guides' ratings of the varieties of exported Champagne used in (Crozet et al., 2012). We estimate the quality of

French manufacturers' exports for six different 6-digit Harmonized System (HS6) categories of consumer products that are economically relevant for French exports and consistent with the assumptions of the discrete choice model of consumer demand.

Our paper relates to recent advancements in the trade literature suggesting that, in addition to the capacity to pay fixed entry costs, the ability to produce higher quality products is an important determinant of selection into exporting and a major driver of success in foreign markets. Iacovone and Javorcik (2008) and Kugler and Verhoogen (2012) find convincing evidence that Mexican plants invest in output quality upgrades before beginning to export, and a series of papers using data on firm-level export flows finds that exporters of more expensive varieties[5] reach more distant destinations and realize higher revenues (Bastos and Silva, 2010; Crozet et al., 2012; Manova and Zhang, 2012). Closer contributions to our study are three recent papers investigating the relationship between financial constraints and export prices. Fan et al. (2012) and Manova et al. (2011) analyze Chinese data and find support for the hypothesis that financial constraints hamper export quality, as they find that firms with better access to internal and external credit export relatively more expensive goods. Conversely, Secchi et al. (2011) find that financially distressed Italian exporters tend to ship more expensive varieties, and they interpret this result as a sign that financial constraints require firms to set less competitive prices to sustain their cash flows. The novelty of our contribution resides in the methodology that we employ to estimate export quality and our greater focus on firm financial structure, which is inspired by a well-developed strand of the financial literature that has thus far remained unaddressed by the trade literature.

The remainder of the paper is structured as follows. Section 2 introduces the conceptual framework underpinning the relationship between leverage and quality. Section 3 describes the data. As a preliminary exercise, Section 4 tests the predictions from the financial literature concerning firm leverage and investment in intangibles. Section 5 introduces the methodology we adopt to obtain our estimator of export quality. Section 6 presents the empirical model for export quality and leverage and the main results. In Section 7, we conduct robustness checks. Section 8 concludes.

2. Leverage, investment and quality

The quality of the exported varieties is bound to depend on firms' investments in intangible assets. On the one hand, Research and Development (R&D) is necessary to develop product characteristics that are broadly recognized as desirable by consumers; on the other hand, managers' skills and human capital are also crucial

[5] Throughout this chapter we refer to a 'variety' as a single product, defined at the 8-digit level of the Combined Nomenclature (CN8), shipped by a single firm to a single export destination.

to identify taste differences across markets and adapt the exported output accordingly. In addition, investment in advertisement is often required to inform potential consumers of product characteristics, establish a brand and enhance consumer appreciation of the products. This type of investment – R&D, human capital and advertising – implies high sunk and firm-specific costs and very low collateral value, notably because it yields returns that are difficult to forecast without acquiring costly information on market demand and competitors' strategies. Therefore, information asymmetries between firm managers and investors are particularly serious with respect to funding quality-enhancing projects, and the form of financing is likely relevant for such investments.

In contrast to the Modigliani-Miller theorem (Modigliani and Miller, 1958), a substantial literature has shown that corporate financial structure may affect firms' investment decisions by emphasizing the role of information asymmetries and agency costs in the relationship between investors and firm managers. Myers and Majluf (1984) examine information asymmetries between insiders (i.e., managers and current shareholders) and outsiders (i.e., potential buyers of shares) to explain the observed pecking order pattern of financing: firms finance their expenses by first using internal resources; when these are insufficient, they use debt, and as a last resort they issue new equities.

The relative costs of different sources of financing affect firms' investment policies, while the nature of the acquired assets determines the degree of information asymmetries in credit relationships and the extent to which one source of financing is preferable to the others. Long and Malitz (1985) investigate how managers' investment decisions are affected by the source of financing, by demonstrating that in the presence of information asymmetries between borrowers and lenders, the use of debt causes firms to invest less than optimally, and this issue is relatively more serious when debt is used to finance investments in intangibles such as R&D and advertisement. Their model predicts that firm-specific intangible investments such as advertisement and R&D are more prone to agency problems because lenders find it more difficult to monitor managers' use of resources, and the greater specificity of the assets (or services) purchased by the firm translates into higher 'agency costs' of debt. Therefore, they argue that firms that employ debt financing more intensively have a relative disadvantage in undertaking intangible investments. They find empirical support for this prediction by analyzing US firms' patterns of investment and financing. More recently, Almeida and Campello (2007) present a model in which the tangibility of assets, by determining the availability of collateral, affects the level of investment undertaken by financially constrained firms. Therefore, the results of these papers suggest that underinvestment due to debt financing more substantially affects activities directly related to quality upgrading or consumers' perceptions of product quality and this issue is particularly serious for financially constrained firms.

An alternative theory predicting a negative relationship between leverage and quality is provided by Maksimovic and Titman (1991). They present a model in which firm investments in product quality are undertaken to develop 'reputation capital' that allows firms to charge higher prices in the future. High leverage increases the probability of future bankruptcy, and it shortens firms' optimization horizons. In turn, leverage results in reduced contemporary investments in quality. In addition, highly leveraged firms that face an immediate threat of bankruptcy may reduce quality (if this reduces costs) to sustain cash flows and repay their debts. In the words of the authors, this strategy is equivalent to "obtaining an involuntary loan from consumers because the reduction in future revenue resulting from the loss of reputation corresponds to the repayment" (Maksimovic and Titman, 1991, pag. 117). By analyzing inventory shortfalls as a measure of poor service quality in the supermarket industry, Matsa (2011) provides empirical support for the negative relationship between firm leverage and output quality, as he finds that highly leveraged firms reduce their product quality (i.e., more frequent shortfalls in inventories) to preserve cash flows for debt servicing purposes. In addition, the literature on R&D provides abundant empirical evidence supporting the hypothesis that the availability of internal funds is more decisive for investing in research activities than it is for financing capital investment (Hall, 2002; Czarnitzki and Binz, 2008; Ughetto, 2008).

The literature surveyed above stresses the costs and distortions introduced by debt financing and the reasons that illiquid firms may be forced to adopt a highly leveraged financial structure that constraints their investment behavior. However, the 'Trade-off Theory' of corporate financial structure provides reasons that debt financing could also enhance firm value. Debt financing may eventually increase investment if the tax shield function of debt (i.e., the possibility of discounting interest rate payments from taxable profits) increases the net present value of investment opportunities. Jensen and Meckling (1976) reveal that in the presence of conflicts between managers and owners, debt is a 'disciplinary device' through which owners control managers, as interest rate payments reduce firms' free cash flows available to managers for unprofitable discretionary spending. These insights suggest that, for some firms, high leverage is an optimal choice, and we should not expect their competitiveness to be negatively affected by their levels of debt. On the basis of the theoretical insights and empirical evidence provided by the financial literature, we formulate two hypotheses relating firm financial structure and export quality:

Hyp 1: Exporters with high levels of debt have a cost-disadvantage or fewer incentives to undertake quality-enhancing activities, and we expect them to export lower quality varieties

Hyp 2: For firms that opt for high leverage as a value-optimizing choice, the beneficial effects of debt may offset the distortions induced by this source of financing. For these firms, a highly leveraged financial structure does not necessarily affect product quality.

3. Data

The empirical analysis is conducted using data obtained from two sources: the *Fichier complet de Systme Unifi de Statistique d'Entreprises* (FICUS) provided by the French National Statistical Office (INSEE) and the French Customs Dataset. FICUS reports balance sheet items and demographic information, covering the population of French firms. We have access to annual files for the period 1997-2007. After appending these files, the resulting firm-year panel dataset includes over two million observations for the manufacturing sector. The leverage of firm f at time t (Lev_{ft}) is constructed using FICUS variables as the book value of total debt to total assets. FICUS also includes information on firm age, ownership, employment, assets, liquidity and their need for external financing. We use this information to construct firm-level controls. Outliers are eliminated by replacing missing observations below the 1st or above the 99th percentiles of each variable's distribution. We also eliminate observations with anomalous values in some of the balance sheet variables[6].

The Customs database reports the export values (euros), quantities (kilograms), destinations and product classes (CN8) of the export flows of French firms. This dataset excludes the flows of small exporters because firms that export products valued below €1,000 outside the EU, or €100,000 within the EU, are not required to report complete declarations of their transactions. The different thresholds for reporting would be problematic if we were to investigate firms' characteristics relative to their export destinations. However, this is not a concern for our identification strategy, as we investigate differences across exporters serving the same market, or variations in quality over time for the same exported variety defined at the firm-product-destination level. Because some product categories are assigned different CN8 product codes at different points in time, we use tables provided by Eurostat to harmonize the classifications with the 2007 version.

Customs data are used to construct unit-values of exported varieties as flow values divided by quantities $UV_{fpd} = \frac{val_{fpd}}{qty_{fpd}}$, where f, p, d are indices for firm, CN8 product class and export destination. Unit-values are very noisy proxies for export prices because measurement errors in quantities generate extreme variations. To mitigate this issue, we drop observations outside the 0.5% extreme percentiles of the unit-value distribution within each CN8 product category and export flows with extreme unit-value variations from one year to next (above and below the 1st and the 99th percentiles respectively). Unit-values and market shares of exported varieties provide sufficient information to estimate quality according to the methodology

[6] We drop firms that report negative levels of revenue or debt in any year. We also drop firms for which total assets (comprising tangible and intangible assets) are lower than tangible or intangible assets, or of the sum of these two asset types.

explained in Section 5[7].

4. Investment in intangibles and leverage: evidence

Before examining the relationship between corporate financial structure and export quality, we assess whether high leverage hampers firm investment as predicted by the financial literature summarized in section 2. We conduct this preliminary exercise for all manufacturing firms (i.e., both exporters and non-exporters) in FICUS. This dataset allows us to separately observe firms' book values of tangible ($Tang$) and intangible ($Intang$) assets[8]. To assess the differential impact of leverage on the growth of these two classes of assets, we estimate two separate investment equations for $\Delta Tang_{t/t-1}$ and $\Delta Intang_{t/t-1}$, which are the log differences in the value of tangible and intangible assets, respectively, between consecutive periods. Table 1 reports the means and standard deviations of the variables in the investment model.

Table 1: Summary statistics investment variables

Variable	Mean	Std. Dev.	Obs.
Lev	0.203	0.225	1,950,977
$\Delta Intang$	0.028	0.192	1,026,211
$\Delta Tang$	0.064	0.215	1,562,687
$\Delta Sales$	0.02	0.291	1,634,642
$Asset$	5.166	1.715	1,918,175

Notes. *Asset* is log of firms' total assets in '000 euros. The mean of this variable is not representative of the sample as it is drive by the presence of a small group of very large firms.

The simple dynamic asset growth models that we estimate incorporate firms' lagged leverage ratios Lev_{it-1} on the right-hand side:

$$y_{it} = \beta_0 y_{it-1} + \sum_{s=0}^{1} \beta_s \Delta Sales_{it-s} + \beta_3 Lev_{it-1} + \beta_4 Asset_{it-1} + e_{it} \tag{1}$$

where y denotes either $\Delta Tang_{t/t-1}$ or $\Delta Intang_{t/t-1}$. Specification 1 includes both current and lagged changes in sales to capture firms' investment opportunities[9], and the model is estimated using three different estimators: Random Effects (RE) and Fixed Effects (FE) models for the static specification (i.e., by imposing $\beta_0 = 0$)

[7] A convenient feature of the FICUS and Customs datasets is that they both identify firms using the same fiscal identification codes (SIREN). Therefore, we can associate individual trade flows in Customs to the firm-level variables that we observe in FICUS to investigate the quality of exported varieties in relation to exporter attributes.

[8] $Tang$ includes land, buildings, plant, equipment and machinery, other fixed assets, and assets under construction. $Intang$ includes the value of firms' assets that are not classified as financial or tangible assets.

[9] Note that these variables are used in the absence of information on the market values of quoted firms that would be necessary to compute Tobin's Q ratios.

and the Arellano-Bond GMM estimator (AB) (Arellano and Bond, 1991) for the dynamic version[10].

Table 2 reports the results obtained when we estimate equation 1 using the three different estimators. In the two static specifications of the model (RE and FE), we find that higher levels of leverage are associated with slower growth in both intangible and tangible assets. However, the Hausman test suggests that RE estimates of Lev_{it-1} are inconsistent, and by comparing RE and FE estimates, we infer that the RE coefficients are upward biased (p-value 0.00). A possible explanation for this bias is that firms that more actively increase tangible and intangible assets might have a higher average demand for credit and higher levels of leverage than those that invest to a lesser extent. A similar rationale might explain why the coefficient on this variable is more negative when estimated by AB in the model on $\Delta Intang_{it}$. In the AB regressions, we treat Lev_{it-1} as an endogenous variable to prevent upward bias due to reverse causality running from investment in intangibles to levels of debt. The case is not the same when we consider the coefficient on Lev_{it-1} from the AB model that uses $\Delta Tang_{it}$, as this is positive and significant at the 1% level, in contrast to the negative coefficients produced by the RE and FE models employing the same variable.
Initially, this finding seems to confirm the hypothesis that debt has a more negative impact on investment in intangibles than on investment in tangible assets, as predicted by the model developed by (Long and Malitz, 1985). On one hand, the Hansen J test of overidentification rejects the joint validity of the instrument set in the model considering $\Delta Tang_{it}$, casting doubt on the consistency of the estimates from this model[11]. Therefore, we prefer not to arrive at a firm conclusion based on this finding in isolation. On the other hand, estimates of the coefficient on Lev_{it-1} when regressed on $\Delta Intang_{it}$ are consistently negative across model specifications

[10]This estimator simultaneously addresses the bias arising from the omission of individual fixed-effects and the endogeneity of the lagged dependent variable and other covariates on the right-hand side of the model. The first issue is addressed by first differencing the data within each panel unit to eliminate individual fixed effects from the error term. The second issue is solved by instrumenting the first-differenced endogenous variables with their lagged levels. The coefficients are identified by exploiting the full set of orthogonality conditions arising from the independence of first-differenced errors from lagged levels of the instrumented variables. One may argue that the System GMM estimator introduced by Blundell and Bond (1998) achieves greater efficiency than AB by exploiting additional moment conditions. However, the system GMM estimator relies on the stronger assumption that changes in instrumental variables are uncorrelated with the fixed effects (Roodman, 2009). In our case, as lagged changes in leverage and sales may be correlated with unobservable firm characteristics, we prefer not to make this assumption and retain the AB estimator.

[11]Nevertheless, some authors argue that given the tendency of overidentification tests to reject the null hypothesis in large samples, a significant Hansen J test statistic should not necessarily be interpreted as a violation of the orthogonality assumption on which identification by GMM relies (e.g., Chen and Guariglia, 2013).

Table 2: Leverage and asset growth

	$\Delta Intang_{it}$			$\Delta Tang_{it}$		
	RE	FE	AB	RE	FE	AB
$\Delta Sales_t$	0.058***	0.040***	0.100***	0.131***	0.094***	0.232***
	(0.001)	(0.001)	(0.034)	(0.001)	(0.001)	(0.032)
$\Delta Sales_{t-1}$	0.031***	0.018***	-0.031**	0.091***	0.061***	0.043***
	(0.001)	(0.001)	(0.013)	(0.001)	(0.001)	(0.011)
Lev_{t-1}	-0.038***	-0.056***	-0.090***	-0.057***	-0.169***	0.044***
	(0.001)	(0.002)	(0.014)	(0.001)	(0.002)	(0.015)
$Asset_{t-1}$	0.014***	-0.015***	0.022	-0.002***	-0.061***	-0.183***
	(0.000)	(0.001)	(0.019)	(0.000)	(0.001)	(0.033)
$\Delta Intang_{t-1}$			0.252***			
			(0.075)			
$\Delta Tang_{t-1}$						0.365***
						(0.047)
$Constant$	-0.066***	0.151***		0.050***	0.370***	
	(0.001)	(0.007)		(0.001)	(0.005)	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hansen-J (p-value)			0.156			0.001
m(1) (p-value)			0.000			0.000
m(2) (p-value)			0.000			0.000
m(3) (p-value)			0.885			0.587
m(4) (p-value)			0.676			0.343
R^2		0.010			0.059	
Obs.	843,556	843,556	632,069	1,271,755	1,271,755	993,388

Notes. * $p < .1$, ** $p < .05$, *** $p < .01$. At the bottom of the table we report diagnostic statistics for the AB models. The Hansen-J (p-value) is the p-value from the overidentification test that is used to verify the null hypothesis of joint validity of the instrument set. $m(i)$ is a test of autocorrelation of the i order on the residuals, where the null hypothesis is no autocorrelation. While first-order autocorrelation is introduced by construction when we first difference observations, higher order autocorrelation suggests excluding closer lags of the endogenous variables from the instrument set. Hence, we use the 3rd and the 4th lags of $\Delta Intang_{t-1}$, $\Delta Tang_{t-1}$, $\Delta Sales_t$, $\Delta Sales_{t-1}$, $Asset_{t-1}$ and Lev_{t-1} as instruments. AB regressions are implemented in Stata with the user-written command xtabond2 (Roodman, 2003).

and estimation techniques. Therefore, we conclude that, overall, the findings reported in Table 2 support the initial hypothesis that firms with higher dependence on debt financing tend to exhibit slower expansion in intangible assets. If investment in intangible assets were closely related to product quality, we would expect to find a negative impact of leverage on this dimension of exporters' competitiveness.

5. Quality Estimates

5.1. Measuring Product Quality

The central concept of Berry's discrete choice model of demand (Berry, 1994) consists in inverting the demand function to use aggregate market information to infer the mean utility level that each variety of a differentiated product delivers to consumers. The model imposes structure on demand by assuming that each individual i consumes only one unit of the variety j that delivers the greatest utility:

$$u_{ij} > u_{ik} \quad \forall \quad k \in K \tag{2}$$

where K is a product class encompassing all varieties sharing a certain degree of substitutability. The set K comprises one or more 'nests', which are groups of varieties (indexed by g) characterized by greater substitutability among one another[12].

[12]For example, K may include all varieties of men's shirts on the market. Although consumers can always substitute one variety for another in K, they are more likely to substitute shirts of the

To allow for the nested structure of K, consumers' utility is modeled according to the following specification (McFadden, 1974):

$$\begin{aligned} u_{ij} = \delta_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij} \quad &, \quad 0 \leq \sigma < 1 \\ \delta_j = X_j'\beta + \alpha p_j + \zeta_j \quad &, \quad \alpha \leq 0 \end{aligned} \tag{3}$$

where δ_j is the expected utility from the consumption of j. This depends on a vector of product attributes X_j and parameters β on price p_j and product quality ζ_j. The terms ζ_{ig} and ϵ_{ij} are consumers' deviations from the mean utility δ_j that are determined by heterogeneous preferences across consumers for different nests of varieties and across varieties belonging to the same nest. The within-group substitutability parameter σ determines the extent to which different consumers agree on the utility they derive from selecting j. Ultimately, the negative parameter α captures the disutility of price that is common across consumers.

By assuming that idiosyncratic deviations in preferences ϵ_{ij} follow a Type I extreme-value distribution, the utility function 3 is the basis for the following nested logit model[13]:

$$s_j = \frac{e^{\delta_j/(1-\sigma)}}{[\sum_{k\in g} e^{\delta_k/(1-\sigma)}]^{\sigma} \times \sum_{g\in K}[\sum_{k\in g} e^{\delta_k/(1-\sigma)}]^{(1-\sigma)}} \tag{4}$$

where s_j is the market share of variety j. This can be understood as the aggregate realization of individual consumers' choices, when the probability that consumer i chooses variety j over any other alternative in K is increasing in the relative utility delivered by j compared to the competing varieties. Berry demonstrates that the log difference between s_j and the market share s_o of an outside variety can be conveniently written in linear form[14]:

$$ln(s_j) - ln(s_o) = X_j'\beta + \alpha p_j + \sigma ln(s_{j/g}) + \zeta_j \tag{5}$$

where $ln(s_j) - ln(s_o)$ is the normalized share of variety j measured over the total market of product class K. Conversely, the 'nest share' $s_{j/g}$ is the share of variety j measured over the market for nest g to which that variety belongs[15]. From the last equation, we can obtain an estimator of product quality Q_j as follows:

$$\begin{aligned} Q_j &= [ln(s_j) - ln(s_o)] - [\alpha p_j + \sigma ln(s_{j/g})] \\ Q_j &\equiv X_j'\beta + \zeta_j \end{aligned} \tag{6}$$

same material (belonging to the same nest g within K).

[13]The assumption that the idiosyncratic error in individual preferences follows a Type I extreme-value distribution is a common assumption of multinomial logit models.

[14]Ideally, the outside variety is a variety for which price and quality are uncorrelated with the price and quality of the varieties with normalized market shares (Nevo, 2000).

[15]In the Appendix, we provide a step-by-step derivation of equation 5.

Equation 6 demonstrates that a quality estimator can be obtained as the normalized market shares of individual varieties that are not explained by their prices or nest-shares. This residual component is the share of demand for variety j determined by product characteristics other than price (X_j), consumer preferences (β) and a 'brand' component (ζ_j). Admittedly, Q_j should be accorded a broad definition of quality encompassing different product aspects such as: similarity to consumer preferences, the quality of the materials, design and consumer appreciation for the brand. Nevertheless this proxy is appropriate for our research question, as our aim is to determine whether firm leverage inhibits activities such as market research, advertising, and product development. These activities pertain to exporters' non-price competitiveness.

5.2. Identification strategy

We apply the model to the data by defining each export flow fpd that we observe in the Customs dataset as an individual exported variety and K as the set of all varieties that belong to the same 6-digit product class. The nests within K are constructed as groups of products belonging to the same 8-digit product class. At time t, the market share of each variety within a destination market is defined as $s_{fpdt} = \frac{q_{fpdt}}{MKT_{dt}}$, where the numerator is the exported quantity (in Kg) of variety fpd and MKT_{dt} is the aggregate quantity demanded by consumers in country d for all varieties belonging to the same 6-digit class. The nest share is instead defined as $ns_{fpdt} = \frac{q_{fpdt}}{MKT_{pdt}}$, where the denominator is the physical volume in market d of all varieties within the same 8-digit class.

The empirical challenge in constructing market shares results from the unavailability of data reporting total demand at the country-product level. To overcome this problem, we proxy for unobserved demand in each country using the aggregate quantity imported in each 6-digit class. We use the BACI dataset to compute the outside varieties' share S_{odt}[16] . This is the share of non-French imports over the total imports of country d in a given 6-digit product class. This share is used to approximate market size: $MKT_{dt} = \frac{\sum_{dt} q_{fpdt}}{1-S_{odt}}$, where the numerator is the total exports from France to country d within a 6-digit product class obtained by aggregating individual export flows[17]. Similarly, we approximate the size of the market at the 8-digit level as $MKT_{pdt} = \frac{\sum_{pdt} q_{fpdt}}{1-S_{odt}}$, where the numerator is the aggregate quantity exported by France to country d within the same 8-digit product class. We estimate the model by individual 6-digit product class to allow parameters α and σ to differ

[16]The BACI dataset reconciles trade declarations from importers and exporters as they appear in the COMTRADE database (Gaulier and Zignago, 2010).

[17]For example, if France exports 2,000 Kg of men's shirts to Italy and its market share over Italy's imports of men's shirts is 0.2, then the share of non-French imports in that product class is the outside variety's share $S_o = 1 - 0.2 = 0.8$. The total market for shirts in Italy is computed as $MKT = \frac{2{,}000kg}{1-0.8} = 10,000Kg$.

across Ks. The specification we adopt is similar to that proposed by Khandelwal (2010):

$$\begin{aligned} ln(s_{fpdt}) - ln(s_{odt}) &= \alpha UV_{fpdt} + \sigma log(ns)_{fpdt} + \delta_t + \delta_c + \hat{Q}_{fpdt} \\ \hat{Q}_{fpdt} &\equiv \delta_{fpd} + \delta_{fpdt} \end{aligned} \quad (7)$$

where UV_{fpdt} is the unit-value of the export flow fpd as a proxy for its price, while the error term $\hat{Q}_{fpdt}$ is the empirical equivalent of the quality estimator Q_j in equation 6. This error term can be decomposed into a firm-product-destination fixed effect δ_{fpd}, which captures the time-invariant features of the variety that affect its market share in d (i.e., the quality of the materials, similarity to consumers' preferences, brand name), and a time-varying component δ_{fpdt}, which demand captures reflecting the positive impact of firms' activities to promote their product in foreign markets (i.e., advertising, improvements in design and materials). Negative variations in δ_{fpdt} instead reflect the incapacity of firm f to keep pace with quality upgrades implemented by French exporters of competing varieties within the same market d. The remaining terms δ_t and δ_d control for macroeconomic shocks common to all French exporters and destination-specific time-invariant factors, respectively.

If higher quality products are priced at higher mark-ups, or if their production involves higher marginal costs, then $\hat{Q}_{fpdt}$ is likely positively correlated with unit-values UV_{fpdt} and the log of the nest-share $log(ns)_{fpdt}$. Therefore, OLS estimates of α are generally upward biased (Nevo, 2000). To address the endogeneity in unit-values and nest-shares, we estimate 7 by adopting a panel Fixed-Effect Instrumental Variable Estimator (FEIV). By setting the panel unit at the level of the individual variety fpd, within-group transformation eliminates the correlation between the regressors and the fixed-effect component of quality δ_{fpd}, hence preventing omitted variable bias. The identification of α and σ now exclusively relies on time-variations in market shares and prices within the same variety defined by the triplet firm-product-destination fpd.

We use three instruments to address the endogeneity of UV_{fpdt} and $log(ns)_{fpdt}$. The first instrument is the average price computed across all French varieties of the same 8-digit product p exported to country d at time t: $z_{1pdt} = N_{pdt}^{-1} \times (\sum_{pdt} UV_{fpdt})$, where N_{pdt} is the number of French varieties exported to that market. Arguably, variations in the average price z_{1pdt} over time may result from shocks to aggregate demand that simultaneously affect the demand for individual varieties. However, we argue that the exogeneity of the instrument is preserved, as the dependent variable in model 7 is the market share of variety fpd rather than its total demand. *Ceteris paribus* a positive shock in demand will affect the demand for a single variety and the aggregate demand for all French varieties proportionately, hence leaving individual market shares unchanged. Conversely, it is reasonable to assume that individual exporters will adjust the mark-ups on their varieties on the basis of variations in the aggregate price. On the basis of this assumption, we expect that the instrument z_{1pdt} will be correlated with the instrumented variable UV_{fpdt}.

The second instrument for prices is the physical productivity of the firm, obtained as output quantity per employee[18]. As the physical productivity of labor does not depend on prices, we expect this instrument to be exogenous with respect to quality variations but correlated with unit-values through marginal costs. Finally, we instrument for the market shares of individual firms using the number of different 8-digit products a given firm exports to d. This last instrument was used by Khandelwal (2010) under the assumption that the intensive (i.e., quantities exported) and the extensive (i.e., the number of different products exported) margins of trade are correlated, but the number of different varieties exported is uncorrelated with the quality of each individual variety.

5.3. Selection of the product categories

Conceptual and methodological issues prevent us from estimating the discrete choice model of consumer demand over the full set of 6-digit product categories observed in the Customs dataset. First, this model is more appropriate to describe consumer behavior than producers' choices of different suppliers of intermediate and capital goods; importers of intermediates, equipment and machinery may be less flexible in selecting among alternative varieties, as contracts and technological factors may constrain their ability to switch suppliers. In addition, individual idiosyncratic shocks in preferences provide the basis for the probabilistic modeling of consumer choice. In contrast, it is more problematic to explain why the same imported intermediate or capital good may contribute differently to the outputs of different importing firms. For these reasons, we restrict our analysis to consumer product exports. To identify the HS6 product categories that correspond to these goods, we refer to the UN 'Classification by Broad Economic Categories' (BEC). Concordance tables are used to map HS6 products into BEC categories, and only those products that this classification defines as 'mainly for household consumption' are retained in the dataset[19].

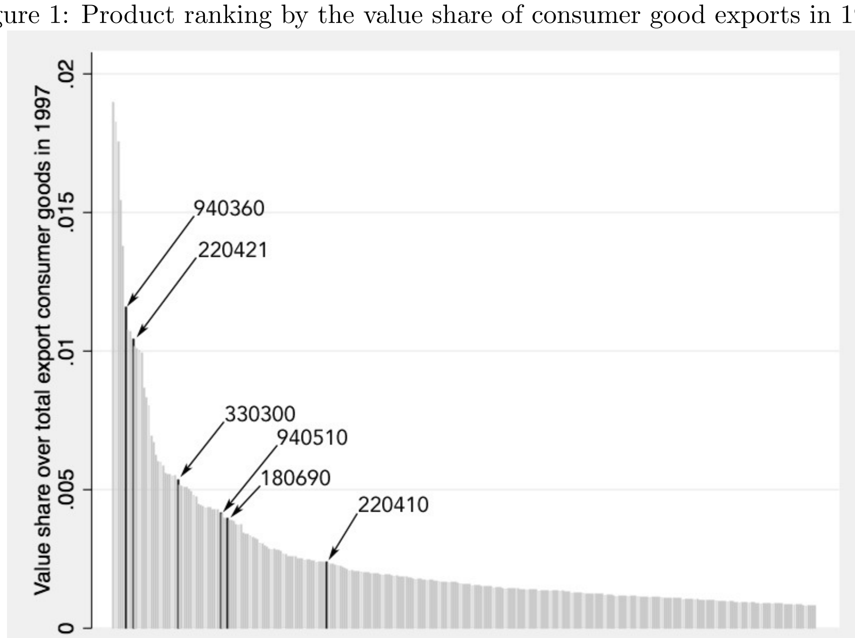
Market shares are computed by aggregating both wholesalers' and manufacturers' exported quantities to estimate the aggregate import demand of foreign countries. However, when we estimate the demand model, we only consider the

[18] Because information on quantities is only available for exported output, we compute the total quantity exported by the firm within a product class q_{exp}, and then we estimate the total quantity produced by the same firm as: $q_{tot} = \frac{v_{tot}}{v_{exp}} \times q_{exp}$, where v_{tot} and v_{exp} are the values of a firm's total sales and total exports, respectively. We lag the instrument to prevent measurement errors in quantities from driving the correlation between unit-values and the instrument.

[19] More precisely, we retain the following BEC classes: 122 (food and beverages for household consumption), 61 (durable consumer goods), 62 (semi-durable consumer goods), and 63 (non-durable consumer goods). Class 51 (passenger motor cars) is excluded due to the very limited number of firms that participate in this segment of French exports.

observations for manufacturers' exports. Two reasons motivate this choice. First, a recent paper by Bernard et al. (2011) highlights differences in the export behaviors of manufacturing firms and wholesalers. These authors find that wholesalers' exports respond differently to macroeconomic shocks (i.e., exchange rate fluctuations) and these firms face different export costs. For these reasons, differences in the market shares of manufacturers and wholesalers may be driven by factors other than quality or prices. Second, the hypotheses concerning the effect of firm financial structure on export quality are based on the assumption that production and sales are performed by the same firm. After restricting our focus to manufacturing firms exporting consumer goods, we select six HS6 product categories for which we obtain satisfactory diagnostic tests after FEIV estimations and demand parameters are significantly different from 0 and precisely estimated. These product categories are: 'Wooden Furniture' (HS6: 940360), 'Sparkling Wine' (HS6: 220421), 'Perfumes' (HS6: 330300), 'Lamps' (940510), 'Chocolate and confectionery' (HS6: 180690) and 'Still Wine' (HS6: 220410)[20].

Figure 1: Product ranking by the value share of consumer good exports in 1997



Notes. The figure is constructed from BACI data. Each bar corresponds to a unique HS6 consumer good exported from France in 1997. We represent here only the first 300 product category for importance on total French exports of consumer goods. The y-axis represents the share of each individual product category over the total exports of consumer goods. Although, France exported more than 1,000 different HS6 product classes, here we represent only the first 300 products for economic relevance.

The six product categories that we selected are also an economically important share of French consumer goods exports. Figure 1 ranks the 300 most important HS6

[20]Table C.11 in the Appendix summarizes the process for selecting these products.

product categories (over 1,042 different ones) on the x-axis in terms of their value share in total French exports of consumer goods in 1997. The products we investigate are highly ranked; the most important is 'Wooden Furniture' (HS6: 940360), ranked 7th, while the least important is 'Still Wine' (HS6: 220410), ranked 92nd. In addition, these products are well suited to our investigation of quality, as their demand is likely determined by the exporters' capacity to engage in 'quality enhancing' activities such as: researching consumer preferences in foreign markets, improving packaging and product design, adopting better materials, switching to quality-enhancing production techniques and investing in advertising to promote their brand.

5.4. Estimation results

FE and FEIV estimates of the demand parameters are reported in the upper and in the lower panels of Table 3, respectively. As expected, the estimates of the coefficient α from the FEIV models are consistently smaller than those obtained from FE models across all product categories. This evidence suggests that by instrumenting unit-values and nest shares, we correct the upward bias resulting from their correlation with the unobserved, time-varying component of quality. In addition, the FEIV estimates of the substitution parameter σ fall in the plausible range $[0-1)$. Overidentification tests for the selected product categories confirm the validity of the instrument set.

Table 3: Estimated demand parameters

	(1) Chocolate and confectionery	(2) Wine (still)	(3) Wine (sparkling)	(4) Perfume and toilet waters	(5) Wooden furniture	(6) Lamps
Estimates from FE models						
α_{FE}	-0.017***	-0.001	-0.006***	-0.001***	-0.002***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_{FE}	0.788***	1.072***	0.946***	0.987***	0.931***	0.884***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.70	0.89	0.89	0.93	0.90	0.80
Obs.	17,390	18,737	29,502	54,598	37,474	14,339
Estimates from FEIV models						
α_{FEIV}	-0.088***	-0.008**	-0.039***	-0.016***	-0.024***	-0.004**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
σ_{FEIV}	0.852***	0.913***	0.977***	0.548***	0.967***	0.747***
	(0.08)	(0.22)	(0.06)	(0.10)	(0.04)	(0.07)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Own-price elasticities						
Median	-4.88	-1.16	-0.62	-1.02	-6.81	-0.36
High	-8.36	-1.51	-4.27	-1.65	-12.60	-0.76
Low	-3.03	-0.55	-1.16	-0.60	-3.53	-0.19
Hansen J (p-value)	0.24	0.24	0.46	0.40	0.67	0.23
R^2	0.68	0.88	0.90	0.73	0.89	0.82
Obs.	8,971	10,809	13,079	28,187	14,833	4,984

Notes. * $p < .1$, ** $p < .05$, *** $p < .01$. The reported estimates are obtained by FEIV estimation of the discrete choice model, implemented by using the user-written command xtreg2 in Stata (Schaffer, 2005). For all product categories we instrument for unit-values and nested-shares using the same set of instruments as described in the body of the text. Cluster robust standard errors are reported in parentheses (cluster unit: product-destination).

Table 3 also reports the median, high (75th percentile) and low (25th percentile) elasticities of market shares to prices. Each exported variety has a unique price elasticity that depends on the estimated parameters α and σ, its market shares s_j and $s_{j|g}$, and its price uv_j[21]. In the nested logit framework, the elasticity of demand is more negative for varieties with higher prices, as idiosyncratic errors in consumer preferences follow a Gumbel distribution[22]. The median response of market share to a 10% increase in prices ranges from -60% for exporters of 'Wooden Furniture' to -0.6% for those exporting 'Sparkling Wine'.

FEIV estimates of the demand parameters are used to construct the predicted market shares of individual varieties. By subtracting these predicted values from the observed market shares, we obtain the quality estimator $\hat{Q}_{fpdt}$, where f indicates the exporting firm, p is the 8-digit product category of the exported variety, d is the destination country, and t is the year. Before studying firm characteristics in relation to export quality, we investigate how $\hat{Q}_{fpdt}$ affects the relationship between the revenues and prices of individual export flows. Prior studies have argued that the positive correlation between export revenue and prices is caused by the correlation of prices with the unobserved quality of exported varieties (e.g., Bastos and Silva, 2010; Manova and Zhang, 2012). If the estimator $\hat{Q}_{fpdt}$ truly captures export quality, its inclusion in regressions of prices on revenue is expected to correct for the omitted variable bias that drives the positive correlation between prices and revenue.

Table 4: Export values, prices and quality

	(1)	(2)	(3)
Dependent:	$log(value)_{fpdt}$	$log(value)_{fpdt}$	$log(value)_{fpdt}$
$log(uv)_{fpdt}$	0.065***		-0.457***
	(0.010)		(0.013)
$\hat{Q}_{fpdt}$		2.062***	2.211***
		(0.016)	(0.013)
Constant	9.534***	9.559***	10.730***
	(0.027)	(0.001)	(0.033)
Product-country-year FE	Yes	Yes	Yes
R^2	0.214	0.574	0.597
Obs.	123,467	121,062	121,062

Notes. * $p < .1$, ** $p < .05$, *** $p < .01$. Cluster robust standard errors are reported in parentheses (cluster unit: product-destination-year).

The first column of Table 4 reports the coefficient on the log of unit-values $log(uv)_{fpdt}$ when these are regressed on the log of export revenue $log(value)_{fpdt}$. This coefficient is identified by exploiting cross-sectional variations in prices and revenue across varieties of the same 8-digit product exported by different firms to the same destination[23]. The positive coefficient on $log(uv)_{fpdt}$ is in line with previous studies. We also observe a positive coefficient on $\hat{Q}_{fpdt}$ when this is substituted for unit-values

[21]Details on the computation of own-price elasticities are provided in the Appendix.

[22]Because of the right skewness of this distribution, the highest realizations of individual preferences for a given variety (i.e., ϵ_{ij} in equation 3) are relatively less frequent than the lowest ones. Thus, an increase in price has a greater adverse impact on the probability of selecting a variety when its price is relatively high.

[23]We include a full set of product-country-year dummies to control for heterogeneity across products, markets and time.

in the regression on $log(value)_{fpdt}$. Consistent with our expectations, when both $log(uv)_{fpdt}$ and $\hat{Q}_{fpdt}$ are regressed on $log(value)_{fpdt}$, we find that the coefficient on prices becomes negative, while the coefficient on the quality estimator is positive and significant at the 0.01 level. This simple test provides encouraging evidence for the appropriateness of our estimator, as it appears to correct for the omitted variable bias affecting the coefficient on prices in column (1).

6. Leverage and export quality

Our simple specification of the model of leverage and export quality is:

$$\hat{Q}_{fpdt} = c_{pdt} + \beta Lev_{ft} + Z'_{ft}\gamma + \eta_f + \eta_{ft} + \epsilon_{fpdt} \tag{8}$$

where c_{pdt} accounts for demand shocks that affect all firms exporting the same HS6 product to the same destination. This term is important for identification because the quality estimator is the residual market share of an exported variety once we control for its price; therefore, it reflects destination-product-specific demand shocks. The terms η_f and η_{ft} represent unobservable fixed and time-varying factors at the firm-level. The parameter Z'_{ft} is a vector of observable firm-level controls. This vector includes: the log number of workers $log(empl)_{ft}$, labor productivity $log(lprod)_{ft}$ computed as value added per employee, the log of a firm's stock of intangible assets $log(Intang)_{ft}$, the log of a firm's age $log(age)_{ft}$ and two dummies that take value one if the exporter belongs to a business group $Group_{ft}$ or is foreign-owned $Foreign_{ft}$. These covariates are included to increase the efficiency of the estimates and control for observable factors that might affect both firm financing decisions and the quality of their exported varieties. For example, older firms may have easier access to credit and be perceived as producers of higher quality products because of their longer track records and well-established brand names. Firms that are part of a business group may have lower leverage due to greater access to the group's internal financing (Boutin et al., 2013), and they may simultaneously benefit from quality-enhancing activities conducted by other affiliates[24].

Pooled OLS with cluster-robust standard errors is the first estimator we apply to equation 8. By including a full set of product-destination-year dummies, we require the identification to rely on variations in quality and leverage across firms exporting the same product to the same destination. These variations are the most appropriate source of identification to answer our research question. We wish to investigate whether differences in financial structures across firms determine differences in export quality. In addition, Lev_{ft} and $\hat{Q}_{fpdt}$ are time-persistent variables; hence we expect that the estimators that exploit time variations may underestimate

[24] In the Appendix, Table D.12 presents pairwise correlations between all variables included in the model.

the impact of leverage on quality. However, OLS would only generate consistent estimates of β if leverage were uncorrelated with η_f and η_{ft}. Because this assumption is highly restrictive, we will also estimate the model using within-group FE and FEIV estimators.

Within-group FE transforms the variables in 8 to eliminate η_f from the right-hand side of the model[25]. By doing so, we prevent the correlation between leverage and certain firm-level, time-invariant factors subsumed in the error term to bias the coefficient on Lev_{ft}. However, FE models are insufficient to address the endogeneity of Lev_{ft} arising from its correlation with firm-level shocks affecting both the firm's financial structure and the quality of its exports. In addition, endogeneity might arise from reverse causality if firms modify their financial structure in response to an increase in revenue from foreign markets or if they reduce their level of debt prior to investing in quality upgrading activities (e.g., this may occur if the cost of credit is relatively higher for this type of investment). We address this issue by using FEIV models to instrument current variations in leverage with past variations in exporters' financial structures. The validity of this approach relies on the assumption that lagged variations in firms' leverage are predetermined with respect to current variations in the quality of the exported varieties. As we use the first and second demeaned lags of the endogenous regressors as instruments for current realizations, and because we have annual data, this assumption does not appear unreasonable.

6.1. Results

Table 5 reports summary statistics on firms' attributes and export patterns for each of the six product categories selected for our analysis. Leverage differs significantly across firms exporting different products. Exporters of perfumes (HS6: 330300), lamps (HS6: 940510) and wooden furniture (HS6: 940360) are characterized by lower debt-to-asset ratios, larger size and a greater share of intangibles in total assets. These product classes also exhibit higher average unit-values, indicating that they include the most expensive varieties in our sample. Conversely, exporters of wines (HS6: 220410 and 220421) are characterized by higher leverage, smaller size and lower ratios of intangibles to total assets. These descriptive statistics appear consistent with the theoretical predictions of Long and Malitz (1985), whereby firms with a greater proportion of 'opaque' assets are relatively disadvantaged in financing intangible investment through debt. The table also reports average exporter liquidity, measured as the difference between working capital and financing needs for operating expenses (normalized over total assets). This variable indicates firms' operational dependence on external financing. Exporters of wine and perfumes appear more reliant on external financing to cover their operative expenses. However, differences in liquidity across product categories are smaller than differences

[25] All variables are demeaned at the level of each panel group, where groups are defined at the level of individual varieties (fpd).

Table 5: Summary statistics for the estimation sample

HS6	Obs.	Firms	Employees	Leverage	Liquidity	lprod	Intangibles	UV	Flows	Dest.
180690	7893	456	203.24	0.20	0.05	3.83	0.12	13.35	5.33	3.67
220410	14042	553	87.33	0.28	-0.01	4.27	0.06	10.15	11.68	8.10
220421	16921	674	169.79	0.23	0.02	4.02	0.07	7.83	5.70	3.43
330300	48376	1114	234.74	0.18	0.02	4.04	0.18	33.41	13.54	10.89
940360	31562	3256	156.07	0.17	0.05	3.66	0.12	20.04	3.53	2.98
940510	7174	706	242.69	0.14	0.06	3.78	0.16	78.08	3.01	2.67

Notes. HS6 product categories are: Chocolate and confectionery (180690), Still wine (220410), Sparkling wine (220421), Perfume and toilet waters (330300), Wooden furniture (940360), Lamps (940510). *Obs.* is the total number of export flows observed, *Firms* is the number of unique exporters in the sample, *Employee* is the average number of employees by exporter, *Leverage* is the average book vale to total asset ratio, *Liquidity* is the difference between firms' working capital and financing need to cover operating expenses normalized over total assets , *lprod* is the log of labor productivity defined as value added per employee, *Intangibles* is the ratio of intangible assets over total assets, *UV* is the average unit-value of exported varieties, *Flows* is the average number of export flows by firm (product-destination), *Dest* is the average number of unique destinations served by exporter.

in leverage, suggesting that heterogeneity in financial structures across exporters of different products might be primarily determined by different patterns of investment financing rather than by different levels of operational dependence on credit.
The results from the estimation of equation 8 are reported in Table 6. We first estimate the model on the entire sample obtained by pooling observations for all HS6 product categories. Then, estimation is repeated separately on the samples of export flows generated by firms with $Liquidity > 0$ and with $Liquidity < 0$. A similar split-sample strategy is employed in Nucci et al. (2005) to capture the differential effect of leverage on TFP for firms that are able to finance productivity-enhancing opportunities with own funds and those that require external financing. These authors find that the effect of leverage on TFP is more negative for firms with low liquidity, confirming that higher levels of debt constrain firms' ability to implement productivity-enhancing activities.

In addition, this separation criterion allows us to partially discriminate firms employing a highly leveraged financial structure by balancing the costs and benefits of debt financing (i.e., Trade-off Theory) from those accumulating debt in the absence of sufficient liquidity to finance operating expenses and investment with internal resources (i.e., Pecking Order Theory). If a firm is left with sufficient internal resources to cover the costs of current operations after investing ($Liquidity_{ft} > 0$), either it does not need any external financing, or it substitutes available internal resources with debt. Therefore, these firms' use of debt financing can be explained by the beneficial effects of debt (e.g., the tax shield function of debt). Conversely, when working capital is insufficient to cover operating expenses ($Liquidity < 0$), debt financing is more likely a forced solution rather than a value-optimizing choice.

The results obtained when considering the full sample confirm **Hyp1** that leverage negatively affects the quality of firms' exports. The coefficients on Lev_{ft} range from -0.066 (FE) to -0.188 (FEIV). The FE estimator might be upward biased because some firms' quality-upgrading investments are financed by debt. Thus, in these cases, leverage and quality move in the same direction. However, we are interested in determining whether firms with higher levels of leverage are less capable of upgrading the quality of their exported products. For this reason, pooled OLS and FEIV estimates are more relevant for our research question. The pooled OLS estimator implicitly assigns more weight to differences in levels of leverage across exporters, while FEIV addresses reverse causality that biases FE estimates upward by instrumenting changes in leverage at time t with lagged changes (i.e., using the first and the second lags of Lev_{ft} as instruments). The estimated coefficient of Lev_{ft} obtained by applying FEIV to the full sample is only significant at the 10% level. This weak significance casts doubt on the result that leverage has a negative impact on quality for all firms.

Estimates from the split samples of liquid and illiquid firms provide a much clearer picture. Leverage is only found to negatively and significantly affect the export quality of illiquid firms. This evidence is in line with hypothesis **Hyp2**. When we consider firms with insufficient internal resources to finance operations, the coefficients on Lev_{ft} are consistently more negative than those obtained when considering the full sample and are all significant at the 1% level across different estimators. Conversely, leverage does not appear to reduce quality for firms with sufficient internal liquidity. Therefore, we conclude that debt financing only constrains firms' ability (or incentive) to compete through quality in foreign markets when an exporter's financial structure is not a value-optimizing choice but rather the consequence of insufficient internal liquidity.

Table 6: Firms' leverage and export quality

	Pooled Sample			Liquidity>0			Liquidity<0		
	OLS	FE	FEIV	OLS	FE	FEIV	OLS	FE	FEIV
Lev_{ft}	-0.131***	-0.066**	-0.188*	-0.029	-0.044	0.309*	-0.242***	-0.129***	-0.828***
	(0.021)	(0.028)	(0.108)	(0.032)	(0.040)	(0.163)	(0.031)	(0.047)	(0.273)
$log(Intang)_{ft}$	0.011***	0.004	0.058***	0.020***	0.013**	0.077***	-0.011***	-0.014*	0.011
	(0.002)	(0.005)	(0.019)	(0.003)	(0.006)	(0.027)	(0.003)	(0.008)	(0.032)
$log(lprod)_{ft}$	0.173***	0.050***	0.045***	0.174***	0.050***	0.026*	0.155***	0.026**	0.040***
	(0.015)	(0.008)	(0.010)	(0.016)	(0.010)	(0.014)	(0.015)	(0.011)	(0.015)
$log(empl)_{ft}$	0.064***	0.111***	0.086***	0.061***	0.104***	0.057**	0.073***	0.097***	0.130***
	(0.008)	(0.012)	(0.020)	(0.009)	(0.016)	(0.027)	(0.008)	(0.022)	(0.034)
$Group_{ft}$	-0.037***	0.024***	0.019	-0.056***	0.022*	0.024	-0.013	0.037***	0.003
	(0.009)	(0.009)	(0.015)	(0.010)	(0.013)	(0.020)	(0.011)	(0.012)	(0.026)
$Foreign_{ft}$	0.057***	-0.019	-0.030	0.030	-0.043*	-0.078**	0.109***	0.042**	0.104***
	(0.017)	(0.015)	(0.022)	(0.019)	(0.023)	(0.039)	(0.024)	(0.020)	(0.040)
$log(age)_{ft}$	-0.000	-0.160*	-0.198**	0.000	-0.172**	-0.230***	-0.000	-0.156	-0.206
	(0.000)	(0.086)	(0.095)	(0.000)	(0.087)	(0.081)	(0.000)	(0.105)	(0.152)
$Constant$	-0.954***			-0.938***			-0.837***		
	(0.091)			(0.102)			(0.085)		
pd FE	y	n	n	y	n	n	y	n	n
hs6-t FE	y	y	y	y	y	y	y	y	y
fpd FE	n	y	y	n	y	y	n	y	y
Hansen (p)	-	-	0.818	-	-	0.024	-	-	0.706
R^2	0.597	0.005	0.003	0.577	0.004	0.002	0.647	0.003	-0.012
Groups		15,654	6,956		10,146	4,581		7,354	3,255
Obs.	85,335	72,227	32,292	52,001	41,274	19,154	33,334	25,821	10,945

Notes. * $p < .1$, ** $p < .05$, *** $p < .01$. Cluster-robust standard errors in parentheses (cluster unit: product-destination). FEIV models are estimated by GMM using the first and the second lags of the endogenous variables (Lev_{ft}, $log(Intang)_{ft}$, $log(lprod)_{ft}$) as instruments. FEIV models are estimated using the user-written command xtivreg2 in Stata (Schaffer, 2005). R^2 for FE and FEIV models are reported but they are not correct as they do not account for the part of variance that is explained by individuals' FEs, therefore they should be not interpret as reliable measure of goodness of fit of the model. $pdFE$ are CN8 product-destination fixed effects, $hs6 - tFE$ are HS6 product-year fixed effects, $fpdFE$ are firm-CN8 product-destination FE. Except for the latter group of FE controlled for by within-group transformation of the variables, the other two FE are introduced in the model by a full set of dummies.

The estimated coefficients on the control variables warrant discussion. Larger and more productive exporters are associated with the export of higher quality varieties across all specifications. This result is in line with the evidence documenting a positive correlation between output price and firm size (Kugler and Verhoogen, 2012). Therefore, our analysis, based on a theoretically grounded estimator of quality, confirms the hypothesis of complementarity among a firm's scale, productivity and quality. In addition, and consistent with the notion that investments in intangible assets contribute to the real or perceived quality of an exporter's good, we find that $log(Intang)_{ft}$ is positively correlated with export quality, although this relationship does not hold for illiquid firms. A possible explanation for this result is that the composition of intangible assets for this group of firms includes elements that are less relevant for quality upgrading. However, this is only a tentative hypothesis for which a proper test of validity is beyond the scope of this paper.

In the FE and FEIV models, the coefficients on the dummy variables $Group_{ft}$ and $Foreign_{ft}$ are exclusively identified through variations in the time series of these variables associated with firms that are acquired by a domestic or foreign group during the period under analysis. The sign of the estimated coefficients on $Group_{ft}$ differs across estimators and samples, and we prefer not to advance any interpretation of the effect of entering a business group on output quality. However, foreign acquisition seems to only have a positive effect on export quality for firms with negative liquidity, while the effect is ambiguous when estimated using the full sample and the group of liquid exporters. Finally, and in contrast to prior expectations regarding the effect of firm age on the 'brand component' of quality, we find that $log(age)_{ft}$ is negatively correlated with quality when its coefficient is estimated using the full sample.

In the FEIV regressions we apply a within-group transformation to eliminate the fixed-effect component from the error term. Given the highly unbalanced structure of our dataset, this transformation preserves a greater number of observations and produces more precise estimates than first-differencing. However, when we apply the within-group transformation, the lagged values of the endogenous covariates may not be valid instruments. This would be the case if the correlation between the error term and the endogenous covariates at time t were strong and if the time-t realization of the endogenous covariate played an important role in the computation of the within-group means of this variable. Conversely, transforming the data by first-differencing does not generate this problem. First-differencing eliminates the fixed-effect from the error term and preserves the validity of the second and greater lags of the endogenous covariates as instruments for their current values (Wooldridge, 2001). Table D.13 in the Appendix reports the FEIV estimates of the model obtained by first-differencing (FD) the data instead of applying the within-group transformation. From a qualitative perspective, the results are in line with the FEIV estimates in Table 6, although the estimated effect of leverage is more negative in regressions using first-differenced data. However, by comparing the number of observations and the estimated standard errors obtained from regressions using first-differencing to those obtained from the model applying the within-group transformation, it is clear that first-differencing the data causes a greater loss of information than the within-group transformation. Because the two approaches deliver the same qualitative result, we prefer the within-group transformation, as it preserves more information and generates more precise estimates.

7. Robustness checks

In this section, we conduct a series of robustness exercises to assess whether the negative correlation between firm leverage and export quality also holds when we change the composition of the estimation sample, when we use alternative proxies for quality and financial structure, and when we evaluate the impact of leverage on different quantiles of the distribution of $\hat{Q}_{ft}$.

We begin by expanding the estimation sample to include the entire list of twenty-one 6-digit products reported in Table C.11. Because overidentification tests reject the appropriateness of the instrument set used in the FEIV regressions for many of these products, we obtain the proxy for quality $\hat{Q}_{FE}$ as the residual computed from the demand parameters estimated by FE. Although $\hat{Q}_{FE}$ still captures the non-price competitiveness of exporters, we are aware that this proxy will underestimate export quality, especially for high-quality varieties[26]. Table 7 reports the results of this first exercise. This robustness check confirms our main qualitative result that leverage is negatively associated with the quality of exported varieties. However, and in contrast to our previous findings, the FEIV estimates using this sample suggest that the negative effect of leverage on quality is stronger for liquid firms than it is for illiquid ones.

This inconsistency calls for a second check to understand whether this different result arises from the expansion of the sample to a wider range of products or, instead, is due to the use of the biased proxy for quality $\hat{Q}_{FE}$. To determine which of these possible reasons is most plausible, we estimate the same set of regressions on $\hat{Q}_{FE}$ using the restricted sample of six products. The results are reported in Table 8. As we find that the inconsistency (i.e., the greater negative impact of leverage on liquid firms) is still present when models are estimated using the restricted sample, we exclude the possibility that our previous results were an artifact of sample composition. Rather, it appears that this inconsistency is related to the use of $\hat{Q}_{FE}$ as a proxy for quality on the left-hand side of the models used in the robustness checks. Therefore, we argue that the first exercise does not undermine the validity of our previous findings.

The second robustness check consists of repeating the estimation of equation 8 by substituting $\hat{Q}_{ft}$ on the left-hand side of the equation with unit-values. As we noted previously, the effect of leverage on unit-values is ambiguous if more leveraged exporters are less capable of implementing productivity-enhancing measures

[26]In the Appendix, we include a discussion on this bias and its causes.

as suggested by empirical studies on leverage and TFP (e.g., Aivazian et al., 2005; Nucci et al., 2005; Nunes et al., 2007; Coricelli et al., 2012). However, if the negative effect of debt on quality dominates the efficiency-hampering one, we would expect more leveraged firms to export relatively less expensive varieties within each product-destination couple. In addition, this robustness check allows us to compare our estimates with previous evidence on firm financial characteristics and export prices. Manova et al. (2011) and Fan et al. (2012) argue that credit-rationed Chinese firms export relatively less expensive varieties within narrowly defined product categories. Conversely, Secchi et al. (2011) find that Italian exporters in financial distress tend to set relatively higher export prices in foreign markets. By comparing the results of regressions on export prices with those previously obtained for the quality estimator, we can better disentangle the effect of financial factors on unit-values and quality.

Table 7: Estimates on the extended sample of 21 products by using $\hat{Q}_{FE}$ as a proxy for quality

	Pooled Sample			Liquidity>0			Liquidity<0		
	OLS	FE	FEIV	OLS	FE	FEIV	OLS	FE	FEIV
Lev_{ft}	-0.026***	-0.020**	-0.097***	-0.022***	-0.015	-0.138***	-0.046***	-0.022	-0.050
	(0.005)	(0.008)	(0.036)	(0.006)	(0.012)	(0.053)	(0.008)	(0.015)	(0.076)
$log(Intang)_{ft}$	-0.002***	0.002	0.008*	-0.003***	0.002	0.003	-0.003***	-0.000	0.007
	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.005)	(0.001)	(0.003)	(0.011)
$log(lprod)_{ft}$	0.012***	0.007***	0.005*	0.011***	0.010***	0.009**	0.013***	0.004	0.008**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
$log(empl)_{ft}$	0.013***	0.022***	0.026***	0.013***	0.025***	0.030***	0.014***	0.020***	0.023**
	(0.001)	(0.003)	(0.005)	(0.002)	(0.004)	(0.006)	(0.002)	(0.007)	(0.012)
$Group_{ft}$	-0.005**	0.004	0.017***	-0.005*	-0.007	0.009	-0.007**	0.022***	0.037***
	(0.002)	(0.004)	(0.006)	(0.003)	(0.005)	(0.008)	(0.003)	(0.006)	(0.011)
$Foreign_{ft}$	0.025***	0.004	0.008	0.031***	-0.000	-0.002	0.010**	0.018*	0.022
	(0.003)	(0.006)	(0.009)	(0.004)	(0.008)	(0.012)	(0.005)	(0.010)	(0.015)
$log(age)_{ft}$	-0.000***	0.053	-0.042	-0.000***	0.065	-0.023	-0.000	-0.023	-0.110
	(0.000)	(0.091)	(0.090)	(0.000)	(0.097)	(0.026)	(0.000)	(0.046)	(0.135)
$Constant$	-0.117***			-0.126***			-0.134***		
	(0.018)			(0.019)			(0.018)		
pd FE	y	n	n	y	n	n	y	n	n
hs6-t FE	y	y	y	y	y	y	y	y	y
fpd FE	n	y	y	n	y	y	n	y	y
Hansen (p)			0.144			0.265			0.820
R^2	0.776	0.000	0.000	0.781	0.000	0.000	0.792	0.000	0.001
Groups		79,777	30,550		55,196	21,356		29,427	11,588
Obs.	415,645	335,657	132,433	274,290	209,100	83,356	141,355	100,680	39,473

Notes. * $p < .1$, ** $p < .05$, *** $p < .01$. Cluster-robust standard errors in parentheses (cluster unit: product-destination). FEIV models are estimated by GMM using the first and the second lags of the endogenous variables (Lev_{ft}, $log(Intang)_{ft}$, $log(lprod)_{ft}$) as instruments.FEIV models are estimated using the user-written command xtivreg2 in Stata (Schaffer, 2005). R^2 for FE and FEIV models are reported but they are not correct as they do not account for the part of the variance that is explained by individuals' FEs, therefore they should be not interpret as reliable measure of goodness of fit of the model. $pdFE$ are CN8 product-destination fixed effects, $hs6-tFE$ are HS6 product-year fixed effects, $fpdFE$ are firm-CN8 product-destination FE. Except for the latter group of FE controlled for by within-group transformation of the variables, the other two FE are introduced in the model by a full set of dummies.

Table 8: Estimates on the restricted sample of 6 products by using $\hat{Q}_{FE}$ as a proxy for quality

	Pooled Sample			Liquidity>0			Liquidity<0		
	OLS	FE	FEIV	OLS	FE	FEIV	OLS	FE	FEIV
Lev_{ft}	-0.035***	-0.040**	-0.178**	-0.043***	-0.062**	-0.246**	-0.059***	-0.019	-0.061
	(0.012)	(0.020)	(0.084)	(0.014)	(0.028)	(0.119)	(0.019)	(0.033)	(0.223)
$log(Intang)_{ft}$	-0.009***	0.001	0.012	-0.012***	0.002	0.002	-0.007***	-0.003	0.021
	(0.001)	(0.004)	(0.011)	(0.002)	(0.004)	(0.013)	(0.002)	(0.007)	(0.026)
$log(lprod)_{ft}$	0.026***	0.005	0.004	0.020***	0.006	0.007	0.034***	0.011	0.018**
	(0.003)	(0.005)	(0.006)	(0.004)	(0.006)	(0.008)	(0.005)	(0.007)	(0.008)
$log(empl)_{ft}$	0.034***	0.040***	0.051***	0.040***	0.038***	0.043***	0.026***	0.049***	0.069***
	(0.003)	(0.009)	(0.013)	(0.003)	(0.011)	(0.017)	(0.004)	(0.014)	(0.023)
$Group_{ft}$	0.007	0.012	0.042***	0.002	-0.010	0.015	0.013*	0.053***	0.087***
	(0.005)	(0.008)	(0.013)	(0.007)	(0.011)	(0.018)	(0.007)	(0.013)	(0.026)
$Foreign_{ft}$	0.059***	0.008	0.019	0.077***	-0.010	-0.020	0.021**	0.037**	0.056*
	(0.008)	(0.012)	(0.021)	(0.011)	(0.017)	(0.034)	(0.010)	(0.018)	(0.034)
$log(age)_{ft}$	-0.001***	0.097	-0.048	-0.002***	0.116	-0.010	-0.000	0.016	-0.100
	(0.000)	(0.096)	(0.092)	(0.000)	(0.105)	(0.098)	(0.000)	(0.106)	(0.129)
$Constant$	-0.267***			-0.211***			-0.258***		
	(0.026)			(0.027)			(0.033)		
pd FE	y	n	n	y	n	n	y	n	n
HS6-Year FE	y	y	y	y	y	y	y	y	y
fpd FE	n	y	y	n	y	y	n	y	y
Hansen (p)			0.492			0.398			0.642
R^2	0.781	0.001	0.001	0.790	0.001	0.000	0.797	0.001	0.002
Groups		22,294	9,641		13,639	5,964		10,655	4,658
Obs.	122,918	101,568	44,314	72,320	55,416	24,964	50,598	38,616	16,226

Notes. * $p < .1$, ** $p < .05$, *** $p < .01$. Cluster-robust standard errors in parentheses (cluster unit: product-destination). FEIV models are estimated by GMM using the first and the second lags of the endogenous variables (Lev_{ft}, $log(Intang)_{ft}$, $log(lprod)_{ft}$) as instruments. FEIV models are estimated using the user-written command xtivreg2 in Stata (Schaffer, 2005). R^2 for FE and FEIV models are reported but they are not correct as they do not account for the part of the variance that is explained by individuals' FEs, therefore they should be not interpret as reliable measure of goodness of fit of the model. $pdFE$ are CN8 product-destination fixed effects, $hs6-tFE$ are HS6 product-year fixed effects, $fpdFE$ are firm-CN8 product-destination FE. Except for the latter group of FE controlled for by within-group transformation of the variables, the other two FE are introduced in the model by a full set of dummies.

Table 9 reports the estimates of regressions considering the unit-values of exported varieties. The results of this exercise are in line with those that we obtained in regressions using $\hat{Q}_{ft}$, as we observe a negative relationship between leverage and export prices in the FE and FEIV estimates from the pooled sample. As in the previous exercise, we still find that the negative correlation between prices and leverage is much stronger within the sample of firms that cannot self-finance current expenses. Regarding the other firm-level covariates, we find that the coefficients of $log(empl)_{ft}$ and $log(lprod)_{ft}$ on prices have the opposite signs of those obtained when using $\hat{Q}_{ft}$. Therefore, we conclude that larger and more productive firms are more competitive on both price and quality. In other words, they charge relatively lower prices, but they can nevertheless sell higher quality products than competitors setting similar prices.

Table 9: Firms' leverage and export prices

	Pooled Sample			Liquidity>0			Liquidity<0		
	OLS	FE	FEIV	OLS	FE	FEIV	OLS	FE	FEIV
Lev_{ft}	0.018	-0.070***	-0.247***	0.188***	-0.063*	-0.152	-0.167***	-0.053	-0.499**
	(0.031)	(0.022)	(0.087)	(0.037)	(0.038)	(0.119)	(0.041)	(0.034)	(0.243)
$log(Intang)_{ft}$	0.055***	0.019***	0.049***	0.062***	0.027***	0.089***	0.043***	0.008	-0.026
	(0.002)	(0.003)	(0.011)	(0.003)	(0.004)	(0.014)	(0.003)	(0.006)	(0.024)
$log(lprod)_{ft}$	-0.010	0.011**	0.005	-0.003	0.030***	0.014	-0.024***	-0.026***	-0.016*
	(0.008)	(0.005)	(0.007)	(0.010)	(0.007)	(0.010)	(0.009)	(0.008)	(0.009)
$log(empl)_{ft}$	-0.025**	0.004	-0.032**	-0.025**	0.052***	0.001	-0.023**	-0.065***	-0.087***
	(0.011)	(0.008)	(0.013)	(0.012)	(0.011)	(0.020)	(0.009)	(0.014)	(0.025)
$Group_{ft}$	-0.051***	0.001	-0.007	-0.087***	0.007	0.010	-0.002	-0.010	0.002
	(0.018)	(0.008)	(0.012)	(0.021)	(0.010)	(0.016)	(0.021)	(0.013)	(0.023)
$Foreign_{ft}$	0.024	-0.004	-0.022	-0.069***	-0.014	-0.066**	0.194***	-0.018	0.024
	(0.023)	(0.012)	(0.018)	(0.026)	(0.016)	(0.028)	(0.027)	(0.018)	(0.034)
$log(age)_{ft}$	0.004***	-0.026	-0.068	0.006***	-0.060	-0.053	0.002***	0.032	-0.050
	(0.000)	(0.040)	(0.052)	(0.000)	(0.048)	(0.081)	(0.000)	(0.049)	(0.053)
$Constant$	2.362***			2.321***			2.425***		
	(0.076)			(0.085)			(0.078)		
pd FE	y	n	n	y	n	n	y	n	n
HS6-Year FE	y	y	y	y	y	y	y	y	y
fpd FE	n	y	y	n	y	y	n	y	y
Hansen (p)			0.640			0.189			0.872
R^2	0.468	0.001	0.001	0.464	0.004	0.005	0.498	0.002	-0.008
Groups		16,482	7,254		10,733	4,805		7,777	3,406
Obs.	90,717	77,021	34,111	55,427	44,187	20,286	35,290	27,495	11,547

Notes. * $p < .1$, ** $p < .05$, *** $p < .01$. Cluster-robust standard errors in parentheses (cluster unit: product-destination). FEIV models are estimated by GMM using the first and the second lags of the endogenous variables (Lev_{ft}, $log(Intang)_{ft}$, $log(lprod)_{ft}$) as instruments. FEIV models are estimated using the user-written command xtivreg2 in Stata (Schaffer, 2005). R^2 for FE and FEIV models are reported but they are not correct as they do not account for the part of the variance that is explained by individuals' FEs, therefore they should be not interpret as reliable measure of goodness of fit of the model. $pdFE$ are CN8 product-destination fixed effects, $hs6-tFE$ are HS6 product-year fixed effects, $fpdFE$ are firm-CN8 product-destination FE. Except for the latter group of FE controlled for by within-group transformation of the variables, the other two FE are introduced in the model by a full set of dummies.

The third sensitivity test is conducted by substituting Lev_{ft} in regressions considering $\hat{Q}_{ft}$ with a different indicator of corporate financial structure called $Equity_{ft}$. This variable is constructed as the ratio of the book value of a firm's initial capital and issued equities over total assets. $Equity_{ft}$ captures the extent to which firms use equity financing for investment and current expenses. On the one hand, according to the Pecking Order Theory of corporate financial structure, we expect that in the presence of information asymmetries between insiders (i.e., managers and current shareholders) and outsiders (i.e., perspective shareholders), equities are the most expensive form of external financing (Myers and Majluf, 1984). On the other, this source of financing does not expose firms to bankruptcy risk or distort firms' incentives to invest in quality-enhancing activities. Therefore, we do not have a strong prior regarding the effect of additional equity financing on output quality when firms substitute internal financing with equity financing. Conversely, for liquidity-constrained firms, we expect equity financing to have a positive effect on output quality when equities substitute for debt. In other words, for liquidity-constrained firms, issuing new shares may constitute a source of financing that is relatively more expensive than debt, but it does not distort the incentives for and the relative costs of quality upgrades.

In table 10, we can see that the point estimates of the coefficients of $Equity_{ft}$ are positive but insignificant when models are estimated using the pooled sample. However, estimates of $Equity_{ft}$ change signs across the samples of 'liquid' and 'illiquid' exporters. Specifically, we find that equity financing is positively correlated with export quality for the group of illiquid exporters. We interpret the positive correlation between equity financing and quality as a sign that, among illiquid exporters, those that have greater scope for substituting equity financing for debt financing have a greater advantage in competing on quality in foreign markets. Conversely, $Equity_{ft}$ appears to have a negative and significant impact on export quality among 'liquid' exporters when the model is estimated using FEIV. However, the Hansen-J test of overidentifying restrictions rejects the joint validity of the instruments (Hansen p-value=0.015) at the 0.05 significance level. Therefore, we prefer not to interpret this coefficient as evidence of a quality-hampering effect of equity financing. Nevertheless, the positive and significant effect of equity financing for 'illiquid' exporters is in line with our main results, according to which firms that resort to debt financing in the absence of alternatives (i.e., either internal or equity financing) are relatively disadvantaged in exporting high-quality products.

We conclude this section by investigating the impact of leverage on different quantiles of the distribution of $\hat{Q}_{ft}$. Our results suggest that firms with higher leverage export varieties with lower expected values of $\hat{Q}_{ft}$. However, this finding is both consistent with a leftward shift of the entire export quality distribution for less leveraged firms or a localized impact on certain quantiles. To better characterize the impact of leverage on quality, we estimate quantile regressions (Koenker and Bassett, 1978) of Lev_{ft} on $\hat{Q}_{ft}$ using only the 2004 cross-section[27]. To control for product-destination fixed effects without including a large number of dummies, we transform the variables in equation 8 by subtracting their means computed at the CN8 product-destination level from each observation[28].

[27]The results are virtually identical when we estimate quantile regressions using the cross-sections for 1997, 2000 and 2007.

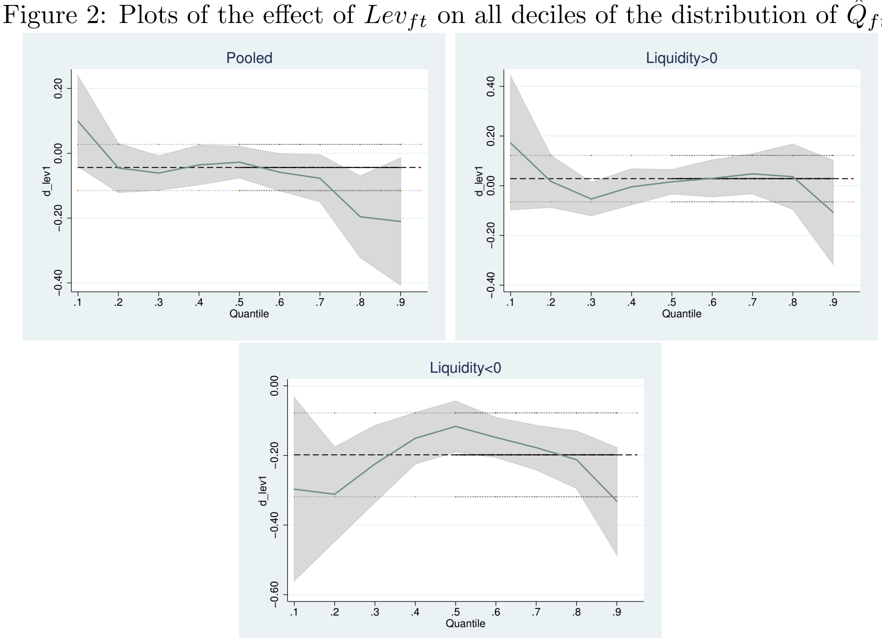
[28]We also estimated an Unconditional Quantile Regressor for Panel Data developed by Powell (2010) by running the code associated with this paper in Stata. This estimator offers the possibility to control for individual firms' fixed effects in quartile regressions without affecting the interpretation of the results, as would be the case for the panel quantile regression estimator proposed by Canay (2011). However, the size of the sample and limitations in computing power prevented us from successfully applying this estimator. Therefore, we decided to estimate a cross-sectional quantile regression using the transformed variables.

Table 10: Firms' equity financing and export quality

	Pooled Sample			Liquidity>0			Liquidity<0		
	OLS	FE	FEIV	OLS	FE	FEIV	OLS	FE	FEIV
$Equity_{ft}$	0.020	0.027	0.028	-0.031	-0.018	-0.379***	0.016	0.056*	0.684***
	(0.017)	(0.018)	(0.068)	(0.024)	(0.024)	(0.102)	(0.018)	(0.031)	(0.164)
$log(Intang)_{ft}$	0.011***	0.004	0.040**	0.021***	0.012*	0.066***	-0.010***	-0.012	-0.025
	(0.002)	(0.005)	(0.018)	(0.003)	(0.007)	(0.022)	(0.003)	(0.009)	(0.030)
$log(lprod)_{ft}$	0.184***	0.052***	0.052***	0.185***	0.053***	0.014	0.159***	0.034***	0.055***
	(0.016)	(0.008)	(0.010)	(0.017)	(0.010)	(0.014)	(0.015)	(0.012)	(0.015)
$log(empl)_{ft}$	0.069***	0.118***	0.095***	0.068***	0.112***	0.041	0.073***	0.107***	0.173***
	(0.008)	(0.012)	(0.020)	(0.010)	(0.016)	(0.025)	(0.008)	(0.021)	(0.035)
$Group_{ft}$	-0.037***	0.024**	0.021	-0.061***	0.019	0.025	0.002	0.042***	0.026
	(0.009)	(0.009)	(0.016)	(0.011)	(0.014)	(0.020)	(0.011)	(0.012)	(0.027)
$Foreign_{ft}$	0.059***	-0.013	-0.023	0.032	-0.049**	-0.081**	0.115***	0.059***	0.139***
	(0.018)	(0.016)	(0.022)	(0.020)	(0.024)	(0.040)	(0.025)	(0.021)	(0.041)
$log(age)_{ft}$	-0.000	-0.166*	-0.167*	0.000*	-0.167*	-0.200**	-0.001*	-0.194*	-0.212
	(0.000)	(0.088)	(0.096)	(0.000)	(0.086)	(0.087)			
$Constant$	-1.041***			-0.957***			-0.966***		
	(0.090)			(0.094)			(0.088)		
pd FE	y	n	n	y	n	n	y	n	n
HS6-Year FE	y	y	y	y	y	y	y	y	y
fpd FE	n	y	y	n	y	y	n	y	y
Hansen (p)			0.705			0.015			0.997
R^2	0.613	0.005	0.005	0.593	0.005	0.002	0.662	0.004	-0.019
Groups		15,717	6,958		9,900	4,444		7,486	3,220
Obs.	85,715	72,530	31,975	51,712	40,921	18,842	34,003	26,468	10,883

Notes. * $p < .1$, ** $p < .05$, *** $p < .01$. Cluster-robust standard errors in parentheses (cluster unit: product-destination). FEIV models are estimated by GMM using the first and the second lags of the endogenous variables (Lev_{ft}, $log(Intang)_{ft}$, $log(lprod)_{ft}$) as instruments. FEIV models are estimated using the user-written command xtivreg2 in Stata (Schaffer, 2005). R^2 for FE and FEIV models are reported but they are not correct as they do not account for the part of the variance that is explained by individuals' FEs, therefore they should be not interpret as reliable measure of goodness of fit of the model. $pdFE$ are CN8 product-destination fixed effects, $hs6-tFE$ are HS6 product-year fixed effects, $fpdFE$ are firm-CN8 product-destination FE. Except for the latter group of FE controlled for by within-group transformation of the variables, the other two FE are introduced in the model by a full set of dummies.

Figure 2: Plots of the effect of Lev_{ft} on all deciles of the distribution of $\hat{Q}_{ft}$



Notes. The three panels plot the coefficients of Lev_{ft} when regressed on the deciles of the distribution of $\hat{Q}_{ft}$. The 'Pooled' panel refers to quantile regression estimates obtained on the whole sample, while $Liquidity > 0$ and $Liquidity >< 0$ refer respectively to estimates on the samples of firms with sufficient and insufficient liquidity to cover operating expenses. The solid line within the shaded area is the plot of the coefficients, while the shaded gray area is the 95% band of confidence of the estimated coefficients. The thicker horizontal line represents the OLS coefficient, and the two thinner horizontal lines delimit the 95% confidence interval for the OLS estimates. These figures are produced by using the user-written Stata command grqreg (Azevedo, 2004).

8. Conclusions

In this paper, we advanced the understanding of the relationship between financial factors and firm export behavior by shedding light on the 'quality channel'. We found that corporate financial structure determines a firm's ability to compete on quality in foreign markets, which is consistent with models predicting that debt financing and financial distress reduce firms' incentives and ability to invest in quality-enhancing activities such as advertising and R&D (Long and Malitz, 1985; Maksimovic and Titman, 1991).

An interesting finding that emerges from our analysis is that the negative impact of leverage on export quality is conditional on firms depending on external financing for operating expenses. We interpret this result by referring to alternative theories of corporate financial structure. For certain firms, an intensive use of debt corresponds to a value-optimizing choice. In our sample, we identify these firms as having higher liquidity, as they are able to substitute debt with internal resources. For others, debt may be the only solution to compensate for insufficient internal resources and a lack of access to equity financing. These firms most likely cannot completely self-finance current expenses. As we find that the effect of leverage on quality is especially strong and significant for the latter group of firms, we argue that debt financing only impedes quality upgrading in the presence of liquidity constraints.

We believe that our study has important implications, as it suggest that policies affecting the use of debt financing (e.g., changes in corporate tax rates) may also indirectly modify firms' incentives to upgrade their product quality and thus their ability to compete in foreign markets. Our findings represent a foundation for further research on the specific contributions of subcategories of intangible assets, such as R&D and advertising, to export quality, firm competitiveness in foreign markets, and the way in which firm-level financial heterogeneity affects investments in these activities.

Appendix A. Derivation of equation 5

Given the assumptions of the discrete choice model of demand, the probability P_j that any individual consumer chooses variety j over all the others possible substitutes in K can be written as:

$$P_j = P_{j/g} \times P_g \tag{A.1}$$

where P_g is the probability that the choice of the consumer falls on one of the products in group g, and g is an index for each of the varieties' 'nests' that compose the wider set K. By expressing the probability P_g according to a multinomial logit model we can write:

$$P_g = \frac{[\sum_{k \in g} e^{\delta_k/(1-\sigma)}]^{(1-\sigma)}}{\sum_g [\sum_{k \in g} e^{\delta_k/(1-\sigma)}]^{(1-\sigma)}} \tag{A.2}$$

$P_{j/g}$ is instead the probability of choosing j conditional on the choice of group g:

$$P_{j/g} = \frac{e^{\delta_j/(1-\sigma)}}{\sum_{k \in g} e^{\delta_k/(1-\sigma)}} \tag{A.3}$$

by multiplying the right-hand sides of A.2 and A.3 we obtain:

$$P_j = \frac{e^{\delta_j/(1-\sigma)}}{[\sum_{k \in g} e^{\delta_k/(1-\sigma)}]^{\sigma} \times \sum_g [\sum_{k \in g} e^{\delta_k/(1-\sigma)}]^{(1-\sigma)}} \tag{A.4}$$

the expression for P_j can be simplified if we normalize the probability of choosing each j by the probability of choosing an outside variety delivering expected utility $\delta_o = 0$[29]. The probability of choosing the outside variety (hence not choosing any of the inside varieties) is:

$$P_o = \frac{1}{\sum_g [\sum_{k \in g} e^{\delta_k/(1-\sigma)}]^{(1-\sigma)}} \tag{A.5}$$

taking the log difference of P_j and P_o we obtain:

$$ln(P_j) - ln(P_o) = \frac{\delta_j}{1-\sigma} - \sigma ln(\sum_{k \in g} e^{\delta_k/(1-\sigma)}) \tag{A.6}$$

by using A.2, A.5 and A.1 we find that $ln(\sum_{k \in g} e^{\delta_k/(1-\sigma)}) = [ln(P_g) - ln(P_o)]/(1-\sigma)$. After substituting the right-hand side of this expression in A.6, and after some simplification we obtain:

$$ln(P_j) - ln(P_o) = X_j'\beta - \alpha p_j + \sigma(P_{j/g}) + \zeta_j \tag{A.7}$$

because the observed market shares s_j, s_o and $s_{j/g}$ can be thought as empirical counterparts of P_j, P_o and $P_{j/g}$, then A.1 is the empirical equivalent of A.7.

Appendix B. Derivation of the elasticity of demand

By defining $D_g = \sum_{j \in g} e^{\delta_j/1-6}$ equation (4) can be written as:

$$s_j = \frac{e^{\delta_j/(1-\sigma)}}{D_g^{\sigma}[\sum_g D_g^{(1-\sigma)}]} \tag{B.1}$$

[29] The outside variety is a variety for which we do not identify the mean utility. Instead we normalize it to 0 and express the mean utility of all other varieties in relation to the outside variety (Nevo, 2000). In practice, the market share of the outside variety is computes as $s_o = 1 - \sum_{j \in K} s_j$, where $\sum_{j \in K} s_j$ is the aggregate share of the inside varieties.

then

$$\frac{\partial s_j}{\partial p_j} = \frac{e^{\delta_j/(1-6)}\frac{\partial \delta_j}{\partial p_j} D_g^{\sigma}[\sum_g D_g^{(1-\sigma)}] - e^{\delta_j/(1-\sigma)}[\frac{\partial (D_g^{\sigma})}{\partial p_j}[\sum_g D_g^{1-\sigma}] + D_g^{\sigma}\frac{\partial (D_g^{1-\sigma})}{\partial p_j}}{(D_g^{\sigma}[\sum_g D_g^{(1-\sigma)}])^2} \tag{B.2}$$

because $\frac{\partial \delta_j}{\partial p_j} = \frac{\alpha}{1-\sigma}$, we can use the definition of s_j in (B.1) and the definition of $P_{j/g} \equiv s_{j/g}$ in (7) to write (B.2) as:

$$\frac{\partial s_j}{\partial p_j} = \frac{\alpha}{1-\sigma} s_j(1 - \sigma s_{j|g} - (1-\sigma)s_j) \tag{B.3}$$

then multiplying (B.3) by $\frac{p_j}{s_j}$ we obtain the formula for the market share elasticity of demand:

$$\frac{\partial s_j}{\partial p_j} \times \frac{p_j}{s_j} = \frac{\alpha}{1-\sigma} p_j(1 - \sigma s_{j|g} - (1-\sigma)s_j) \tag{B.4}$$

Appendix C. Selection of the product categories

In the first column we rank each HS6 product category by the number of observations in the dataset. The FEIV specification of the demand model is indeed estimated for the 30 products with the greatest number of observations. The 21st product (HS6: 180690) in this ranking is the one with the smallest number of observations for which we obtain significant estimates of the demand parameters. In addition, column (5) reports the product categories for which the FEIV estimates of the demand parameters are different from 0 at the 0.05 level of significance. Lastly, because our proxy of export quality depends on the consistency of the estimated parameters, in column (4) we mark those products for which the Hansen-J test fails to reject the joint validity of the instrument set at the 0.05 level.

Table C.11: Selection of the 6-digit products

(1) Rank flows	(2) HS6	(3) Obs.	(4) Insignificant Hansen-J	(5) Significant estimates	(6) Consumer good	(7) Num. nests
1	330300	57,851	✓	✓	✓	2
2	330499	54,958	✗	✓	✓	1
3	940360	39,635	✓	✓	✓	3
4	490199	35,702	✓	✗	✓	1
5	490290	33,046	✗	✓	✓	3
6	300490	33,046	✗	✓	✓	1
7	220421	32,899	✓	✓	✓	32
8	392690	32,289	✓	✗	✓	4
9	621149	31,155	✗	✓	✓	1
10	621050	28,746	✗	✗	✓	1
11	420292	27,008	✓	✗	✓	5
12	610990	26,315	✗	✓	✓	3
13	210690	25,825	✓	✗	✓	7
14	621143	25,378	✓	✗	✓	5
15	620462	22,450	✗	✗	✓	6
16	610910	22,208	✗	✗	✓	1
17	620463	21,520	✓	✗	✓	5
18	220410	20,966	✓	✓	✓	3
19	940510	20,409	✓	✓	✓	6
20	620469	19,417	✗	✗	✓	6
21	180690	18,984	✓	✓	✓	8

The table refers only to the 21 6-digit consumer products with the greater number of observations in the Custom dataset once we drop the exports associated with wholesalers. In columns (4), (5) and (6) the (✓) indicates that the product category satisfies the condition in the headings of the table. Column (7) reports the number of different 8-digit product sub-classes (nests) belonging to same 6-digit class.

The significance of the estimated coefficients appears mostly related to the number of observations in each product class, however it should be recognized that by restricting the analysis to the products for which we obtain negative and significant estimates of the price coefficient, we risk over-representing product classes with higher price elasticity of demand. However, the main objective of this study is to compare the output quality of firms exporting the same HS6 product, rather than to determine how the relationship between financial structure and quality differs across product categories. Therefore, even thus our methodology is difficult to apply to the analysis of a wide range of different exported products, it nevertheless serves the main focus on firms' heterogeneity.

Appendix D. Additional tables

Table D.12 reports pairwise correlation between all variables included in the models of export quality and financial structure.

Table D.12: Correlations between the main variables used in regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) $\hat{Q}_{fpdt}$	1							
(2) $log(UV)_{fpdt}$	0.0246***	1						
(3) Lev_{ft}	-0.0362***	-0.0998***	1					
(4) $log(Intang)_{ft}$	0.0659***	0.266***	-0.0749***	1				
(5) $log(empl)_{ft}$	0.0770***	0.197***	-0.150***	0.756***	1			
(6) $log(age)_{ft}$	0.00671*	0.0376***	0.0206***	0.148***	0.238***	1		
(7) $Group$	-0.0122***	0.101***	0.00730*	0.242***	0.307***	0.144***	1	
(8) $Foreign_{ft}$	0.0373***	0.150***	-0.0533***	0.336***	0.317***	-0.0172***	-0.390***	1
(9) $log(lprod)_{ft}$	0.0581***	0.171***	-0.102***	0.278***	0.0810***	0.0297***	0.128***	0.133***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.13 reports FEIV estimates after first-differencing the data to eliminate firm-product-destination fixed effects from the error. Results are qualitatively similar to those obtained from FEIV models applying within-group transformation to the data.

Table D.13: FEIV estimates with first-differencing of the data

	Pooled	Liquidity>0	Liquidity<0
ΔLev_{ft}	-2.844***	-0.188	-1.098*
	(0.750)	(2.565)	(0.578)
$\Delta log(Intang)_{ft}$	-0.442*	0.580	-0.124
	(0.236)	(1.056)	(0.195)
$\Delta log(empl)_{ft}$	0.070**	0.018	0.191**
	(0.035)	(0.045)	(0.086)
$\Delta Group_{ft}$	-0.022	0.111	-0.029
	(0.028)	(0.168)	(0.031)
$\Delta Foreign_{ft}$	0.182***	0.065	0.218***
	(0.055)	(0.161)	(0.078)
$\Delta log(lprod)_{ft}$	0.034*	-0.027	0.024
	(0.020)	(0.096)	(0.021)
hs6-t FE	y	y	y
Hansen (p)	0.716	0.064	0.153
R^2	-0.378	-0.245	-0.038
Groups	5,430	3,887	2,931
Obs.	18,778	12,202	6,576

Notes. * $p < .1$, ** $p < .05$, *** $p < .01$. Cluster-robust standard errors in parentheses (cluster unit: product-destination). FEIV models are estimated by GMM using the second and third lags of the endogenous variables as instruments. The model is in first-differences, for this reason the coefficient on $log(age)_{ft}$ is not identified.

Table D.14: Coefficients on Lev_{ft} in quantile regressions on $\hat{Q}_{ft}$

Quantiles:	Pooled Sample	Liquidity>0	Liquidity<0
q10	0.099	0.172	-0.297**
	(0.085)	(0.109)	(0.128)
q20	-0.045	0.017	-0.312***
	(0.047)	(0.054)	(0.065)
q30	-0.061**	-0.053	-0.225***
	(0.025)	(0.035)	(0.050)
q40	-0.036	-0.005	-0.151***
	(0.024)	(0.032)	(0.035)
q50	-0.027	0.016	-0.117***
	(0.019)	(0.028)	(0.037)
q60	-0.058***	0.029	-0.148***
	(0.022)	(0.033)	(0.034)
q70	-0.077**	0.048	-0.178***
	(0.032)	(0.044)	(0.038)
q80	-0.196***	0.036	-0.212***
	(0.058)	(0.080)	(0.054)
q90	-0.210**	-0.107	-0.331***
	(0.088)	(0.112)	(0.097)
Obs.	8,048	5,095	2,953
Bootstrap(rep.)	200	200	200

Notes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Quantile regressions are run on the 2004 cross-section of the panel dataset. The table reports estimated coefficients of Lev_{ft}. Standard errors are obtained by bootstrap (200 replications). We use the command sqreg in Stata that estimates simultaneously the coefficients of the covariates on different quantiles of the dependent variable's distribution. Control variables are included but their coefficients are not reported.

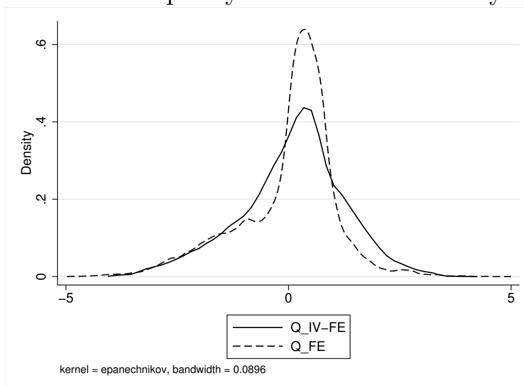
Table D.14 reports estimates of the coefficient of Lev_{ft} in quantile regressions on $\hat{Q}_{ft}$ for all deciles of the dependent variable's distribution. We run the regression on the whole sample and on the samples of firms that have sufficient liquidity to cover current expenses ($Liquidity > 0$) and of those with insufficient liquidity ($Liquidity < 0$). Point estimates are generally positive and not significantly different from zero along the distribution of the quality measure for liquid firms. The contrary is true when we estimate quantile regressions for illiquid firms. Hence, higher levels of debt affect negatively all moments of the distribution of export quality for illiquid firms.

Appendix E. Comparing quality estimates obtained by FEIV and by FE

Figure E.3 compares the empirical densities of $\hat{Q}_{FEIV}$ and $\hat{Q}_{FE}$. These are respectively the proxies for export quality obtained by estimating the model of demand by FEIV and by FE for the six 6-digit product categories included in the analysis. We find the distribution of $\hat{Q}_{FE}$ to be more leptokurtic than the one of $\hat{Q}_{FEIV}$. This is mostly due to the underrepresentation in this distribution of higher values of $\hat{Q}_{FE}$ when compered to the distribution of $\hat{Q}_{FEIV}$. Under the assumptions that the FEIV estimates are consistent, $\hat{Q}_{FE}$ is underestimating the quality of exported varieties, but this happens only in the upper part of the distribution.

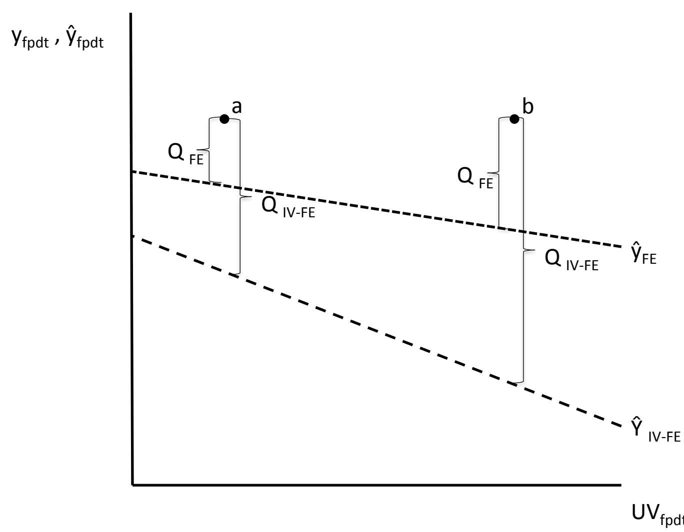
In diagram E.4 we provide the intuition of why $\hat{Q}_{FE}$ underestimates the quality of high-quality varieties when compared to $\hat{Q}_{FEIV}$. On the y-axis we represented observed market-shares y_{fpdt} and predicted market shares $\hat{y}_{fpdt}$, that are computed from the estimated coefficients α_{FE} and α_{FEIV} on unit-values. The schedule of $\hat{y}_{FEIV}$ is more negative than the one relative to the predictions by FE, because we expect α_{FE} to be positively biased due to the correlation between prices and the unobserved time-varying component of quality. The points (a) and (b) in the diagram represent two varieties with the same observed market shares but with different prices. Given the assumptions of the model, we expect variety (a) to have lower quality, as it has the same market share of (b) even thus its price (UV on the x-axis) is lower. Because the proxy for quality measures the distance between observed and predicted market shares, when the intercept of the schedule $\hat{y}_{FEIV}$ is lower than the one of $\hat{y}_{FE}$, then $\hat{Q}_{FE}$ underestimate quality, and especially so for varieties with higher-quality and higher prices. This intuition is consistent with what we observe in Figure E.3.
However, in that figure we see also that $\hat{Q}_{FE}$ may over-estimate quality for some low-quality varieties. This can be easily reproduced in the diagram by shifting the intercept of the $\hat{y}_{FEIV}$ schedule above of the one of the $\hat{y}_{FE}$ schedule. Unfortunately, we cannot check the relative position of the intercepts because both the FE and the FEIV estimators do not allow to identify the constant of the model.

Figure E.3: Densities of the quality estimator obtained by FEIV and by FE



Notes. The figures compare the distributions of the estimators of quality obtained by estimating the disrete choice model by FEIV and by FE for the six 6-digit product categories included in the headings of Table 3. Densities are estimated using the Epanechnikov kernel function. Bandwidth are selected automatically by Stata (kdensity command).

Figure E.4: Why does $\hat{Q}_{FE}$ underestimate quality?



Notes. (a) and (b) are two hypothetical varieties exported to the same market. The different slopes of the two schedules reflect the fact that the price coefficient α_{FE} is less negative than α_{FEIV} because of the positive bias due to the positive correlation between prices and unobserved quality. Q_{FEIV} and Q_{FE} are differences between predicted and observed market shares and they represent the quality measures respectively obtained by FEIV and FE.

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