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Credit constraints, quality, and export prices: Theory and evidence from China ☆

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ABSTRACT

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This paper presents theory and evidence from highly disaggregated Chinese data that tighter credit constrains force firms to produce lower quality. The paper modifies Melitz's (2003) model of trade with heterogeneous firms by introducing quality choice and credit constraints. The quality sorting model predicts that tighter credit constraints faced by a firm reduce its optimal prices due to its choice of lower-quality products. However, when quality cannot be chosen by a firm in an efficiency sorting model, there is an opposite prediction that prices increase as firms face tighter credit constraints. An empirical analysis using Chinese bank loans data and a merged sample of large trading firms based on Chinese firm-level data from the National Bureau of Statistics of China (NBSC) and Chinese customs data strongly supports quality sorting and confirms the mechanism of quality adjustment: firms optimally choose to produce lower-quality products when facing tighter credit constraints. Moreover, the predictions of the efficiency sorting model are supported by using quality-adjusted prices in regression analysis and by using quality variation across firms within the same product. *Journal of Comparative Economics* **43** (2) (2015) 390–416. School of International Business Administration, Shanghai University of Finance and Economics, Shanghai, China; The Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong, China.

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1. Introduction

There is a growing body of literature on the effects of credit constraints on international trade, especially after the financial crisis of 2008. Most prior studies have focused on either explaining the mechanism of why exporters need more credit than domestic producers (e.g., Amiti and Weinstein, 2011; Feenstra et al., 2014), or the consequences of different credit conditions on export performance, comparative advantage, multinational activities and spillovers.[2] However, to the best of our knowledge, the impacts of credit constraints on a firm's choice of optimal quality and optimal price have not been explored. This paper fills a gap in the literature by linking credit constraints to firm attributes and action such as its productivity and its choice of product quality and optimal prices.

Understanding the mechanism through which credit constraints affect export prices helps us better understand how credit constraints affect a firm's exporting behavior via optimal choice of quality and pricing. In particular, it helps to explain the differential impacts of credit constraints on the intensive margin of trade across products through their effects on the unit value prices of different products.[3] Tighter credit constraints would affect upfront costs and therefore distort a firm's choice of optimal price more than before. As noted in the literature on financial distress, binding credit constraints may cause firms to act in ways that would be suboptimal in normal times, which may lead them to produce lower-quality products, which in turn lowers the unit value price of the product (Phillips and Sertsios, 2011). However, ***how*** and ***why*** credit constraints affect the export prices of different products differently has not been studied thoroughly. Our investigation tries to fill this gap in the literature and provides a novel perspective to study the behaviors of credit constrained firms, yielding important implications for developing countries that usually have less developed, immature financial markets.

To study the impacts of credit constraints on export prices, we build a heterogenous-firm trade model incorporating credit constraints and quality choice. The introduction of credit constraints acts through two channels. First, we assume that firms must externally finance a certain fraction of its fixed costs in order to produce as well as to enter foreign markets.[4] This fraction captures the *credit needs* of the firm. The higher is this fraction, the more likely the firm faces binding credit constraints. Second, we assume that due to frictions in the financial markets, a firm cannot borrow more than a certain fraction of its expected cash flow. This fraction of a firm's expected cash flow capture the firm's *credit access*. To sum up, a firm is more likely to have tighter credit constraints if it has a higher level of "*credit needs*" or faces a lower level of "*credit access*".

The theory indicates that the impacts of credit constraints on prices depends on *the quality adjustment effect*, which lowers product quality and therefore reduces prices when credit constraints are more stringent. When product quality is a choice variable for a firm (i.e., a quality sorting model) and there is a large scope for quality variation, the quality adjustment effect leads to lower prices when firms face tighter credit constraints. On the contrary, when the quality choice is not allowed (i.e., an efficiency sorting model), the theory predicts the opposite outcome: the existence of more stringent credit constraints would **raise** optimal prices in the full model when both variable and fixed costs are financed externally.[5] Meanwhile, the relationship between export prices and firm productivity also depends on whether the quality is a choice variable by the firm: prices increase in productivity under the quality sorting case while decrease in productivity under the efficiency sorting case.[6]

Next, we test our model using a matched Chinese firm-product level dataset, based on Chinese firm-level production data from the National Bureau of Statistics of China (NBSC) and Chinese customs data at the transaction-product level. The unique advantage of this matched database is that it contains information on unit value prices of exports at the product-firm level as well as the information needed to measure credit constraints and firm productivity as well as other firm characteristics. This advantage comes at the expense of unavoidable sample selection bias due to the matching process such that our merged sample is skewed toward large trading firms (see a more thorough and comprehensive analysis in Yu (forthcoming)). Thus our findings are valid for Chinese large trading firms.

To measure the severity of credit constraints via *credit needs* faced by firms, we first follow Manova et al. (2014) to employ four different measures at the industry level: external finance dependence, R&D intensity, inventory-to-sales ratio, and asset tangibility. We use US data for those measures in our main regressions because the US financial markets are mature and they could reflect true credit needs by industry. Another advantage of using US data is to alleviate the endogeneity concern of credit needs measures since using Chinese data for measuring credit needs may not well reflect the true credit needs at industry level due to the immature financial market in China. Also the measures based on US data have been widely used in cross-country studies in the literature. Nevertheless, we also follow Rajan and Zingales (1998) and Manova et al. (2014) to calculate external finance dependence using Chinese firm-level data for the purpose of robustness. To proxy for credit access, we collect balances of bank credits, long-term bank loans and short-term bank loans by province (normalized

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[2] See Manova (2013), Manova et al. (2014), Chor and Manova (2012), Minetti and Zhu (2011), Ju and Wei (2011), Chaney (2013), Agarwal et al. (2013), Jarreau and Poncet (2011), Besedeš et al. (2013), Wang (2012), among others.

[3] As the intensive margin of a product is measured by the total value of its exports, the change in the intensive margin is affected by two factors: the change in the quantity exported, and the change in the unit value price of the exported product. Therefore, a thorough analysis on the effect of credit constraints on unit value prices can help us better understand their effect on the intensive margin of trade. Moreover, credit constraints affect bank loans to firms, which are used to cover upfront costs.

[4] In the Appendix B we provide the full-fledged model where firms must externally finance a fraction of total costs.

[5] In the simple model when only fixed costs are financed externally, credit constraints do not affect optimal price in an efficiency sorting model.

[6] For a comprehensive review of quality sorting versus efficiency sorting, please see Manova and Zhang (2012).

by province GDP) in China to reflect the credit access by firms located in different regions. In addition, we compare different types of firm ownership in China as each type is expected to be associated with a different level of credit access. To carefully address the potential endogeneity issues of the measures of credit needs and credit access, we use external finance dependence measure from early data in 1980–1989 and the province level data on bank branches and bank employees before the Chinese banking system reform to conduct instrumental variable estimations. Finally, to compute productivity, we use the augmented Olley and Pakes's (1996) approach, which alleviates simultaneity bias and selection bias, to estimate a firm's total factor productivity.

We test the empirical implications of our model and the results strongly support the theoretical predictions of the quality sorting case: First, tighter credit constraints (i.e., either a higher level of credit needs or a lower level of credit access) significantly reduce export prices, ceteris paribus. Second, when a firm faces more stringent credit constraints, it produces lower-quality products. Third, there is a positive relationship between export prices and firm productivity. Our results are robust to various specifications, including the estimations with different fixed effects and clustering at different levels.

We also verify the quality-adjustment mechanism and test the efficiency sorting case through two exercises. First, we estimate quality and quality-adjusted prices by adopting Khandelwal et al.'s (2013) method, in which quality-adjusted price is defined as observed price less estimated quality. We then replicate the baseline regressions with estimated quality and quality-adjusted prices as dependent variable. When we regress quality-adjusted prices, the results are consistent with the predictions of the efficiency sorting case: tighter credit constraints through higher credit needs raise export prices; more productive firms set lower prices; the positive effects of credit access on prices are attenuated, and, sometimes, become significantly negative. Second, we compare the results based on a set of products with higher variation in product quality and those based on another set of products with lower variation in product quality. We find that the effects of credit constraints on prices are more pronounced for product categories featuring more quality variation, thus validating the mechanism of quality adjustment.

The main contribution of this paper is that it presents theory and evidence from highly disaggregated Chinese data that tighter credit constraints induce firms to lower the quality of products they export and thus reduce export prices. This contributes to the emerging literature on the role of financial constraints in international trade. To the best of our knowledge, this paper provides the first compelling analysis of the impacts of credit constraints on export prices under a heterogeneous-firm framework. This paper also complements the large quality-and-trade literature in confirming the prevalence of product quality heterogeneity at the firm level and explaining the mechanism of quality adjustment. Our finding of a positive relationship between export prices and firm productivity is consistent with the findings in the literature on product quality (e.g., Verhoogen, 2008; Kugler and Verhoogen, 2012; Hallak, 2010; Johnson, 2012; Hallak and Sivadasan, 2011; Baldwin and Harrigan, 2011).

The remainder of the paper is organized as follows. Section 2 presents a simple trade model with heterogeneous firms, featuring product quality choice and credit constraints to illustrate the impact of credit constraints on the optimal prices of exports. Section 3 describes the data and introduces the strategy of the empirical analysis. Section 4 presents the empirical results and Section 5 provides more discussion including the interaction between credit needs and credit access. Section 6 address endogeneity issues and Section 7 provides robustness checks. The final section concludes.

2. A simple model of credit constraints, quality, and export prices

In this section we present a simple, partial equilibrium model to study the behavior of the unit value export prices across firms that compete for the same product-destination market and how credit constraints affect prices and quality of exports.[7] The model modifies the heterogeneous-firm trade model of Melitz (2003), by incorporating quality choice and credit constraints in the analysis. Goods are differentiated, and each good is produced by one firm. The main departure from the existing literature is that firms are heterogeneous in both their productivity and the degree of credit constraints they face. Firms choose not only the optimal price but also the optimal product quality.

2.1. Preferences and the market structure

We denote the source country by i and the destination country by j, where $i,j \in 1,\ldots,N$. Country j is populated by a continuum of consumers of measure L_j. Consumers in country j have access to a set of goods Ω_j, which is potentially different across countries. In each source country i, there is a continuum of firms that ex ante differ in their productivity level, ϕ, the degree of credit access, θ, and the credit needs, d. A firm facing higher θ has more credit access; a firm with higher d has greater credit needs. A lower level of θ or a higher level of d implies tighter credit constraints for this firm (see Section 2.2 for more detail). We assume that a representative consumer in country j has a constant-elasticity-of-substitution (CES) utility function given by:

$$U_j = \left(\int_{\omega \in \Omega_j} \left[q_{ij}(\omega) x_{ij}(\omega) \right]^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}$$

[7] In a general equilibrium setting, changes in credit constraint conditions would in general affect the overall price index. Nevertheless, we derive that this would not affect the direction of the effect of credit constraints on export quality and export price (see later analysis in footnote 13 for more detail).

where $q_{ij}(\omega)$ is the quality of variety ω originated from country i; $x_{ij}(\omega)$ is country j's quantity consumed of variety ω originated from country i; and $\sigma > 1$ is the elasticity of substitution between varieties. Therefore, consumer optimization yields the following demand function for variety ω:

$$x_{ij}(\omega) = \left[q_{ij}(\omega)\right]^{\sigma-1} \frac{\left[p_{ij}(\omega)\right]^{-\sigma}}{P_j^{1-\sigma}} Y_j \tag{1}$$

where $p_{ij}(\omega)$ is the price of variety ω, $P_j = \left(\int_{\omega\in\Omega_j} \left[p_{ij}(\omega)/q_{ij}(\omega)\right]^{1-\sigma} d\omega\right)^{\frac{1}{1-\sigma}}$ is an aggregate price index (adjusted by the demand shifter), and Y_j represents the total expenditure of country j. Given the same price, higher-quality products generate a larger demand.

2.2. The firm's problem

A firm's technology is captured by a cost function that features, for any given quality, a constant marginal cost with a fixed overhead cost. Labor is the only factor of production. Following convention, we assume that there is an iceberg trade cost such that $\tau_{ij} \geqslant 1$ units of good must be shipped from country i in order for one unit to arrive in j. Firms face no trade costs in selling in its home market, i.e., $\tau_{ii} = 1$. To simplify notation, the subscripts for source and destination as well as the index for variety are suppressed hereafter. In addition, the wage rate of the source country is normalized to one.

We assume that there is a positive relationship between quality and marginal cost of production. The rationale is that a higher marginal cost is required to produce a higher-quality product. The positive relationship between quality and marginal cost is common to the recent quality-and-trade literature, for instance, Verhoogen (2008) and Johnson (2012). In this paper, the marginal cost of production is assumed to be q^α/ϕ, where $\alpha \in (0,1)$. Hence, the marginal cost increases in quality q, and α captures the elasticity of marginal cost with respect to quality.

Except for variable cost, firms face fixed cost in producing and exporting goods, fq^β ($\beta > 0$), where f is a constant and $1/\beta$ measures the effectiveness of fixed investment in raising quality. The fixed cost represents the fixed investments in production and export associated with quality improvement (e.g., costs of employing higher-quality inputs, R&D expenditures to improve the product quality, or the changes in modes of international shipping from ocean freight to air freight, etc.).[8]

We posit that all firms are subject to possible liquidity constraints in financing their foreign sales. Following Manova (2013), to make the model more tractable, here we assume that a fraction $d \in (0,1)$ of the fixed cost associated with foreign sales is borne up-front, and must be funded by outside capital, while variable costs can be funded internally.[9] Thus, this fraction d represents the *financial needs* of a firm. The higher the financial needs, the higher is d, and we call this fraction d the "*credit needs*" parameter. We also assume that, constrained by the level of financial development, firms cannot borrow more than a fraction θ of the expected cash flow from exporting. If θ is higher, firms can borrow more from external finance (mainly through bank loans). Therefore, θ is referred to as the *credit access* by firms. A higher level of *credit needs d* or a lower level of *credit access* θ implies that firms are more likely to face tighter credit constraints. Consequently, the optimization problem of a firm with productivity ϕ, credit access θ, and credit needs d is given by[10]:

$$\max_{p,q,a} \left(p - \frac{\tau q^\alpha}{\phi}\right) q^{\sigma-1} \frac{p^{-\sigma}}{P^{1-\sigma}} Y - fq^\beta \tag{2}$$

$$\text{s.t. } \theta\left[\left(p - \frac{\tau q^\alpha}{\phi}\right) q^{\sigma-1} \frac{p^{-\sigma}}{P^{1-\sigma}} Y - (1-d) fq^\beta\right] \geqslant dfq^\beta \tag{3}$$

where budget constraint (3) can be viewed as the "cash flow constraint" condition, in the same spirit as Manova (2013) and Feenstra et al. (2014).[11] Note that if we follow the standard set-up of the model with financial contracting as in Manova (2013) where financial access is captured by the uncertainty for the fund-provider to get money back, we would derive the same firm's optimization problem which in turn would generate the same predictions as in the current model (see Appendix A for the derivation). Solving this optimization problem by choosing price p and quality q yields

$$p = \frac{\sigma}{\sigma-1} \frac{\tau q^\alpha}{\phi} \tag{4}$$

$$q^{\sigma-1} \frac{p^{1-\sigma}}{P^{1-\sigma}} Y = \frac{\sigma\beta}{(1-\alpha)(\sigma-1)} \left(1 + d\frac{(1-\theta)\lambda}{\theta(1+\lambda)}\right) fq^\beta \tag{5}$$

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8 In this paper we only consider exporting firms.

9 We also derive the full-fledged model under the assumption that firms face credit constraints in financing all costs associated with foreign sales, including variable costs and fixed costs (see Appendix B). The model's major predictions with quality choice under quality sorting would remain the same under both assumptions.

10 For simplicity of notation, we suppress variety ω and subscripts of country (i,j). It should be also pointed out that we do not consider the intertemporal structure of costs of borrowing from banks as the current model is a static, one-period model.

11 Here, we implicitly assume that the firm decision is destination-market specific.

where λ is the Lagrangian multiplier associated with budget constraint (3). The budget constraint (3), together with the first-order conditions (4) and (5), imply

$$\frac{\beta}{(1-\alpha)(\sigma-1)}\left(1+d\frac{(1-\theta)\lambda}{1+\theta\lambda}\right) \geqslant 1-d+\frac{d}{\theta} \tag{6}$$

When budget constraint (3) is non-binding, the above condition (6) simplifies to $\frac{\beta}{(1-\alpha)(\sigma-1)} \geqslant 1-d+\frac{d}{\theta}$ as λ is zero. Thus, given credit needs d, there exists a cutoff level of credit access θ_h such that budget constraint (3) is binding if and only if $\theta < \theta_h$.[12] Likewise, given credit access θ, there exists a cutoff level of credit needs above which the budget constraint (3) is binding. Next, we further analyze two cases separately according to whether budget constraint (3) is binding.

2.2.1. Case 1: The budget constraint (3) is binding, i.e., $\theta < \theta_h$

Now, Eq. (4), together with (6), imply that the optimal quality chosen by firms satisfy the following condition:

$$q^{\beta-(1-\alpha)(\sigma-1)} = \left(\frac{1}{(1-d+\frac{d}{\theta})\sigma f}\right)\left(\frac{\sigma}{\sigma-1}\frac{\tau}{\phi}\right)^{1-\sigma}\frac{Y}{P^{1-\sigma}} \tag{7}$$

Define Condition (i) as $\beta > (1-\alpha)(\sigma-1)$. Under condition (i), there is a positive correlation between firm productivity ϕ and quality q, given credit access θ and credit needs d. This suggests that more productive firms choose higher quality, which is consistent with the findings of the quality-and-trade literature. Condition (i) ensures the existence of the optimal quality. Otherwise, if β is too small, it implies that the firm could easily improve quality without incurring large fixed cost (recall that fq^{β} represents the fixed cost), and then the firm would choose quality q to be infinite. Given firm productivity, condition (i) also ensures that a firm with more credit access or less credit needs chooses higher optimal quality, which in turn leads to a higher price set by the firm. We call this mechanism the *quality adjustment effect*.

Combining the pricing rule (4) and the quality Eq. (7) yields the optimal price in this case:

$$p = \left(\frac{1}{(1-d+\frac{d}{\theta})\sigma f}\right)^{\Psi}\left(\frac{\sigma}{\sigma-1}\frac{\tau}{\phi}\right)^{1+(1-\sigma)\Psi}\left(\frac{Y}{P^{1-\sigma}}\right)^{\Psi} \tag{8}$$

where $\Psi = \frac{\alpha}{\beta-(1-\alpha)(\sigma-1)}$. Define Condition (ii) as $\beta < (\sigma-1)$. If Condition (ii) holds (in addition to Condition (i)), then a firm's optimal price is positively correlated with firm productivity as conditions (i) and (ii) together imply that $1+(1-\sigma)\Psi < 0$. The condition (ii) ensures that β is not too large. If β is too large, it would be difficult for the firm to adjust quality as the elasticity of fixed cost with respect to quality is high: a small improvement in quality would incur a large increase in fixed cost. Therefore, a very large β is equivalent to the case that the firm cannot flexibly choose optimal quality, and thus quality variance is small. This case will be similar to an efficiency sorting model where quality choice is not allowed. In this paper, our focus is quality choice in a quality sorting model but we will also compare the implications of both quality sorting model and efficiency sorting model in the end of this section.

Let us define Condition (A) as $\frac{1}{\beta} > \frac{1}{\sigma-1} > \frac{1-\alpha}{\beta}$. Condition (i) and (ii) combined is equivalent to condition (A). When condition (A) holds, a firm with higher productivity charges higher optimal prices. The intuition behind this positive correlation between firm productivity and export prices is due to two opposing forces: the *quality adjustment effect* (i.e., higher-productivity firms set higher prices via selling higher-quality products) and the *productivity effect* (i.e., higher-productivity firms are able to charge lower prices via having lower marginal cost for any given quality). When the quality adjustment effect dominates the productivity effect, there exists a positive relationship between firm productivity and export prices.

In addition, under Condition (A), tighter credit constraints via either less credit access (i.e., a lower θ) or higher credit needs (i.e., a higher d) leads to lower prices. This suggests that given condition (A) satisfied, firms facing more stringent credit constraints would automatically choose to charge lower export prices due to their choice of lower product quality.

2.2.2. Case 2: The budget constraint (3) is nonbinding, i.e., $\theta > \theta_h$

Now λ is zero, and hence Eqs. (4) and (5) imply:

$$q^{\beta-(1-\alpha)(\sigma-1)} = \frac{(1-\alpha)(\sigma-1)}{\sigma\beta f}\left(\frac{\sigma}{\sigma-1}\frac{\tau}{\phi}\right)^{1-\sigma}\frac{Y}{P^{1-\sigma}} \tag{9}$$

Under Condition (i), the firm with higher productivity will choose higher quality. The previous Eq. (9), together with (4), imply that the optimal pricing rule is given by:

$$p = \left(\frac{(1-\alpha)(\sigma-1)}{\sigma\beta f}\right)^{\Psi}\left(\frac{\sigma}{\sigma-1}\frac{\tau}{\phi}\right)^{1+(1-\sigma)\Psi}\left(\frac{Y}{P^{1-\sigma}}\right)^{\Psi} \tag{10}$$

[12] Eq. (6) implies that budget constraint (3) is binding if and only if $\theta < \theta_h$, where $\theta_h = \frac{d(\sigma-1)(1-\alpha)}{\beta-(1-d)(\sigma-1)(1-\alpha)}$. When deriving the cutoff condition, we assume that $\lambda = 0$, i.e., we start with the non-binding condition to derive the cutoff.

When condition (A) holds, then $1 + (1 - \sigma)\Psi < 0$, and so Eq. (10) implies that there is a positive relationship between price and productivity. However, the optimal prices are not affected by credit access or credit needs anymore, as firms have sufficient credit access (i.e., $\theta > \theta_h$).

2.3. Predictions

In the rest of this paper, we will concentrate on the central case when Case 1 and Condition (A) both hold. These parameter conditions are supported by empirical evidence presented by the quality sorting literature. For example, based on the data of Chinese exporting firms, Manova and Zhang (2012) propose that more successful exporters with higher export revenue or larger export scope produce higher quality goods and charge higher export prices, implying that the parameter restrictions given by condition (A) tend to hold for Chinese data. Ge et al. (2012) also find that more productive firms charge higher export prices using Chinese firm data. Later, our empirical results also confirm this point. Henceforth, unless otherwise noted, we focus on Case 1 when Condition (A) holds. Therefore, we have the following testable propositions[13]:

Proposition 1. *Given firm productivity, tighter credit constraints resulting from either lower level of credit access (i.e., a lower θ) or from higher credit needs (i.e., a higher d) reduce the optimal export price set by a firm. In this case, export prices increase with productivity, ceteris paribus.*

Proposition 2 (*Quality Adjustment Effect*). *Given productivity, tighter credit constraints (i.e., higher d or lower θ) lower the optimal product quality chosen by a firm.*

Propositions 1 and 2 are based on the assumption that quality is chosen by firms and therefore there could be heterogeneity of product quality across firms (i.e., there exists quality sorting). It would be also interesting to carry out analyses based on the original Melitz-type model (Melitz, 2003), i.e., the efficiency sorting model, in which quality is out of the firm's decision choice. By doing so, we are able to examine the implications of the quality sorting model vis-à-vis the efficiency sorting model. When only fixed costs are externally financed, the model simply goes back to the conventional Melitz-type model under an efficiency sorting case and the optimal price is given by $p = \frac{\sigma}{\sigma-1}\frac{\tau}{\phi}$. Hence, the optimal price decreases in productivity but is independent of credit constraints. Note that this result only holds when only fixed costs are financed externally. When we relax this simplified assumption and allow firms to face credit constraints in covering both fixed and variable costs, we find that the optimal price is affected by credit constraints even under efficiency sorting. Thus, we also analyze when both fixed costs and variables costs are externally financed.

2.3.1. All costs are externally financed

In the earlier discussion, we assume that all firms are subject to credit constraints in paying only fixed costs. Now we assume that both variable costs and fixed costs cannot be totally financed internally and firms need to raise outside capital for a fraction $d \in (0, 1)$ of all costs. We derive this full-fledged model in Appendix B. As a result, the optimal prices increase with tighter credit constraints under efficiency sorting. Nevertheless, the predictions under the quality sorting model remain unchanged.

We illustrate the predictions of the full model by Fig. 1. The graph in the left panel of Fig. 1 illustrates the relationship between (log) price, (log) TFP, and credit constraints when Condition (A) holds and the budget constraint is binding: the solid line corresponds to more relaxed credit constraint (i.e., a higher θ and a lower d), and the dashed line captures the tighter credit constraint situation (i.e., a lower θ and a higher d). The left panel of Fig. 1 shows that export prices increase in productivity and tighter credit constraints force firms to lower export prices in a quality sorting model when the budget constraint is binding.[14] The right panel of Fig. 1 presents the properties for the efficiency sorting model that when quality is not a

[13] If instead of a partial equilibrium model we assume a general equilibrium setting, changes in credit constraint conditions would in general affect the overall price index. It can be derived that the price index is given by $P_j = \left[\sum_i \int_0^{\infty} \left(\frac{Y_j}{\left(1-d_i+\frac{d_i}{\theta_i}\right)\sigma f}\right)^{\frac{(1-\alpha)(\sigma-1)}{\beta-(1-\alpha)(\sigma-1)}} \left(\frac{\sigma}{\sigma-1}\frac{\tau_{ij}}{\phi}\right)^{\frac{\beta(1-\sigma)}{\beta-(1-\alpha)(\sigma-1)}} dG(\phi)\right]^{\frac{\beta-(1-\alpha)(\sigma-1)}{\beta(1-\sigma)}}$, where the subscripts i and j index a firm with productivity ϕ in country i exports the goods to destination country j, and $G(\phi)$ denotes a cumulative distribution function of firm productivity. In our model fixed cost is an increasing function of quality choice. Therefore, low productivity firms or firms facing tighter credit constraints would automatically choose lower quality such that they face lower fixed costs and they are also able to overcome fixed costs to export. Thus, we focus on intensive margin effect of continuing exporters. However, we acknowledge that this comes at the expense of ignoring the effect of credit constraints on firm entry and exit (please see Manova (2013) and Manova et al. (2014) for a comprehensive analysis of the impact of credit conditions on different trade margins). As we will use the merged sample of Chinese above-scale firms and Chinese Customs data to test our theory, our sample is intrinsically biased towards large, more productive firms. Hence, the set-up that firms have survived the entry barriers of entering foreign market is reasonable here. Given this set-up, based on the previous expression of the price index, tighter credit constraints (i.e., higher d or lower θ) will increases $1 - d_i + \frac{d_i}{\theta_i}$ and hence decrease the aggregate price P_j. From the quality Eq. (7), the effect of tighter credit constraints via its effect on P_j will further decrease the export quality. Also the effect of tighter credit constraints via its effect on P_j will further decrease the export price according to the price Eq. (4). To sum up, in a general equilibrium setting, changes in credit constraint conditions would not affect the direction of the impact of credit constraints on export quality and prices in the current partial equilibrium model.

[14] In a quality sorting model when the budget constraint is nonbinding, the solid line in the left panel of Fig. 1 still describes the relationship between (log) price and (log) TFP. However, the optimal prices are not affected by credit access θ or credit needs d anymore, as firms have sufficient credit access (i.e., $\theta > \theta_h$). Therefore, the solid line in the left panel of Fig. 1 does not shift as θ or d changes.

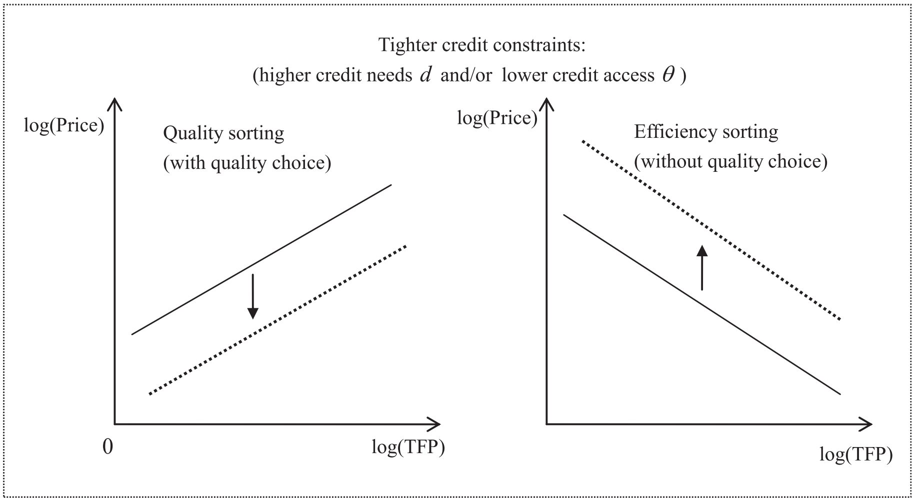

Fig. 1. The relationship between prices, TFP, and credit constraints.

choice variable, export prices decrease with productivity, and given firm productivity, tighter credit constraints (higher d or lower θ) increase the optimal price set by a firm.

We summarize the properties for the full model (i.e., when both fixed and variable costs are subject to external finance) in the following proposition (see Appendix B for the proof of Proposition 3):

Proposition 3. *Under quality sorting, tighter credit constraints (i.e., a higher d or a lower θ) lower the optimal product quality chosen by a firm and thus reduce the optimal price. In this case, prices increase with productivity, ceteris paribus. However, when there is no quality choice (i.e., under efficiency sorting), given firm productivity, tighter credit constraints (i.e., a higher d or a lower θ) increase the optimal price set by a firm. In this efficiency sorting case, export prices decrease with productivity, ceteris paribus.*

The discussion in this section suggests that, according to whether the quality is a choice by the firm (i.e., under quality sorting or efficiency sorting), there could be different predictions on the impact of credit constraints on export prices as well as the relationship between export prices and firm productivity. As illustrated in the left panel of Fig. 1, the quality sorting model that assumes quality to be a firm's choice yields a positive relationship between productivity and export prices, and we expect tighter credit constraints to lower the optimal prices set by the firm as the quality adjustment effect dominates. On the other hand, the efficiency sorting model that assumes no quality choice yields a negative relationship between productivity and export prices, and we expect that tighter credit constraints increase the optimal prices when both variable costs and fixed costs need to be financed by outside capital. We will use Chinese data to test both theories based on the full model. Our results lend support to the quality sorting model and confirm the mechanism of quality adjustment.

3. Empirical specification, data and measurement

In this section, we specify our econometric models and describe the data and measurements that are used to estimate them.

3.1. Estimating equations

3.1.1. Baseline specification: price equations

The propositions in Section 2 imply that export prices are affected by credit access or credit needs. We test the proposed propositions with the following baseline reduced-form equation:

$$\log price_{fh(c)rt} = b_0 + b_1 \log(TFP_{ft}) + \gamma X_{ft} + \chi_1 FinDev_r + \chi_2 ExtFin_i + \varphi_{h(c)} + \varphi_t + \epsilon_{fh(c)t} \quad (11)$$

where $price_{fh(c)rt}$ represents the unit value export price of product h (disaggregated at HS 8-digit level, which is the most disaggregate level for Chinese products) exported by firm f located in province r to destination country c in year t (where the country subscript c is optional when product is defined as HS8 product category instead of HS8-country combination); TFP_{ft} denotes a firm f's productivity in year t; X_{ft} is a vector of time-varying attributes of firm f in year t which can potentially affect export prices, including firm size (denoted by employment), capital intensity, and average wage per worker; $FinDev_r$ captures the credit access in province r where the firm is located; $ExtFin_i$ reflects the credit needs at industry i and external finance dependence is one of the most important credit needs measures; $\varphi_{h(c)}$ and φ_t are fixed effect terms of HS8 product (or HS8-destination) and year, respectively; $\epsilon_{fh(c)t}$ is the error term that includes all unobserved factors that may affect export prices.

As there are different sources of variation of export prices (e.g., firm, product, destination country, and year), we deal with them carefully in identification. Except for the year fixed effects, in the baseline regression we employ the variation across firms within a product (or product-destination market) by including the product (or product-destination) fixed effect terms. We do not include the province fixed effects in the baseline specification because province fixed effect terms absorb the effects of credit access measures. We also cluster error terms at firm level in the baseline specification to address the potential correlation of error terms within each firm across different products over time.

It is worth noting the different mappings between industry i and product h when we use the US data and Chinese data to compute credit needs measures. Therefore, the product or product-destination fixed effect terms refer to different aggregation levels of product in different context of data. When we use Chinese data to compute credit needs measure at industry level based on Chinese Industrial Classification, we can include HS8-product-destination fixed effects in our baseline regressions. However, if we follow the standard literature in trade and finance (e.g., Manova, 2013; Kroszner et al., 2007) to measure credit needs based on US data, our product fixed effect terms will be measured at HS4 level, or roughly speaking, at broader *industry* level, due to the mapping between HS product and ISIC (International Standard Industrial Classification) industry. See more detailed discussion on this issue in Section 3.3.2 about measures of credit needs.

3.1.2. Quality equations

Quality can only be inferred indirectly from observed prices and demands. Following Khandelwal et al. (2013), we estimate export "quality" of product h shipped to a destination country c by firm f in year t, q_{fhct}, via the following empirical demand equation based on Eq. (1), the demand equation, in our model:

$$x_{fhct} = q_{fhct}^{\sigma-1} p_{fhct}^{-\sigma} P_{ct}^{\sigma-1} Y_{ct} \tag{12}$$

where x_{fhct} denotes the demand for a particular firm's export of product h in destination country c.[15] We then take logs of the above equation, and use the residual from the following OLS regression to infer quality[16]:

$$\log x_{fhct} + \sigma \log p_{fhct} = \varphi_h + \varphi_{ct} + \epsilon_{fhct} \tag{13}$$

where the product fixed effect φ_h captures the difference in prices and quantities across product categories due to the inherent characteristics of products; the country-year fixed effect φ_{ct} collects both the destination price index P_{ct} and income Y_{ct}. Then estimated quality is $\ln(\hat{q}_{fhct}) = \hat{\epsilon}_{fhct}/(\sigma - 1)$. Consequently, quality-adjusted prices are the observed log prices less estimated effective quality, i.e., $\ln(p_{fhct}) - \ln(\hat{q}_{fhct})$, denoted by $\ln(\widetilde{p}_{fhct})$. The intuition behind this approach is that conditional on price, a variety with a higher quantity is assigned higher quality.[17] Given the value of the elasticity of substitution σ, we are able to estimate quality from Eq. (13).

The literature yields and employs various estimates of σ. For example, Anderson and van Wincoop (2004) survey gravity-based estimates of the Armington substitution elasticity, such as Head and Ries (2001), and conclude that a reasonable range is $\sigma \in [5, 10]$.[18] In our estimation, we allow the elasticity of substitution to vary across industries (σ_i) by using the estimates of Broda and Weinstein (2006), but our results are not sensitive to larger choices of σ as in Eaton and Kortum (2002) or a lower and narrower range of σ as in Simonovska and Waugh (2014).[19] Our results of estimated quality and export price are highly correlated (see Table 1), indicating the validity of the estimates and also suggesting that the unit value export prices indeed well capture export quality: according to Feenstra and Romalis (2014), "the observed differences in export unit-values are attributed predominantly to quality". After obtaining estimated quality and quality-adjusted price, we replace the dependent variable in the baseline regression, Eq. (11), by quality or quality-adjusted price to examine the effect of credit constraints on quality and net-quality prices.

3.2. Firm-level data and firm-product-level trade data

To investigate the relationship between firms' productivity and their export prices as well as the role of credit constraints, we merge the following two highly disaggregated large panel Chinese data sets: (1) the firm-level production data, and (2) the firm-product-level trade data. The sample period is between 2000 and 2006.

[15] The quality estimates inferred from Eq. (12) belong to "demand-side" estimates, as summarized in Feenstra and Romalis (2014). The advantage of demand-side quality estimates is that we do not need to worry about the "potential" effect of credit constraints on demand side because the credit constraints are faced by firms rather than by consumers. Thus, even with credit constraints imposed on producers, the demand equation could still reflect true, realized demand from consumers' perspective.

[16] Here our task is to estimate export quality where destination country and product fixed effects should be incorporated. One may modify the method in Khandelwal (2010) that estimates *import* quality from different countries to the US, but the caveat is that it is difficult to find good instrumental variables to overcome the endogeneity issues as acknowledged by Khandelwal (2010). By following Khandelwal et al. (2013), we do not have much concern about endogeneity in estimating export quality given the value of elasticity of substitution.

[17] See Khandelwal et al. (2013) for detailed review of this approach.

[18] Waugh (2010) obtain similar estimates based on the sample including both rich and poor countries, though the parameter has different structural interpretations.

[19] Broda and Weinstein (2006) estimate the elasticity of substitution for disaggregated categories and report that the average and median elasticity for Standard International Trade Classification 5-digit goods is 7.5 and 2.8, respectively. We use the concordance between HS 6-digit products and SITC to merge their estimates with our sample.

Table 1
Export price and export quality of Chinese firms (2000–2006).

Chinese Industrial Classification (2-digit code)	Export quality		Export price	
	Mean	Median	Mean	Median
Processing of Food from Agricultural Products (13)	−0.0316	−0.0300	0.6293	0.4386
Manufacture of Foods (14)	−0.1904	−0.2332	0.6189	0.3314
Manufacture of Beverages (15)	−0.3283	−0.1711	0.0666	−0.2744
Manufacture of Tobacco (16)	−0.3642	−0.0803	1.1254	1.1569
Manufacture of Textile (17)	−0.0079	0.0223	0.8717	0.8119
Manufacture of Textile Wearing Apparel, Footware, and Caps (18)	−0.0141	−0.0033	1.4113	1.4351
Manufacture of Leather, Fur, Feather and Related Products(19)	0.2414	0.2824	1.5387	1.4881
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products (20)	−0.0802	−0.065	1.4172	0.8221
Manufacture of Furniture (21)	0.2750	0.2456	2.3362	2.4162
Manufacture of Paper and Paper Products (22)	−0.0808	−0.0849	0.6574	0.5465
Printing, Reproduction of Recording Media (23)	0.0254	0.0376	0.8248	0.7872
Manufacture of Articles For Culture, Education and Sport Activity (24)	−0.1532	−0.1198	0.7305	0.7606
Processing of Petroleum, Coking, Processing of Nuclear Fuel (25)	0.1721	−0.0252	1.8260	1.6096
Manufacture of Raw Chemical Materials and Chemical Products (26)	−0.1293	−0.1612	0.9231	0.8028
Manufacture of Medicines (27)	0.3105	0.1554	2.8182	2.6412
Manufacture of Chemical Fibers(28)	−0.0928	−0.1401	0.7893	0.7119
Manufacture of Rubber (29)	−0.1026	−0.1634	1.1597	0.9818
Manufacture of Plastics (30)	−0.1484	−0.1173	1.0225	0.9467
Manufacture of Non-metallic Mineral Products (31)	−0.0832	−0.0905	0.5303	0.3536
Smelting and Pressing of Ferrous Metals (32)	−0.2218	−0.2183	0.1708	−0.2396
Smelting and Pressing of Non-ferrous Metals (33)	0.0638	−0.0241	1.5290	1.2130
Manufacture of Metal Products (34)	−0.0892	−0.0553	1.2214	1.1446
Manufacture of General Purpose Machinery (35)	−0.0001	−0.1501	2.3863	1.8546
Manufacture of Special Purpose Machinery (36)	0.4042	0.3018	3.7961	2.8439
Manufacture of Transport Equipment (37)	0.0059	−0.0086	2.2042	1.6094
Manufacture of Electrical Machinery and Equipment (39)	−0.0414	−0.0563	1.8318	1.5740
Manufacture of Communication Equipment, Computers and Other Electronic Equipment (40)	0.0887	−0.0917	2.2446	2.0588
Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work (41)	0.1204	−0.0250	1.9048	1.4498
Manufacture of Artwork and Other Manufacturing (42)	−0.0126	0.0238	1.0861	1.0232
The correlation between mean of quality and mean of price by CIC 2-digit industries is 0.8004				
The correlation between median of quality and median of price by CIC 2-digit industries is 0.6974				

Notes: Prices and quality are in natural logarithm.

The data source for the firm-level production data is the annual surveys of Chinese manufacturing firms, which was conducted by the National Bureau of Statistics of China (NBSC). The database covers all state-owned enterprises (SOEs), and non-state-owned enterprises with annual sales of at least 5 million RMB (Chinese currency).[20] Between 2000 and 2006, the approximate number of firms covered by the NBSC database varied from 163,000 to 302,000. This database has been widely used by previous studies of Chinese economy and other economic issues using Chinese data (e.g., Cai and Liu, 2009; Lu et al., 2010; Feenstra et al., 2014; Brandt et al., 2012; among others) as it contains detailed firm-level information of manufacturing enterprises in China, such as ownership structure, employment, capital stock, gross output, value added, firm identification (e.g., company name, telephone number, zip code, contact person, etc.), and complete information on the three major accounting statements (i.e., balance sheets, profit & loss accounts, and cash flow statements). Of all the information contained in the NBSC Database, we are mostly interested in the variables related to measuring firm total factor productivity and credit constraints. In order to merge the NBSC Database with the product-level trade data so as to obtain the export prices for each firm, we also use firm identification information.

As there are some reporting errors in the NBSC database, to clean the NBSC sample, we follow Feenstra et al. (2014), Cai and Liu (2009), and the General Accepted Accounting Principles to discard observations for which one of the following criteria is violated: (1) the key financial variables (such as total assets, net value of fixed assets, sales, gross value of industrial output) cannot be missing; (2) the number of employees hired by a firm must not be less than 10; (3) the total assets must be higher than the liquid assets; (4) the total assets must be larger than the total fixed assets; (5) the total assets must be larger than the net value of the fixed assets; (6) a firm's identification number cannot be missing and must be unique; and (7) the established time must be valid (e.g., the opening month cannot be later than December or earlier than January).

The second database we use is the Chinese trade data at HS 8-digit level by each firm, provided by China's General Administration of Customs. This Chinese Customs Database covers the universe of all Chinese exporters and importers in 2000–2006. It records detailed information of each trade transactions, including import and export values, quantities,

[20] It equals US$640,000 approximately, according to the official end-of-period exchange rate in 2006, reported by the central bank of China.

quantity units, products, source and destination countries, contact information of the firm (e.g., company name, telephone, zip code, contact person), type of enterprises (e.g. state owned, domestic private firms, foreign invested, and joint ventures), and customs regime (e.g. "Processing and Assembling" and "Processing with Imported Materials"). Of all the information in the customs database, export values and quantities are of special interest to this study as they yield unit value export prices. Note that unit value export prices are computed by dividing the deflated export value by physical quantities of exported products, as in De Loecker et al. (2012).[21]

In order to merge the above two databases, we match the firm-product-level trade data contained in the Chinese Customs Database to data on manufacturing firms contained in the NBSC Database, based on the contact information of firms, because there is no consistent coding system of firm identity between these two databases.[22] Our matching procedure is done in three steps. First, the vast majority of firms (89.3%) are matched by company names exactly. Second, an additional 10.1% are matched by telephone number and zip code exactly. Finally, the remaining 0.6% of firms are matched by telephone number and contact person name exactly.[23] Compared with the manufacturing exporting firms in the NBSC Database, the matching rate of our sample (in terms of the number of firms) varies from 52% to 63% between 2000 and 2006, which covers 56–63% of total export value reported by the NBSC Database between 2000 and 2006. In total, the matched sample covers more than 60% of total value of firm exports in the manufacturing sector reported by the NBSC Database and more than 40% of total value of firm exports reported by the Customs Database. Finally, we acknowledge that the advantage of using a merged sample comes at the expense of unavoidable sample selection bias due to the matching process such that our merged sample is skewed toward large trading firms (see Yu (forthcoming) for a more comprehensive discussion). Thus, our empirical findings are valid for Chinese large trading firms.

3.3. Measurement

3.3.1. Measures of credit access

In order to measure credit access, we collect data on the balances of total bank credits, long-term bank loans, and short-term bank loans and calculate the average bank loans to GDP ratio over the sample period (2000–2006) at the provincial level.[24] As regional heterogeneity in available bank credits and loans to firms is huge in China, we believe that bank loans by province serve as a good proxy for credit access, which reflects regional financial development. Our sample includes 31 provincial-level regions (including 22 provinces, 4 municipalities, and 5 autonomous regions). The data source is Almanac of China's Finance and Banking (2000–2007). If the level of financial development is higher, then there is more credit access for firms and so we expect to see increases in optimal prices under quality sorting.

Another measure we use to proxy for credit access is firm ownership. We compare state-owned enterprises (SOE) with domestic private enterprises (DPE) and multinational corporation (MNC) with joint venture (JV).[25] We compare different types of firms in China because the literature clearly suggests that given the underdevelopment of Chinese financial markets, the Chinese DPE face less credit access than SOE do, because SOE can finance a larger share of their investments through external financing from bank loans provided by state-owned banks. For example, Boyreau-Debray and Wei (2005) point out that the Chinese banks–mostly state owned–tend to offer easier credit to SOE. Dollar and Wei (2007) and Riedel et al. (2007) report that private firms rely significantly less on bank loans and significantly more on retained earnings as well as family and friends to finance investments. Song et al. (2011) also show that SOE finance more than 30 percent of their investments through bank loans compared to less than 10 percent for domestic private firms, and other forms of official market financing (through bank loans) are marginal for private firms in China as private firms rely more on internal or informal financing. Therefore, it is safe to conclude that SOE in China face more credit access, compared to DPE. At the same time, the literature also indicates that multinational companies have better credit access than joint ventures as multinational companies are able to reallocate resources on a global scale and finance their subsidiaries from headquarters or other affiliates. Therefore, according to the theory presented above, when the scope for quality differentiation is large, we expect that, ceteris paribus, the optimal prices set by SOE to be higher than those by DPE and the optimal prices set by MNC higher than those by JV, respectively.

3.3.2. Measures of credit needs

Following Manova et al. (2014), we employ four different measures of an industry's financial vulnerability to proxy for credit needs at the industry level. The idea is that if an industry is more financially vulnerable, it is more likely to face binding credit constraint. These measures have been widely used in the literature on the role of credit constraints in international trade and growth. It should be noted that these measures are meant to reflect technologically determined characteristics

[21] We deflate the export value using industry-specific output deflators from Brandt et al. (2012). In De Loecker et al. (2012), the authors deflate all nominal values for their analysis and unit values are deflated by sector-specific price indexes.

[22] In the NBSC Database, firms are identified by their corporate representative codes and contact information. While in the Customs Database, firms are identified by their corporate custom codes and contact information. These two coding systems are neither consistent, nor transferable with each other.

[23] In order to obtain more precise matching, we do not use contact person and zip code to match trade transactions to manufacturing firms since there are many different companies, which have the same contact person name in the same zip-code region.

[24] Since the variation of regional credit access is persistent over time, this measure has been averaged over years.

[25] We define SOE, DPE, MNC, and JV based on the information from the NBSC firm survey data. We also experiment with using information from the Chinese Customs Database to differentiate firm ownership as in Manova et al. (2014), and obtain qualitatively the same results. Note that we exclude firms from Hong Kong, Taiwan, and Macau when we define MNC and JV here.

of each industry that are beyond the control of individual firms. Therefore, these measures of industrial financial vulnerability are inherent to the nature of the industry, which should be viewed as exogenously given for each individual firm.[26]

These four measures are external finance dependence, R&D intensity, inventory-to-sales ratio, and asset tangibility. An industry's external finance dependence ($ExtFin_i$) is defined as the share of capital expenditure not financed with cash flows from operations. If external finance dependence is high, the industry is more financially vulnerable and have higher credit needs. R&D intensity is defined as R&D spending to total sales ratio (RD_i), which can also reflect the industry's financial vulnerability, because research and development activities are capital-intensive. Typically, R&D expenditures, as the impetus for production, occur before products can be manufactured and successfully marketed and thus require large financial resource input. Third, we use inventory-to-sales ratio ($Invent_i$) as it captures the duration of the manufacturing process and the working capital that a firm requires in order to maintain inventory so as to meet demand. Last but not least, a measure of asset tangibility ($Tang_i$) can also capture the liquidity situation of an industry and it is defined as the share of net value of fixed assets (such as plants, properties and equipments) in total book value assets. Among these four measures, higher external finance dependence, R&D intensity, and inventory-to-sales ratio imply tighter credit constraint (i.e., a higher d), while higher asset tangibility implies less stringent credit constraints (i.e., a lower d or, equivalently, a higher θ) as tangible assets can serve as collateral for borrowing and help to alleviate credit constraints. It may be debatable whether asset tangibility belongs to credit needs measure or credit access measure. Nonetheless, regardless of whether we view tangibility as indicator of credit needs or credit access, it does not change the fact that higher tangibility implies less stringent credit constraint and, therefore, according to the theory, induces higher export prices set by the firm. So we expect that the coefficients on $ExtFin_i, RD_i$, and $Invent_i$ are negative, while the coefficient on $Tang_i$ is positive.

In the main tests, we employ these four measures of industrial financial vulnerability constructed by Kroszner et al. (2007), based on data on all publicly traded US-based companies from Compustat's annual industrial files. These measures have also been used by Manova et al. (2014). They are constructed following the methodology of Rajan and Zingales (1998) and Claessens and Laeven (2003). They are averaged over the 1980–1999 period for the median US firm in each sector, and appear to be very stable over time. The four indicators of industries' financial vulnerability are available for 29 sectors in the ISIC 3-digit classification system. As our dependent variable is export price of products, we match the HS 6-digit product codes to those ISIC 3-digit sector categories by employing Haveman's concordance tables.[27] This matching method has been adopted by Manova et al. (2014). The rationale behind this matching is that we can categorize firms into different industries according to what products they produce and, hence, sell to foreign markets. Therefore, when we use credit needs measures based on US data in the baseline regression, we include product or product-destination fixed effects at HS4 level rather than HS6 or HS8 level, because HS6-product fixed effects will absorb the effect of credit needs. We acknowledge that this matching based on US data cannot be perfect. Hence, in order to avoid any potential bias from the matching, we also use Chinese firm-level data to directly construct the Chinese-data-based measure of credit needs at industry level to complement our analysis using the US-data-based measures.

The reasons why we employ these credit needs measures based on US data in our main regressions are twofold. First, the US is a developed country with mature financial markets. Thus, the credit needs measures computed by US data are not distorted by limited credit supply, a typical situation in developing countries, and can reflect the real credit needs associated with industrial characteristics. Second, the differences of industrial credit needs based on US data are also persistent in a cross-country setting. In fact, the application of these measures calculated based on US data to countries other than the US is quite common in the literature (e.g., Rajan and Zingales, 1998; Kroszner et al., 2007; Manova et al., 2014). The rationale is that these measures in an industry of financial needs are determined by the nature of the industry, which is supposed to be the same across countries. As argued by Rajan and Zingales (1998), Kroszner et al. (2007) and Claessens and Laeven (2003), among others, there is a technological reason why some industries depend more on external finance than others and these technological differences persist across countries. Manova et al. (2014) also argue that the ranking of industries in terms of their financial vulnerability remains relatively stable across countries. In fact, Rajan and Zingales (1998) explicitly indicate that "most of the determinants of ratio of cash flow to capital are likely to be similar worldwide: the level of demand for a certain product, its stage in the life cycle, and its cash harvest period". This implies that, in principle, the measures calculated based on data from any country with well-functioning capital markets should be applicable to our study. Therefore, we use an industry's financial vulnerability calculated based on US data as measures of its credit needs in our baseline regressions.

Finally, as a further test to show the robustness of our results, we also construct the major indicator of credit needs, *ExtFin*, based on Chinese firm-level data.[28] Our results are reported in Table A.1 in the online Appendix (in ascending order of credit needs), which can be easily compared with the measures calculated based on US data.[29] Due to the immaturity of Chinese

[26] This is also one of the important reasons that we use industry-level credit needs measures rather than firm-level measures, because firm-level measures are endogenous to firm decision while industry-level measures could be viewed as exogenous to each individual firm. Moreover, we use credit needs measures based on US data rather than Chinese data as main results because the advantage of using US data is to better alleviate the endogeneity concern of credit needs measures given that Chinese data may not reflect the true credit needs at industry level due to the immature financial market in China. Nevertheless, we also calculate external finance dependence using Chinese data for the purpose of robustness.

[27] The concordance table can be accessed via http://www.macalester.edu/research/economics/page/haveman/Trade.Resources/tradeconcordances.html.

[28] The *ExtFin* based on Chinese data is calculated at the 2-digit Chinese Industrial Classification (CIC) level.

[29] Data available in year 2004–2006 in the NBSC Database. We calculate the aggregate rather than the median external finance dependence at 2-digit industry level, because the median firm in Chinese database often has no capital expenditure. In our sample, approximately 68.1% firms have zero capital expenditure. Hence, we cannot use median firm approach to calculate external finance dependence.

financial markets, capital expenditure by Chinese firms could only reflect the part of their actual credit needs. As a result, the mean external finance dependence in China is lower than that of the US.[30] Nonetheless, we find that the rankings of industries in external finance dependence in China and in the US are similar to each other, with reasonable difference across industries as the two countries use different industrial classification system. This is consistent with the finding in prior studies that the external finance dependence of US firms is a good proxy for other countries. For example, the tobacco industry is always at the top of the ranking list and is less credit-constrained, while the petroleum products industry and professional and scientific equipment industry are at the bottom of the ranking list as they are usually more technology-intensive and need more external capital. It is worth noting that the CIC industry code is a different classification system compared with HS or ISIC. Each firm belongs to one CIC, but it can produce and export multiple HS8 products. To sort out the price variation due to product-level characteristics and the potential correlation of error terms within each firm across products, when we use *ExtFin* based on Chinese data, we include HS8-product or HS8-product-destination fixed effects and also cluster errors at the firm level.[31]

3.3.3. Measures of productivity

To capture firms' productivity as a control variable in our regression analysis, we estimate total factor productivity (TFP). We use a Cobb-Douglas production function as estimation specification:[32]

$$Y_{ft} = A_{ft} L_{ft}^{\beta_l} K_{ft}^{\beta_k} \tag{14}$$

where production output of firm f at year t, Y_{ft}, is a function of labor, L_{ft}, and capital, K_{ft}; A_{ft} captures firm f's TFP in year t. We use deflated firm's value-added to measure production output. We do not include intermediate inputs (materials) as one of the input factors in our main results because the prices of imported intermediate inputs are different from those of domestic intermediate inputs. As processing trade in China accounts for a substantial proportion of its total trade since 1995, using China's domestic deflator to measure its imported intermediate input would raise another unnecessary estimation bias (Feenstra et al., 2014). However, for robustness check, we also estimate TFP by treating material as an intermediate input. It turns out that including intermediate inputs (materials) in the estimation of TFP does not alter the results of our empirical test of the theory.

As the traditional OLS estimation method suffers from simultaneity bias and selection bias, we employ the augmented Olley and Pakes (1996) approach to deal with both the simultaneity bias and selection bias in the measured TFP in the main part of our empirical test. Our approach is based on the recent development in the application of the Olley–Pakes method, for example, Amiti and Konings (2007), Feenstra et al. (2014), and Yu (forthcoming). However, to check for robustness, we also employ other approaches to estimate TFP (e.g., Levinsohn and Petrin, 2003; Ackerberg et al., 2006; De Loecker and Warzynski, 2012). We find that all variants of TFP estimate support the predictions of the quality sorting model that tighter credit constraints lower export prices. We briefly describe the augmented Olley–Pakes method used in our TFP estimation as follows.

First, to measure a firm's inputs (labor and capital) and output in real term, we use different input price deflators and output price deflators, drawing the data directly from Brandt et al. (2012).[33] In Brandt et al. (2012), the output deflators are constructed using "reference price" information from China's Statistical Yearbooks and the input deflators are constructed based on output deflators and China's national input–output Table (2002).

Second, we construct the real investment variable by adopting the perpetual inventory method to model the law of motion for real capital and real investment. To capture the depreciation rate, we use each firm's real depreciation rate provided by the Chinese firm-level data.

Furthermore, to take into account firm's trade status in the TFP realization, we include two trade-status dummy variables–an export dummy (equal to one for exports and zero otherwise) and an import dummy (equal to one for imports and zero otherwise), as in Amiti and Konings (2007). In addition, as we are dealing with Chinese data and our sample period is between 2000 and 2006, we include a WTO dummy (i.e., one for a year after 2001 and zero for before) in the Olley–Pakes estimation, as have been done by Feenstra et al. (2014) and Yu, forthcoming. The WTO dummy can capture the effect of China joining WTO on the realization of the TFP because the WTO accession in 2001 was a positive demand shock for China's exports. Our estimates of TFP coefficients at the 2-digit industry level are reported in Table A.2 (in the online Appendix) and the magnitudes of our estimates are similar to those reported by Feenstra et al. (2014).

4. Main results

In this section, we report our main results to support the predictions of our quality sorting model. Interestingly, we also find evidence to support the efficiency sorting case and thus indirectly confirm the mechanism of quality adjustment.

[30] According to our calculation, the mean external finance dependence in China is approximately −0.57 while the mean external finance dependence from the US data is about −0.16.

[31] If we cluster error term at HS8-product or HS8-product-destination level, the results remain robust.

[32] An alternative specification would be to use a trans-log production function, which also leads to similar estimation results.

[33] The data can be accessed via http://www.econ.kuleuven.be/public/N07057/CHINA/appendix/.

4.1. Credit constraints and export prices

Our main interest is to study the impacts of credit access and credit needs on export prices. According to Proposition 1, when output quality is a choice by the firm, we expect that lower credit access or higher credit needs lowers the optimal price set by the firm in a quality sorting model.

We report our baseline results of Eq. (11) with the firm-product-country level prices as dependent variable based on four measures of credit needs computed by US data in Tables 2 and 3. The reasons why we employ these credit needs measures based on US data in our main regressions haven been discuss in Section 3.3.2. In each of the four sets of results, we use three types of bank loans to GDP ratio and the different types of firm ownership to control for credit access, and employ one of the four measures of financial vulnerability (i.e., external finance dependence, R&D intensity, inventory-to-sales ratio, and asset tangibility) to proxy for credit needs. Table 2 presents the results using external finance dependence in specifications (1)–(5) and R&D intensity in specifications (6)–(10). On the other hand, Table 3 reports the results based on inventory-to-sales ratio in specifications (1)–(5) and asset tangibility in specifications (6)–(10).

In Tables 2 and 3, specifications (1)–(3) and (6)–(8) show the regression results under three different measures of credit access using bank loans. Specifications (4)–(5) and (9)–(10) include two firm-type dummy variables: SOE, which is equal to 1 if the firm belongs to state-owned enterprises (SOE) and 0 if it belongs to domestic private enterprises (DPE); and MNC, which is equal to 1 if the firm is a multinational corporation (MNC) and 0 if it belongs to a joint venture (JV). According to Proposition 1 and further discussion on measures of credit access in Section 3.3.1, we expect the coefficients on three types of bank loans as well as SOE and MNC to be positive under quality sorting. We find that the coefficients on all measures of credit access are positive and significant at 1% level, implying that firms with more access to bank loans set higher prices, and the prices set by SOE and MNC are higher than the prices set by DPE and JV, respectively.[34] These results fully support Proposition 1 that tighter credit constraints resulting from lower level of credit access reduce the optimal export price set by a firm, ceteris paribus.

Likewise, if quality is indeed a choice by the firm under quality sorting, according to Proposition 1 and the further discussion of credit needs measures in Section 3.3.2, we expect the coefficients on external finance dependence, R&D intensity, and inventory-to-sales ratio to be negative while the coefficients on asset tangibility to be positive. This is because firms in industries with higher external finance dependence, R&D ratio, and inventory-to-sales ratio face tighter credit constraints whereas those with more tangible assets have more relaxed credit constraints. Again, the results presented in Tables 2 and 3 confirm Proposition 1: ceteris paribus, higher credit needs lowers the optimal prices with statistical significance at 1% level.[35]

We also employ the firm-product level prices (i.e., log price by firm *f* for product *h* at year *t*) as dependent variable and report the results in Tables A.3 and A.4 in the online Appendix. The results are consistent with those in Tables 2 and 3 with the only exception that the coefficients on tangibility are less significant (but significant at 10 percent level in the first two specifications), yet still act at expected direction with firm-product level prices in all specifications. The possible reason for less significant results for firm-product level price is perhaps because prices at the firm-product level are less precisely measured compared with the ones at the firm-product-destination level.[36]

Moreover, Proposition 1 predicts that export prices increase in productivity. The reason is that firm productivity affects product prices through two channels. On the one hand, higher-productivity firms have lower marginal costs, leading to lower product prices. On the other hand, more productive firms choose to produce goods of higher quality, leading to higher product prices. As the quality effect dominates, the total effect is that prices increase in productivity. In all specifications of the baseline results in Tables 2 and 3 (as well as the results in Tables A.3 and A.4 in the online Appendix), the coefficients on TFP are always significantly positive, consistent with the predictions of the quality sorting case.

As all the above results use the credit needs measures based on US data, to further verify our baseline results, we also compute the key measurement of credit needs—external finance dependence—using Chinese firm data, and report regression results in Table 4. Specifications (1)–(5) of Table 4 use (log) average export price by firm at the HS8-product-destination level as dependent variable, while specifications (6)–(10) use (log) average export price by firm at the HS8-product level as dependent variable. As discussed in Section 3.3.2, the ranking of industries in external finance dependence calculated based on Chinese data is quite similar to the one based on US data. Thus, as expected, the results based on the external finance dependence from Chinese data are also consistent with the predictions in Proposition 1: the coefficients on credit access are significantly positive; the coefficients on credit needs are significantly negative; the coefficients on TFP are significantly positive as well. The results are stated in Table 4.[37]

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[34] The credit constraint literature sometimes uses firm size as an indicator for credit access (see, e.g., Manova et al. (2014)). In our paper, total employment (and also TFP) could capture firm size effect. Thus, in some specifications when we use SOE or MNC as credit access measure, coefficients on labor changed a lot perhaps because SOE and MNC also reflect firm size effect.

[35] According to the corporate finance literature, external finance dependence might vary by nature for young firms and mature firms. Therefore, in an alternative specification, we include firm age as control variable in the baseline regressions and our baseline results are robust after controlling for firm age.

[36] Think about the same firm exports the same HS6 product to two destination countries with two different prices, say, one country is a high-income country where the price charged is high and another is a low-income country where the price is low. The unit value prices at the firm-product level average out the different export prices to two different markets and thus may not be as precise as the price measured at firm-product-destination level.

[37] We report the results using the US-based measure of external finance dependence in the main tables, but most results still hold when using the Chinese-based measure.

Table 2
Credit constraints and export prices across product-destination: external finance dependence and R&D.

Regressor	Credit needs measured by *ExtFin$_i$*					Credit needs measured by *RD$_i$*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Firm characteristics										
log(TFP)	0.062***	0.061***	0.060***	0.025*	0.081***	0.062***	0.061***	0.060***	0.025*	0.081***
	(0.007)	(0.007)	(0.007)	(0.013)	(0.011)	(0.007)	(0.007)	(0.007)	(0.013)	(0.011)
log(Labor)	0.026***	0.025***	0.025***	−0.018*	0.009	0.026***	0.025***	0.026***	−0.018	0.009
	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)
log(Cpaital/Labor)	0.043***	0.043***	0.044***	0.023**	0.051***	0.042***	0.042***	0.043***	0.023**	0.050***
	(0.005)	(0.005)	(0.005)	(0.011)	(0.008)	(0.005)	(0.005)	(0.005)	(0.011)	(0.008)
log(Wage)	0.257***	0.269***	0.249***	0.173***	0.317***	0.258***	0.269***	0.249***	0.175***	0.317***
	(0.016)	(0.016)	(0.016)	(0.024)	(0.021)	(0.016)	(0.016)	(0.016)	(0.024)	(0.021)
Credit needs										
Extfin	−3.353***	−3.357***	−3.337***	−3.715***	−2.787***					
	(0.298)	(0.298)	(0.299)	(0.578)	(0.311)					
RD						−30.514***	−30.612***	−30.344***	−34.098***	−21.847***
						(4.118)	(4.114)	(4.110)	(8.283)	(4.606)
Credit access										
All Credits to GDP Ratio	0.293***					0.293***				
	(0.023)					(0.023)				
Short-term Loans to GDP Ratio		0.546***					0.545***			
		(0.050)					(0.051)			
Long-term Loans to GDP Ratio			0.489***					0.490***		
			(0.036)					(0.036)		
SOE				0.262***					0.263***	
				(0.059)					(0.060)	
MNC					0.077***					0.077***
					(0.023)					(0.023)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-destination fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,809,014	2,809,014	2,809,014	694,968	825,963	2,809,014	2,809,014	2,809,014	694,968	825,963
Adjusted R^2	0.571	0.571	0.571	0.628	0.519	0.569	0.569	0.570	0.626	0.518

Notes: Cluster-robust standard errors in parentheses, clustered by firm. All regressions include a constant term.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

4.2. Credit constraints and export quality

If the mechanism of quality adjustment is correct, according to Eq. (7) and Proposition 2, we expect that given productivity, a firm with more credit access or less credit needs chooses higher product quality. We now use estimated quality and quality-adjusted price to test this proposition.

Table 5 replicates the baseline regressions (specifications 1–5 in Table 2) by replacing export prices with the estimated product quality as dependent variable in the left panel (columns 1–5). We find that the coefficients on external finance dependence are negative, and the coefficients on credit access measures are positive. Hence, quality choice is indeed affected by credit constraints. Moreover, the effect of TFP on quality is also positive. Most effects are significant at 1% level with the predicted signs, which verify the mechanism of quality adjustment.[38]

On the other hand, columns 6–10 in the right panel of Table 5 report the results of modified baseline regressions by replacing export prices with *quality-adjusted* export prices as dependent variable. Note that the quality-adjusted price is net-quality price, which already sorts out quality embodied in price. Therefore, we expect the results based on quality-adjusted price are consistent with the predictions of the efficiency sorting case, i.e., higher credit needs increase (quality-adjusted) prices, a higher level of credit access decreases the optimal prices, and a more productive firm set a lower price.

In Table 5, we do find that the coefficients on external finance dependence become significantly positive, and the coefficients on TFP become significantly negative, exactly consistent with the predictions of the efficiency sorting case. As for the credit access measures, among all five measures of credit access, one of them now presents significantly negative effect on

[38] There is an exception for the coefficient on MNC which is still positive but less significant, perhaps because the intra-firm trade volume and price could not totally reflect the product quality, which may lead to estimation bias for product quality of MNC.

Table 3
Credit constraints and export prices across product-destination: inventory ratio and tangibility.

Regressor	Credit needs measured by $Invent_i$					Credit needs measured by $Tang_i$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Firm characteristics										
log(TFP)	0.063***	0.062***	0.061***	0.026**	0.082***	0.063***	0.062***	0.061***	0.027**	0.082***
	(0.007)	(0.007)	(0.007)	(0.013)	(0.011)	(0.007)	(0.007)	(0.007)	(0.013)	(0.011)
log(Labor)	0.026***	0.025***	0.025***	−0.018*	0.009	0.026***	0.024***	0.025***	−0.018*	0.009
	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.008)	(0.008)	(0.008)	(0.011)	(0.012)
log(Cpaital/Labor)	0.043***	0.042***	0.044***	0.022**	0.050***	0.043***	0.042***	0.044***	0.023**	0.051***
	(0.005)	(0.005)	(0.005)	(0.011)	(0.008)	(0.005)	(0.005)	(0.005)	(0.011)	(0.008)
log(Wage)	0.257***	0.269***	0.249***	0.173***	0.314***	0.259***	0.270***	0.250***	0.174***	0.316***
	(0.016)	(0.016)	(0.016)	(0.024)	(0.021)	(0.016)	(0.016)	(0.016)	(0.024)	(0.021)
Credit needs										
Invent	−16.646***	−16.594***	−16.569***	−22.799***	−12.084***					
	(1.592)	(1.592)	(1.590)	(4.104)	(1.759)					
Tang						0.939***	0.935***	0.902***	0.837	0.745*
						(0.284)	(0.285)	(0.284)	(0.678)	(0.422)
Credit access										
All Credits to GDP Ratio	0.293***					0.293***				
	(0.023)					(0.023)				
Short-term Loans to GDP Ratio		0.541***					0.544***			
		(0.051)					(0.051)			
Long-term Loans to GDP Ratio			0.490***					0.491***		
			(0.036)					(0.036)		
SOE				0.267***					0.269***	
				(0.060)					(0.061)	
MNC					0.075***					0.077***
					(0.023)					(0.023)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-destination fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,809,014	2,809,014	2,809,014	694,968	825,963	2,809,014	2,809,014	2,809,014	694,968	825,963
Adjusted R^2	0.570	0.569	0.570	0.626	0.518	0.569	0.568	0.569	0.625	0.518

Notes: Cluster-robust standard errors in parentheses, clustered by firm. All regressions include a constant term.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

quality-adjusted prices. The other four show smaller, less significant positive effect on quality-adjusted prices, compared with the baseline regression results (see specifications 1–5 in Table 2). This suggests evidence to support the quality sorting case and the mechanism of quality adjustment, because the prediction of the efficiency sorting case holds once we sort out quality effect from prices using quality-adjusted price.

4.3. Further verification of mechanism: effects of quality variation across firms

Our empirical results above show that predictions from the quality sorting model are supported by the data. To further compare the predictions of quality sorting and efficiency sorting, we ask: compared with the benchmark estimation results (see Table 2), what if quality presents more variation across firms? It is safe to conjecture that in the product categories where there is more quality variation across goods, the firms are more likely to behave according to the predictions of the quality sorting model. Conversely, in the categories where there is less quality variation across firms, we expect that firms are more likely to behave according to the predictions of the efficiency sorting case. Therefore, if our theory is correct, we expect that the effects of credit constraints on prices are more pronounced for product categories featuring more quality variation. In other words, in product categories with more quality variation across goods we expect the product prices to be more negatively affected by tighter credit constraints.

To confirm our conjecture, we use the variance of estimated product quality by different firms for the same HS6-product to measure the variation of product quality for that product. Then we rank products according to the variance of their estimated quality (i.e., quality variation) and create a dummy variable which is equal to one if the product's quality variation belongs to the top 50 percentile of quality variation among the whole sample, and equal to zero if it belongs to the bottom 50 percentile. Next we redo the baseline regressions by adding the dummy variable and the interaction between the dummy

Table 4
Credit constraints and export prices: external finance dependence based on Chinese data.

Regressor	Across product-destination					Across product				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log(TFP)	0.045***	0.044***	0.043***	0.006**	0.061***	0.046***	0.046***	0.045***	0.014***	0.051***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
log(Labor)	0.026***	0.025***	0.026***	0.003	0.015***	0.031***	0.030***	0.032***	0.002	0.040***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
log(Cpaital/Labor)	0.029***	0.029***	0.030***	0.006***	0.042***	0.035***	0.034***	0.036***	0.001	0.051***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
log(Wage)	0.190***	0.199***	0.182***	0.103***	0.235***	0.219***	0.230***	0.209***	0.126***	0.256***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.005)	(0.007)	(0.007)	(0.006)	(0.008)	(0.009)
Extfin	−0.040***	−0.039***	−0.041***	−0.035***	−0.030***	−0.030***	−0.029***	−0.031***	−0.033***	−0.017
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)	(0.012)	(0.014)
All Credits to GDP Ratio	0.263***					0.262***				
	(0.005)					(0.009)				
Short-term Loans to GDP Ratio		0.488***					0.495***			
		(0.010)					(0.020)			
Long-term Loans to GDP Ratio			0.451***					0.452***		
			(0.007)					(0.012)		
SOE				0.166***					0.152***	
				(0.011)					(0.020)	
MNC					0.079***					0.082***
					(0.005)					(0.008)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-destination fixed effect	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Product fixed effect	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	2,809,014	2,809,014	2,809,014	694,968	825,963	1,045,764	1,045,764	1,045,764	225,640	355,866
Adjusted R^2	0.744	0.743	0.744	0.799	0.705	0.652	0.651	0.652	0.709	0.607

Notes: Cluster-robust standard errors in parentheses, clustered by firm. All regressions include a constant term.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

variable and the measures of credit constraints and report the results in Table 6. Our approach is in a similar spirit to Kugler and Verhoogen (2012) where the interaction of firm size with quality differentiation is included.[39] Specifications (1)–(5) of Table 6 present the results across product and country, and specifications (6)–(10) report the results across product.

The coefficients on the interaction terms are of special interest to us. We find that the coefficients on the interaction term, *ExtFin* × *Dummy*, are significantly negative, and the coefficients on the interaction between the credit access measures and the dummy variable are significantly positive. This implies that firms producing in product categories with more quality variation across goods are more negatively affected by tighter credit constraints. Therefore, this exercise further lends support to the predictions of quality sorting.

5. More discussion

In this section, we discuss the interaction between credit needs and credit access as well as their implications. Next we address the potential issue of multi-product firms by showing that our results are robust to single-product firms.

5.1. Interaction between credit access and credit needs

It is interesting to explore the potential interaction effect between credit needs and credit access as they are combined nonlinearly in the theoretical model. In Table 7, we report the results with the interaction term between credit needs and credit access. After introducing the interaction term, all the model predictions still hold: the coefficients on credit needs are all significantly negative at 0.1 percent level, and all coefficients on credit access are significantly positive at, at least, 1 percent level. Furthermore, the coefficients on the interaction term are significantly positive in most specifications, indicating that the positive effect of credit access on export prices is strengthened in industries where credit constraints are

[39] Note that we do not interact the estimated quality level directly with credit constraints; instead, we interact quality *variation* with credit constraints. This is because the effect of credit constraints on export price depends on the scope of quality differentiation (e.g., whether there is quality sorting or efficiency sorting) rather than the quality level.

Table 5
Export prices across product and destination: quality and net-quality price (σ_i based on Broda and Weinstein (2006)).

Regressor	Dependent variable: quality					Dependent variable: net-quality price				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log(TFP)	0.068***	0.068***	0.066***	0.035***	0.084***	−0.007***	−0.007***	−0.006***	−0.006***	−0.005**
	(0.007)	(0.007)	(0.007)	(0.013)	(0.011)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
log(Labor)	0.026***	0.025***	0.025***	−0.005	−0.006	0.001	0.001	0.002	−0.012***	0.015***
	(0.009)	(0.009)	(0.009)	(0.011)	(0.012)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
log(Cpaital/Labor)	0.044***	0.043***	0.045***	0.022**	0.051***	−0.001	−0.000	−0.001	−0.003	0.000
	(0.005)	(0.005)	(0.006)	(0.011)	(0.009)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
log(Wage)	0.235***	0.245***	0.230***	0.156***	0.290***	0.020***	0.021***	0.017***	0.014***	0.017***
	(0.017)	(0.017)	(0.017)	(0.023)	(0.020)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)
Extfin	−3.539***	−3.543***	−3.523***	−4.053***	−3.101***	0.078***	0.078***	0.078***	0.067	0.159***
	(0.334)	(0.334)	(0.335)	(0.616)	(0.358)	(0.026)	(0.026)	(0.026)	(0.043)	(0.053)
All Credits to GDP Ratio	0.299***					−0.004				
	(0.024)					(0.005)				
Short-term Loans to GDP Ratio		0.583***					−0.027**			
		(0.053)					(0.011)			
Long-term Loans to GDP Ratio			0.467***					0.024***		
			(0.038)					(0.007)		
SOE				0.222***					0.045***	
				(0.055)					(0.009)	
MNC					0.026					0.051***
					(0.023)					(0.005)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-destination fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,809,014	2,809,014	2,809,014	694,968	825,963	2,809,014	2,809,014	2,809,014	694,968	825,963
Adjusted R^2	0.095	0.095	0.096	0.132	0.115	0.936	0.936	0.936	0.957	0.924

Notes: Cluster-robust standard errors in parentheses, clustered by firm. All regressions include a constant term.
Using *ExtFin* computed by Chinese data does not alter the results in this table.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

tighter through higher credit needs measure. In other words, in a more financially vulnerable industry, the positive effect of credit access on export price is more profound. It also implies that the negative effect of credit needs on export price is attenuated in the area with better credit access. Our results are consistent with Rajan and Zingales (1998) who point out that financial development has more stimulating effect on economic growth in industries that more rely on external financing.

5.2. Single product firms

As the main measures of credit needs are at product level, one exporter may have different measures of credit needs if it exports multiple products. Thus, as Manova et al. (2014) pointed out, there may be an internal ranking of products by an exporter in exporting value according to their financial vulnerability. Then it would be possible that an exporting firm may switch their export product mix when facing credit constraints. A more thorough analysis calls for further investigation of resource reallocation across core versus non-core product products within firm but this would be out of the scope of the current paper. To alleviate this concern, we repeat our baseline regressions for all single-product firms in Table A.5 (see the online Appendix) to rule out the possibility of switching export product mix by a firm. In the left panel (see columns 1–5), we present results for price at firm-product-country level where the single product refers to one HS8 product-country combination; in the right panel (see columns 6–10), we report results for price at firm-product level where the single product refers to one HS8 product. This exercise indeed lowers the significance level of the coefficients on the measure of credit needs, external finance dependence, implying that the aforementioned stronger effect of credit needs on export prices partially go through the resource reallocation across products within firm. Nevertheless, the coefficients on credit needs measures are still significant in most specifications, indicating the robustness of our results and confirming the validity of the quality adjustment mechanism along the intensive margin.

6. Endogeneity

We consider three types of potential endogeneity issues in this section, including: (1) the potential endogeneity of our key variables of interest—credit needs and credit access; (2) the potential endogeneity issue due to revenue-based TFP measures; and (3) other potential endogeneity issues due to omitted variables. We now discuss each in turn.

Table 6
Credit constraints and export prices: effects of quality variation.

Regressor	Across product-destination					Across product				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log(TFP)	0.061***	0.060***	0.059***	0.029**	0.079***	0.056***	0.056***	0.055***	0.032**	0.064***
	(0.007)	(0.007)	(0.007)	(0.013)	(0.010)	(0.006)	(0.006)	(0.006)	(0.013)	(0.009)
log(Labor)	0.029***	0.028***	0.029***	−0.017*	0.009	0.037***	0.036***	0.037***	−0.005	0.042***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)	(0.006)	(0.006)	(0.006)	(0.009)	(0.010)
log(Cpaital/Labor)	0.042***	0.041***	0.043***	0.019*	0.050***	0.044***	0.043***	0.045***	0.010	0.057***
	(0.005)	(0.005)	(0.005)	(0.010)	(0.008)	(0.005)	(0.005)	(0.005)	(0.014)	(0.007)
log(Wage)	0.254***	0.265***	0.246***	0.158***	0.309***	0.247***	0.260***	0.237***	0.144***	0.297***
	(0.016)	(0.016)	(0.016)	(0.021)	(0.020)	(0.011)	(0.011)	(0.011)	(0.025)	(0.017)
Extfin	−2.828***	−2.835***	−2.817***	−3.257***	−2.417***	−2.063***	−2.081***	−2.032***	−2.403***	−1.741***
	(0.305)	(0.304)	(0.304)	(0.540)	(0.314)	(0.126)	(0.126)	(0.126)	(0.290)	(0.197)
Extfin × Dummy	−0.872***	−0.865***	−0.891***	−1.096***	−0.755***	−0.550***	−0.530***	−0.593***	−0.837***	−0.573***
	(0.065)	(0.065)	(0.064)	(0.120)	(0.102)	(0.036)	(0.036)	(0.036)	(0.065)	(0.059)
All Credits to GDP Ratio	0.181***					0.195***				
	(0.023)					(0.019)				
All Credits to GDP Ratio × Dummy	0.192***					0.177***				
	(0.015)					(0.009)				
Short-term Loans to GDP Ratio		0.354***					0.372***			
		(0.050)					(0.043)			
Short-term Loans to GDP Ratio × Dummy		0.363***					0.345***			
		(0.028)					(0.017)			
Long-term Loans to GDP Ratio			0.241***					0.298***		
			(0.036)					(0.029)		
Long-term Loans to GDP Ratio × Dummy			0.422***					0.355***		
			(0.031)					(0.022)		
SOE				−0.010					−0.042	
				(0.042)					(0.040)	
SOE × Dummy				0.570***					0.516***	
				(0.068)					(0.049)	
MNC					−0.005					0.005
					(0.020)					(0.019)
MNC × Dummy					0.147***					0.138***
					(0.032)					(0.023)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-destination fixed effect	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Product fixed effect	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	2,809,014	2,809,014	2,809,014	694,968	825,963	1,045,764	1,045,764	1,045,764	225,640	355,866
Adjusted R^2	0.573	0.573	0.574	0.627	0.528	0.482	0.481	0.482	0.537	0.437

Notes: Cluster-robust standard errors in parentheses, clustered by firm. All regressions include a constant term.
Using *ExtFin* computed by Chinese data does not alter the results in this table.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

6.1. Instruments for credit needs and credit access

In our main results, we use industrial credit needs measures based on US data and the provincial bank loans data as proxy for credit access that could be viewed as exogenous from an individual firm's perspective. To some extent, the existing strategy has already alleviated the concern of the potential endogeneity of credit needs and credit access measures. However, there might be still some measurement errors or potential reverse causality. Thus, we will use instrumental variable (IV) estimations to better tackle this concern.

First, for the key credit needs measure—external finance dependence, we use another set of external finance data in the earlier period (1980–1989) from Kroszner et al. (2007) as instrument for the current measure of external finance dependence.[40]

[40] The original external finance dependence measures refer to the data in the period of 1980–1999. We acknowledge that it would be better if we can find data earlier than 1980, but unfortunately we could not find such data. Thus, as a remedy, we use the data from 1980 to 1989 as instruments.

Table 7
Interaction between credit needs and credit access.

Regressor	Across product-destination					Across product				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log(TFP)	0.061***	0.061***	0.059***	0.030**	0.079***	0.056***	0.056***	0.055***	0.031**	0.064***
	(0.007)	(0.007)	(0.007)	(0.012)	(0.010)	(0.006)	(0.006)	(0.006)	(0.013)	(0.009)
log(Labor)	0.028***	0.026***	0.027***	−0.019*	0.009	0.037***	0.035***	0.037***	−0.005	0.043***
	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.006)	(0.006)	(0.006)	(0.009)	(0.010)
log(Cpaital/Labor)	0.043***	0.042***	0.044***	0.020*	0.051***	0.045***	0.044***	0.046***	0.013	0.057***
	(0.005)	(0.005)	(0.005)	(0.010)	(0.008)	(0.005)	(0.005)	(0.005)	(0.014)	(0.007)
log(Wage)	0.255***	0.266***	0.246***	0.165***	0.307***	0.248***	0.262***	0.237***	0.156***	0.296***
	(0.016)	(0.016)	(0.016)	(0.022)	(0.020)	(0.011)	(0.011)	(0.011)	(0.025)	(0.017)
Extfin	−3.714***	−3.557***	−3.688***	−3.991***	−2.951***	−2.771***	−2.628***	−2.745***	−3.089***	−2.227***
	(0.340)	(0.349)	(0.332)	(0.583)	(0.346)	(0.147)	(0.156)	(0.137)	(0.305)	(0.204)
Extfin × Credit Access	0.213***	0.141	0.503***	0.901***	0.023	0.221***	0.174	0.492***	0.903***	0.051
	(0.079)	(0.180)	(0.118)	(0.174)	(0.074)	(0.056)	(0.128)	(0.085)	(0.120)	(0.055)
All Credits to GDP Ratio	0.309***					0.316***				
	(0.025)					(0.022)				
Short-term Loans to GDP Ratio		0.568***					0.574***			
		(0.057)					(0.050)			
Long-term Loans to GDP Ratio			0.524***					0.546***		
			(0.040)					(0.033)		
SOE				0.336***					0.283***	
				(0.057)					(0.054)	
MNC					0.078***					0.085***
					(0.025)					(0.020)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-destination fixed effect	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Product fixed effect	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	2,809,014	2,809,014	2,809,014	694,968	825,963	1,045,764	1,045,764	1,045,764	225,640	355,866
Adjusted R^2	0.571	0.570	0.571	0.625	0.526	0.481	0.480	0.481	0.536	0.436

Notes: Cluster-robust standard errors in parentheses, clustered by firm. All regressions include a constant term.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

The results are presented in Table A.6 in the online Appendix. Using IV estimation does not alter our main results, and the coefficients on external finance dependence measure are still significantly negative in most specifications. As the error term is assumed to be heteroskedastic in our econometric model, we invoke the heteroskedastic-robust Kleibergen and Paap (2006) *rk* underidentification test statistic for assessing the strength of identification, i.e., the Kleibergen and Paap (2006) *rk* statistic is to test whether an instrument is relevant to an endogenous variable (i.e., the original external finance dependence measure). The null hypothesis that the model is underidentified is rejected at the 0.1 percent significance level. Moreover, the Kleibergen and Paap (2006) Wald F-statistics provide strong evidence to reject the null hypothesis that the first stage is weakly identified at a highly significant level. That is to say, in all specifications, the instrument of external finance dependence earlier period provides a good fit in the first stage, and performs as a valid instrument.

Second, our strategy to tackle the potential endogeneity of credit access measures (i.e., bank loans) is to identify exogenous restrictions on the local supply of banking services, as in Minetti and Zhu (2011). During the early 2000s, China launched a national wide reform in her banking systems. As more and more non-state owned banks appears during that period, both the number of employees and branches changed dramatically after the reform. Although more private financial institutions appear during 2000–2006, the national financial system shifts little regarding geographic distribution. Thus, we observe a parallel rise in the number of bank branches and in the number of bank employees across all provinces between 2000 and 2006. Also note that under the Chinese banking system in the sample period (2000–2006) it is almost impossible for firms to obtain bank loans from other provinces. Thus, firms established in financially developed provinces are always at liquidity advantage than those located in undeveloped areas. It is also reasonable to believe that the previous banking service has little impact on firms' export prices at later period. Even if it has "some" potential effect on future export prices, it acts through the current bank loans. All the above arguments justify that the supply of bank loans before 2000 (via either the number of bank branches or the number of bank employees) serves as a valid instrument for credit access after 2000. Similar instrumental variables can also be found in some related studies (e.g., Guiso et al., 2004; Minetti and Zhu, 2011; Herrera and Minetti, 2007, among others).

We report the IV estimation results for credit access measures in Table A.7 in the online Appendix where the left panel (columns 1–6) are across product-country combinations and the right panel (columns 7–12) are across HS6 products only. We use the median number of bank branches and of bank employees by province between 1998 and 1999 to instrument credit access measures. We report results using the number of bank branches as instrument in columns 1–3 and 7–9, and those using the number of bank employees as instrument in columns 4–6 and 10–12. The two diagnostic statistics prove that the instrument is valid and fits well in the first stage. According to Table A.7 in the online Appendix, our previous main result that tighter credit constraints through less credit access lower export prices still hold after using IV estimation.

Finally, we want to test the prediction on the effect of credit constraints on export quality using IV estimation. The results are reported in Table A.8 in the online Appendix. The columns 1–5 use external finance dependence from 1980–1989 as instrument for the main measure of credit needs in the baseline regression; the columns 6–11 employ the number of bank branches (in columns 6–8) and the number of bank employees (in columns 9–11) as instrument for credit access measures. The dependent variable is the estimated quality at firm-product-country level. All the previous results remain significant with IV estimation and also the validity of instruments is confirmed through diagnostic statistics.

6.2. Revenue-based TFP measures

Due to data availability, we are only able to compute revenue-based TFP. Thus, there is a potential endogeneity between price (and estimated quality) and our TFP measure. When computing TFP, we use industry level deflators that partially alleviate this concern but still are not satisfactory in solving this problem since the industry level deflators cannot account for within-industry price difference and since our TFP measures are revenue-based. Given that we do not have the quantity production data to compute physical TFP, our remedy is to rerun our baseline regressions without including TFP as explanatory variable since our focus is on credit constraints instead of TFP that merely serves as a control variable in the baseline. We report results using export prices as dependent variable in Table A.9 in the online Appendix in which columns 1–5 repeat the baseline regression using fixed effect estimation and columns 6–10 use IV estimation with external finance dependence instrumented by data from early period (1980–1989).[41] By dropping productivity, we can directly observe the overall impact of credit constraints on prices and we find strong evidence to support the negative impact of credit needs and the positive impact of credit access on export prices in Table A.9: the effects of credit constraints (via either external finance dependence or credit access) are all significant at 0.1 percent level and consistent with model predictions.

6.3. Omitted variables

First, in our baseline specification, Eq. (11), after controlling the destination-product pair fixed effects and year fixed effects, there is still the variation over time within the same firm. Thus, it would be helpful to control for destination market demand that varies by country and time. We address this issue by either using the product-country-year fixed effects or adding GDP and GDP per capita in the destination market over time. The results are reported in Table A.10 in the online Appendix, where columns 1–5 use product-country-year fixed effects to control for time-variant demand changes within the same firm, and columns 6–10 add GDP and GDP per capita as control variables in the baseline regression. As reported in Table A.10 in the online Appendix, the effects of external finance dependence and credit access on export prices in all specifications are consistent with our main results and remain to be significant at 0.1 percent level.

Second, we acknowledge the limitation of the current measures of credit access and of credit needs as they are time-invariant at province level and industry level, respectively. Therefore, there are possibly many confounding factors omitted and they will affect export price and quality through the broad measure of credit access and credit need. For example, regions with less financial development may also be less developed in other economic indicators, and therefore export cheaper and lower-quality products. To address this concern, we add more control variables to capture industry-variant factors and regional economic factors. To better control for industry level factors that are potentially related with industrial credit needs, we follow Manova et al. (2014) and add more industry characteristics such as physical capital intensity, human capital intensity, and contract intensity.[42] To tackle the regional confounding factors, we include three indexes of financial related factors at province level in China, which reflect the institutional arrangement regarding financial development in each province. These three indexes are the development of market intermediaries, the protection of producer's legal rights, and the intellectual property protection. All three indexes reflect the financial and economic development in each province. The data source is the Institutional Environment Indices, developed by the National Economic Research Institute (NERI) for regional marketization levels in China (Fan et al., 2009).[43] We also include GDP at province level as control variable. As reported in Table A.11 in the online Appendix, adding more control variables regarding industry characteristics and regional development does not alter our main results: the effects of credit needs and credit access on export prices are all significant and consistent with our previous findings.

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[41] We also experiment with instruments for credit access and with quality as dependent variable, and obtain similar results. To save space, those results are not reported in the main text but will be available upon request.

[42] Data on physical capital intensity, human capital intensity, and contract intensity are obtained from Manova et al. (2014) and Kroszner et al., 2007.

[43] The NERI indexes and sub-indexes were computed by NERI using data from the statistical yearbooks, reports from the administration of industry and commerce, survey data, and other sources and so on. The NERI indexes have been widely used in economics, finance, and other business studies in China.

Lastly, one may concern that using SOE or MNC dummy as a proxy for credit access may not be reliable since it may also represent other important factors such as size or productivity. This is confirmed in the previous results: when we use SOE or MNC dummy as credit access measures, the coefficients on labor and TFP often change a lot while they behave very stably when we use three types of bank loans as credit access measures. This suggests that it would be better to check whether all main results still hold if we add ownership types as additional controls of firm characteristics into existing baseline regressions. The results are reported in Table A.12 in the online Appendix where we incorporate fixed effect terms of six ownership types as firm level control.[44] Columns 1–3, 4–6, and 7–9 in Table A.12 report results with export prices across product-destination, export quality, and prices across product as dependent variable, respectively. All our main results, regarding the impact of credit needs and credit access on price and quality, remain to be robust.

7. Robustness

7.1. Cross-sectional estimation

The predictions from our model are cross sectional, i.e., we compare firms facing tighter credit constraints with those who are not. Also the measures of credit constraints only capture the cross-sectional pattern: the industry-level credit needs measures and the regional-level credit access measures are both persistent and thus averaged over time. Therefore, to fully sort out the time variation effect, we also conduct cross-sectional estimation using both one-year sample and between estimator. The estimation equation with one-year sample is given by

$$\log price_{fh(c)r} = b_0 + b_1 \log(TFP_f) + \gamma X_f + \chi_1 FinDev_r + \chi_2 ExtFin_i + \varphi_{h(c)} + \epsilon_{fh(c).} \tag{15}$$

Table A.13 in the online Appendix reports the cross-sectional results using the sample in 2004[45]: Columns (1)–(5) report results of Eq. (15) with country index c and columns (6)–(10) report results without destination country index. The results show that coefficients on credit access are all significantly positive across different specifications and coefficients on external fiance dependence are all significantly negative. This suggests that tighter credit constraints resulting from either lower credit access or higher credit needs indeed reduce export prices. Also, most coefficients on TFP are still significantly positive, except for SOE in column (4). This is potentially because larger SOE typically employ a lot of unnecessary labor to produce. As a result, the estimated TFP of SOE may not accurately reflect their productivity.

In Table A.14 in the online Appendix, we report the between estimation results by averaging out the dependent and explanatory variables to check the across-section average effect. Again, the left panel (columns 1–5) and the right panel (columns 6–10) report results for firm-product-country prices and firm-product prices, respectively. As reported in Table A.14, tighter credit constraints (through either higher external finance dependence or less credit access) significantly lower export prices.

7.2. Different fixed effects

We acknowledge that the baseline specification works with different dimensions of the data, including firm, product, destination, year, and region, which makes the identification more complicated. The complication is unavoidable not only due to the merging process between the US data and Chinese data but also due to the nature of credit constraint measures: credit access and credit needs are measured at different dimensions of the data, i.e., the key measures of credit access is regional while the measures of credit needs are at industry level.

The issue of adding different fixed effects terms is not straightforward since our data contains multiple dimensions and the merging between US data and Chinese data further complicates this issue. Nevertheless, we try different combinations of fixed effects terms with the baseline regressions in Table A.15 in the online Appendix. The left panel (columns 1–6) in Table A.15 report results based on prices across product-destination and the right panel (columns 7–12) report results of prices across product. In each panel, the first five columns add 2-digit industry fixed effects, and all results regarding the effects of credit constraints on export prices as well as the relationship between productivity and prices remain similar as in the baseline.

It is more interesting to add firm fixed effects. The last column of each panel in Table A.15 in the online Appendix adds firm-product-destination (or firm-product) fixed effects in column 6 (or 12) to identify whether the relationship between credit needs (via external finance dependence) and export prices is operative at the within-firm-product-country (or firm-product) level.[46] Such a specification would moreover provide a more stringent set of controls against the possibility of firm-level omitted variables. Again, the results in columns 6 and 12 confirm the significantly negative coefficients on external finance dependence, indicating that tighter credit constraints resulting from higher credit needs indeed lower export prices even at the most disaggregated, within-firm-product-country level. Also the positive relationship between productivity and export prices still holds after adding such fixed effects.

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[44] These six ownership types refer to SOE, DPE, MNC, JV, firms from Hong Kong/Macau/Taiwan, and other types.

[45] The results also hold if we pick up any other year in the sample period and those results are available upon request.

[46] The credit access variables are dropped in these two specifications since they vary by firm.

7.3. Clustering at different level

Another potential issue is a multi-way clustering issue (Cameron et al., 2011) since our data contains multiple dimensions and also involves merging between US data and Chinese data. To better address this clustering issue, we report the results by different clustering in Table A.16 in the online Appendix. We cluster standard errors by 3-digit ISIC in columns 1–5, by province in columns 6–8, by ownership in columns 9–10, and by product in columns 11–15. We cluster by province and by ownership in some specifications because our credit access measures are computed either by region or by ownership.

When clustering by ISIC or by product, the previous results, such as negative coefficients on external finance dependence, still hold, further confirming that tighter credit constraints resulting from higher credit needs indeed reduce the optimal price set by exporting firms. When clustering by region, coefficients on total credits to GDP ratio and long-term loans to GDP ratio still remain positive and significant at 1% level, and the coefficient on short-term loans to GDP ratio is also positive.[47] When clustering by ownership, the two coefficients on SOE and MNC are both significantly positive, further confirming that the relationship between credit access and export prices is consistent with Proposition 1.

7.4. Alternative computation method of TFP

To show the robustness of our results, productivity is also estimated using different production functions and using different estimation approaches. With the Olley and Pakes's (1996) method, except for the main results we report, we also estimate TFP with material as an input factor. We find that different TFP estimates do not change our main results of the impact of credit constraints on export prices. Furthermore, we employ De Loecker and Warzynski's (2012) (henceforth DLW) augmented ACF approach together with the two sets of structural techniques suggested by Olley and Pakes (1996) (henceforth OP) and Levinsohn and Petrin (2003) (henceforth LP).[48] We report our regression results with TFP estimates based on the LP- and OP-embedded ACF approaches in Table A.17 in the online Appendix.[49] Again, the results with both variants of TFP estimates support the predictions under quality sorting: tighter credit constraints lead to lower export prices.[50]

7.5. Samples including processing trade

Our results reported in the main tables are estimated using ordinary trade (as opposed to "processing trade") data as we believe firms doing processing trade behave differently from other firms in their exporting behavior. In our sample, ordinary trade accounts for more than 73% of total transactions. Thus the results based on ordinary trade in fact reflect the average situation in our sample. However, to be cautious about the effect of credit constraints on export prices in the entire sample, which includes different modes of trade, we include the data for processing trade with trade mode fixed effects in the robustness checks and find that all predictions under the quality sorting model continue to hold (see Table A.18 in the online Appendix).

8. Conclusion

In this paper we build a tractable trade model with heterogeneous firms to investigate the impacts of credit constraints (via credit needs and credit access) on optimal export prices. Our model incorporates product quality as a choice by the firm and credit constraints. The endogenous determination of product quality is key to our model. As firms choose optimal product quality in the production of goods according to the productivity and the credit constraints they face, tighter credit constraints induce firms to choose lower product quality. We call this the *quality adjustment effect*. When the quality adjustment effect plays an important role, optimal prices decrease with tighter credit constraints. On the contrary, under the efficiency sorting case where quality cannot be chosen by the firm, the exact opposite effects would hold when both variable costs and fixed costs need to be financed by outside capital. In other words, the optimal prices would increase with tighter credit constraints and decrease with productivity. These contrasting empirical implications enable us to test empirically quality sorting versus efficiency sorting.

To test the predictions, we use different types of bank loans and firm ownership to proxy for different levels of credit access and employ external finance dependence, R&D intensity, inventory-to-sales ratio, and asset tangibility to proxy for credit needs. Our empirical results support the predictions under quality sorting. Interestingly, we also find evidence to support efficiency sorting by using quality-adjusted prices and using quality variations across firms, which further verifies the mechanism of quality adjustment.

[47] Financial development in a region is usually a long-run effect. This potentially could explain why the coefficient on short-term loans to GDP ratio is not significant when clustering at province level.

[48] We follow DLW and ACF closely by using a value added translog production function $y = \beta_l l + \beta_k k + \beta_{ll} l^2 + \beta_{kk} k^2 + \beta_{lk} lk + \omega + \varepsilon$, where ω is productivity, and ε is error term (see Eq. (10) in De Loecker and Warzynski (2012).

[49] To save space we move this table into online Appendix as various measures of TFP are not the focus of this paper.

[50] Note that the coefficients on TFP for SOE in columns (4) and (9) are not significant. This is potentially because SOE with larger scale typically employ unnecessary labor to produce. Thus, the estimated TFP may not accurately reflect SOE productivity.

The main contribution of this paper is to offer both a theory and the empirical evidence concerning the impacts of credit constraints on export prices set by firms. Our paper contributes to the emerging literature on credit constraints and trade by linking credit constraints with firm attributes and actions such as quality choice, optimal export prices, and productivity. Our paper also contributes to the quality-and-trade literature by providing empirical evidence in support of the quality adjustment mechanism as well as testing quality sorting versus efficiency sorting.

There are undoubtedly some limitations to our present study. One concern is that, like the previous studies of credit constraints, we aggregate credit needs measures at the 2-digit industry level, without taking into account the distribution effects of credit constraints within an industry. As Chaney (2013) indicates, intra-industry distribution of liquidity constraints may impact exporting behavior. It is reasonable to suspect that there are significant impacts of the distribution of credit constraints on export prices as well as on the relationship between productivity and export prices. A thorough analysis of this issue would be fruitful and is left to future research. Another limitation is that our empirical findings and the theoretical predictions both build upon exogenous credit constraints. If credit constraints are endogenously determined, some dynamic effects may emerge, and this would affect the exit and entry of firms. We also acknowledge that the current paper focuses on the intensive margin of existing firms and existing products at the cost of limiting a complete assessment that allows for the extensive margin of product switching. Thus, a more comprehensive analysis of the resource reallocation between core and non-core products within multi-product firm is stimulating and rewarding for an expansion in research along these lines. Moreover, in the present paper, our database does not include non-exporting firms because data on domestic prices are not available at the firm-product level. Thus, our findings are valid for Chinese large trading firms. If domestic-price data are available, we should be able to construct a model to analyze the difference in firm dynamics between exporters and non-exporters with respect to the impacts of credit constraints. For this endeavor, it would be useful to acquire and construct firm- and product-level data on prices in domestic markets.

Appendix A. The set-up of the model with financial contracting

In this appendix, we show that our model set-up yields qualitatively the same firm's optimization problem as the model with financial contracting as in Manova (2013).

Firms face liquidity constraints in financing their foreign sales. While variable costs can be funded internally, a fraction $d \in (0,1)$ of the fixed trade cost is borne up-front and has to be covered with outside capital. Producers thus have to borrow dfq^{β} to serve country i. The parameter d reflects the financial needs by the firm and varies across sectors for technological reasons. From the perspective of individual firms, d is exogenous. Moreover, the level of financial contractibility also differs. An investor can expect to be repayed with probability $\theta \in (0,1)$, which is exogenous to the model and determined by the strength of financial institutions. With probability $(1-\theta)$ the financial contract is not enforced, the firm defaults, and the creditor seizes zero.

Financial contracting proceeds as follows. In the beginning of each period, every firm makes a take-it-or-leave-it offer to a potential investor. This contract specifies the amount the firm needs to borrow, the repayment F in case the contract is enforced. Revenues are then realized and the investor receives payment at the end of the period with the probability θ.

Firms choose their export price and quantity to maximize profits:

$$\max_{p,q} \left(p - \frac{\tau q^{\alpha}}{\phi}\right) q^{\sigma-1} \frac{p^{-\sigma}}{P^{1-\sigma}} Y - (1-d) f q^{\beta} - \theta F(\phi) \tag{16}$$

$$\text{s.t.} \left(p - \frac{\tau q^{\alpha}}{\phi}\right) q^{\sigma-1} \frac{p^{-\sigma}}{P^{1-\sigma}} Y - (1-d) f q^{\beta} \geqslant F(\phi) \tag{17}$$

$$\theta F(\phi) - dfq^{\beta} \geqslant 0 \tag{18}$$

The expression for profits reflects the fact that the firm finances all its variable costs and a fraction $(1-d)$ of its fixed costs internally, pays the investor $F(\phi)$ when the contract is enforced (with probability θ). In the absence of credit constraints, exporters maximize profits. With external financing, two conditions bind firms' decisions. In case of repayment, entrepreneurs can offer at most their net revenues to the creditor. Also, investors only fund the firm if their net return is larger than zero.

With competitive credit markets, investors always break even in expectation. This implies that producers adjust their payment $F(\phi)$ so as to bring the financier to his participation constraint, i.e. $\theta F(\phi) = dfq^{\beta}$. Since the condition (18) is always binding, the firm's decision becomes:

$$\max_{p,q} \left(p - \frac{\tau q^{\alpha}}{\phi}\right) q^{\sigma-1} \frac{p^{-\sigma}}{P^{1-\sigma}} Y - (1-d) f q^{\beta} - \theta F(\phi) \tag{19}$$

$$\text{s.t. } \theta\left(\left(p - \frac{\tau q^{\alpha}}{\phi}\right) q^{\sigma-1} \frac{p^{-\sigma}}{P^{1-\sigma}} Y - (1-d) f q^{\beta}\right) \geqslant dfq^{\beta} \tag{20}$$

This is equivalent to our model setting.

Appendix B. All costs are subject to external finance (proof of Proposition 3)

We again analyze two cases: the quality sorting case and the efficiency sorting case.

B.1. Quality sorting

The optimization problem of a firm with productivity ϕ, credit access θ, and credit needs d becomes:

$$\max_{p,q} \left(p - \frac{\tau q^{\alpha}}{\phi}\right) q^{\sigma-1} \frac{p^{-\sigma}}{P^{1-\sigma}} Y - f q^{\beta} \tag{21}$$

$$\text{s.t. } \theta\left[\left(p - (1-d)\frac{\tau q^{\alpha}}{\phi}\right) q^{\sigma-1} \frac{p^{-\sigma}}{P^{1-\sigma}} Y - (1-d) f q^{\beta}\right] \geqslant d\left[\frac{\tau q^{\alpha}}{\phi} q^{\sigma-1} \frac{p^{-\sigma}}{P^{1-\sigma}} Y + f q^{\beta}\right] \tag{22}$$

Solving this optimization problem by choosing price p and quality q yields

$$p = \frac{\sigma}{\sigma-1}\left(1 + d\frac{(1-\theta)\lambda}{\theta(1+\lambda)}\right)\frac{\tau q^{\alpha}}{\phi} \tag{23}$$

$$q^{\sigma-1}\frac{p^{1-\sigma}}{P^{1-\sigma}} Y = \frac{\sigma\beta}{(1-\alpha)(\sigma-1)}\left(1 + d\frac{(1-\theta)\lambda}{\theta(1+\lambda)}\right) f q^{\beta} \tag{24}$$

where λ is the Lagrangian multiplier associated with the budget constraint condition (22) (see Appendix D.1 for the detailed derivation of first-order conditions).

The budget constraint (22), together with conditions (23) and (24), yield:

$$\frac{\sigma\beta}{(1-\alpha)(\sigma-1)}\left(1 + d\frac{(1-\theta)\lambda}{\theta(1+\lambda)}\right) \geqslant \left(1 - d + \frac{d}{\theta}\right)\left(\frac{\beta}{1-\alpha} + 1\right) \tag{25}$$

Given credit needs d, there exists a cutoff level of credit access θ_h such that budget constraint (22) is binding if and only if $\theta < \theta_h$.[51] Likewise, given credit access θ, there exists a cutoff level of credit needs above which the budget constraint (22) is binding. Next, we analyze two cases according to whether budget constraint (22) is binding.

B.1.1. Case 1: The budget constraint (22) is binding, i.e., $\theta < \theta_h$

Let $\Delta \equiv \left(1 + d\frac{(1-\theta)\lambda}{\theta(1+\lambda)}\right)$, which reflects the price distortion based on Eq. (23). According to Eq. (25), we obtain the expression for Δ after eliminating $\lambda : \Delta \equiv \left(1 + d\frac{(1-\theta)\lambda}{\theta(1+\lambda)}\right) = \left(1 - d + \frac{d}{\theta}\right)\left(\frac{\sigma-1}{\sigma}\right)\left(1 + \frac{1-\alpha}{\beta}\right)$. Therefore, Δ is only related to credit access θ and credit needs d. In other words, credit access θ and credit needs d form a sufficient statistic for the price distortion. We call this effect the *price distortion effect*. It is obvious that the extent to which price is distorted is related to credit access θ and credit needs d. Lower credit access θ or higher credit needs d increases the price distortion caused by the binding budget constraint.

Now, Eqs. (22) and (23) imply that the optimal quality chosen by firms satisfies the following condition:

$$q^{\beta-(1-\alpha)(\sigma-1)} = \frac{(1-\alpha)(\sigma-1)}{\sigma\beta f}\Delta^{-\sigma}\left(\frac{\sigma}{\sigma-1}\frac{\tau}{\phi}\right)^{1-\sigma}\frac{Y}{P^{1-\sigma}} \tag{26}$$

Under Condition (i) that $\beta > (1-\alpha)(\sigma-1)$, there is a positive correlation between firm productivity ϕ and quality q, given credit access θ and credit needs d. This suggests that more productive firms choose higher quality, which is consistent with the aforementioned results in the simple model in the main text as well as the findings of the quality-and-trade literature.

Given firm productivity, Condition (i) also ensures that a firm with more credit access or less credit needs chooses higher optimal quality. This is because Eq. (26) tells us that, given productivity, an increase in θ or a reduction in d (i.e., more credit access or lower credit needs) relaxes the firm's credit constraints through the change in Δ, and therefore induces the firm to choose a higher optimal quality q, which in turn leads to a higher price set by the firm. This is also consistent with the aforementioned *quality adjustment effect* in the main text.

Hence, the optimal pricing rule (23), together with (26), yield:

$$p = \left(\frac{(1-\alpha)(\sigma-1)}{\sigma\beta f}\right)^{\Psi}\Delta^{1-\sigma\Psi}\left(\frac{\sigma}{\sigma-1}\frac{\tau}{\phi}\right)^{1+(1-\sigma)\Psi}\left(\frac{Y}{P^{1-\sigma}}\right)^{\Psi} \tag{27}$$

where $\Psi = \frac{\alpha}{\beta-(1-\alpha)(\sigma-1)} > 0$. When Condition (ii) ($\beta < (\sigma-1)$) holds (in addition to Condition (i)), a firm's optimal price is positively correlated with firm productivity as conditions (i) and (ii) together imply that $1 + (1-\sigma)\Psi < 0$.

[51] Eq. (25) implies that budget constraint (22) is binding if and only if $\theta < \theta_h$, where $\theta_h = \frac{d(\sigma-1)(1-\alpha+\beta)}{\sigma\beta-(1-d)(\sigma-1)(1-\alpha+\beta)}$.

Condition (i) and (ii) combined is equivalent to Condition (A): $\frac{1}{\beta} > \frac{1}{\sigma-1} > \frac{1-\alpha}{\beta}$. When condition (A) holds, a firm with higher productivity charges higher optimal prices. Under condition (A), $1-\sigma\Psi < 0$ is also satisfied. Hence, tighter credit constraints (via either higher credit needs d or lower credit access θ) eventually reduce the optimal price. Here, the impact of credit constraint on export prices also depends on two opposing forces: One is caused by the price distortion Δ induced by credit constraints (i.e., the price distortion effect). The other is caused by the optimal product quality chosen by the firm (i.e., the quality adjustment effect). The former effect tends to increase the optimal price when a firm faces higher credit needs d and lower credit access θ. However, the latter effect tends to reduce the optimal price when a firm faces tighter credit constraints. This is because tighter credit constraints induce Δ to increase, and hence induce firms to produce a lower-quality product according to Eq. (26), which in turn lowers optimal price according to Eq. (23). Under condition (A), the quality adjustment effect dominates, and therefore, firms facing tighter credit constraints set lower prices (see the graph in the left panel of Fig. 1 for illustration).

B.1.2. Case 2: The budget constraint (22) is nonbinding, i.e., $\theta > \theta_h$

Eqs. (23) and (24) imply:

$$q^{\beta-(1-\alpha)(\sigma-1)} = \frac{(1-\alpha)(\sigma-1)}{\sigma\beta f}\left(\frac{\sigma}{\sigma-1}\frac{\tau}{\phi}\right)^{1-\sigma}\frac{Y}{P^{1-\sigma}} \tag{28}$$

Under Condition (i), the firm with higher productivity will choose higher quality. Thus, Eq. (28), together with (23), imply that the optimal pricing rule is given by

$$p = \left(\frac{(1-\alpha)(\sigma-1)}{\sigma\beta f}\right)^{\Psi}\left(\frac{\sigma}{\sigma-1}\frac{\tau}{\phi}\right)^{1+(1-\sigma)\Psi}\left(\frac{Y}{P^{1-\sigma}}\right)^{\Psi} \tag{29}$$

When condition (A) holds, then $1+(1-\sigma)\Psi < 0$, and so Eq. (29) implies that there is a positive relationship between price and productivity. However, the optimal prices are not affected by credit access θ or credit needs d anymore, as firms have sufficient credit access (i.e., $\theta > \theta_h$).

B.2. Efficiency sorting

When there is no quality choice by the firm, the optimization problem of a firm with productivity ϕ, credit access θ, and credit needs d becomes:

$$\max_{p,a}\left(p-\frac{\tau}{\phi}\right)\frac{p^{-\sigma}}{P^{1-\sigma}}Y - f \tag{30}$$

$$\text{s.t. } \theta\left[\left(p-(1-d)\frac{\tau}{\phi}\right)\frac{p^{-\sigma}}{P^{1-\sigma}}Y-(1-d)f\right] \geqslant d\left(\frac{\tau}{\phi}\frac{p^{-\sigma}}{P^{1-\sigma}}Y+f\right) \tag{31}$$

Solving this optimization problem with respect to price p yields:

$$p = \frac{\sigma}{\sigma-1}\left(1+d\frac{(1-\theta)\lambda}{\theta(1+\lambda)}\right)\frac{\tau}{\phi} \tag{32}$$

where λ is the Lagrangian multiplier associated with budget constraint condition (31). Next, we analyze this optimization problem under two cases.

Case I: The budget constraint (31) is binding. Now, the budget constraint (31) can be rewritten as:

$$\frac{p^{1-\sigma}}{P^{1-\sigma}}Y = \left(1+\frac{1-\theta}{\theta}d\right)\left(\frac{\tau}{\phi}\frac{p^{-\sigma}}{P^{1-\sigma}}Y+f\right) \tag{33}$$

This equation implies that the budget constraint (31) holds only in the zone $p \in [p_L, p_H]$ as shown in Fig. 2. When the budget constraint is binding, **the first-best solution** does not belong in this zone. Now, the firm's profit satisfies:

$$\left(p-\frac{\tau}{\phi}\right)\frac{p^{-\sigma}}{P^{1-\sigma}}Y - f = \frac{1-\theta}{\theta}d\left(\frac{\tau}{\phi}\frac{p^{-\sigma}}{P^{1-\sigma}}Y+f\right) \tag{34}$$

Then the firm will choose **the second-best solution** p_H in order to maximize its profit. We use Fig. 2 to illustrate: In Fig. 2, the horizontal axis denotes $p^{1-\sigma}$ and the vertical axis denotes any multiplicative scale of $p^{1-\sigma}$. The dotted curve represents the right-hand-side of equality (33) with intercept $(1+\frac{1-\theta}{\theta}d)f$. The solid line represents the left-hand-side of equality (33). As shown in Fig. 2, given firm's productivity ϕ, the dotted curve in Fig. 2 will shift upward as credit needs d increases or credit access θ decreases. As a result, $p^{1-\sigma}$ decreases and hence the optimal price increases due to a rise in the optimal price distorted by $1+d\frac{(1-\theta)\lambda}{\theta(1+\lambda)}$ according to Eq. (32). Therefore, tighter credit constraints (i.e., a higher d or a lower θ) lead to higher prices when there is no quality choice under efficiency sorting. Given credit access θ and credit needs d, the dotted line in Fig. 2 will shift downward when productivity ϕ increases, implying that the optimal price decreases in productivity.

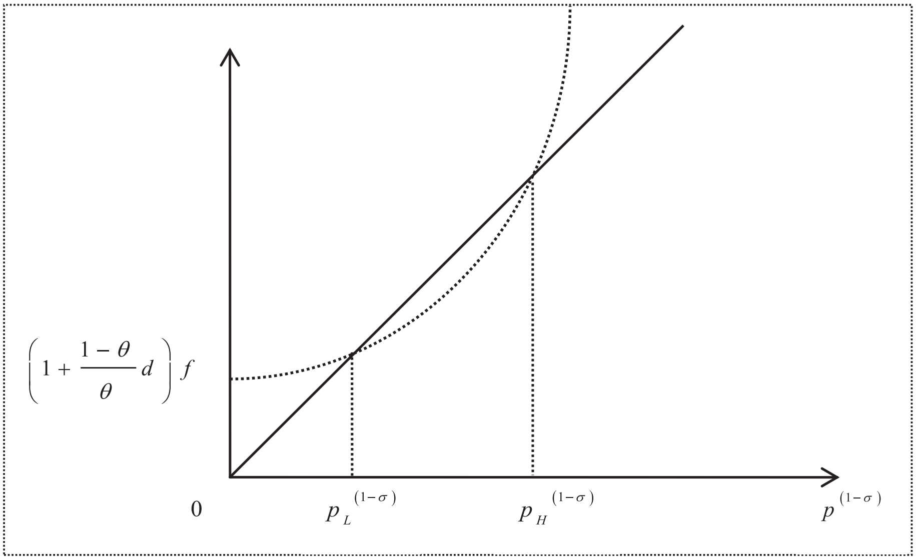

Fig. 2. When there is no quality choice (efficiency sorting).

Case II: The budget constraint (31) is nonbinding. There is no distortion caused by credit constraint in price setting and the optimal pricing rule is given by $p = \frac{\sigma}{\sigma-1}\frac{\tau}{\phi}$. Hence, the optimal price is unrelated to credit constraint and decreases in productivity. □

Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jce.2015.02.007.

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