Trade, Finance and Endogenous Firm Heterogeneity*

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Abstract

We study how financial frictions affect firm-level heterogeneity and trade in a model where productivity differences across monopolistically competitive firms are endogenous and depend on investment decisions at the entry stage. By increasing entry costs, financial frictions reduce the exit cutoff thereby lowering the value of investing in bigger projects with more dispersed outcomes. Hence, credit frictions make firms more homogeneous and hinder the volume of exports both along the intensive and the extensive margin. Export opportunities, instead, shift expected profits to the tail and increase the value of technological heterogeneity. We test these predictions using comparable measures of sale dispersion within 365 manufacturing industries in 119 countries, built from highly disaggregated US import data. Consistent with the model, financial development increases sale dispersion, especially in more financially vulnerable industries; sale dispersion is also increasing in measures of comparative advantage. These results are quantitatively important for explaining the effect of financial development and factor endowments on export sales.

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1 Introduction

Why firms differ so much in sales and productivity, and how these differences vary across industries, countries and time are among the most pressing questions across the fields of international trade, macroeconomics and economic development. Although the literature on firm heterogeneity has exploded since the late 1990s, the existing evidence is often limited to few countries or sectors and theoretical explanations are still scarce.[1] One well-established stylized fact is that average firm size increases with per capita income and, according to recent work, so does its dispersion.[2] Since financial markets are much less developed in poor countries, a plausible conjecture is that credit frictions may play a role at shaping firm heterogeneity. Financial constraints have also been found to restrict significantly international trade.[3] Since export participation is concentrated among the most productive firms, it is then plausible to conjecture that financial frictions may hinder trade by affecting the firm size distribution.

The goal of this paper is to formalize and test these hypotheses. In particular, we study how financial development affects firm-level heterogeneity and trade in a model where productivity differences across firms are endogenous and depend on investment decisions at the entry stage. In most of the literature, credit frictions distort the allocation of resources among existing firms who differ in productivity for exogenous reasons. On the contrary, we focus on the problem of financing an up-front investment, such as innovation, which affects the variance of the possible realizations of technology. This approach has several advantages. First, credit frictions at the entry stage are highly relevant in practice, especially when financing an investment with uncertain returns. Second, it allows us to highlight some of the economic decisions that shape the equilibrium degree of firm heterogeneity. Next, we take the model to the data. Starting from highly disaggregated product-level US imports, we show how to build comparable measures of sale dispersion across a large set countries, sectors and time and use them to test the model. With this uniquely rich dataset, we provide new evidence that financial frictions compress the sale distribution, which in turn has a significant negative effect on export volumes.

We now describe more in detail what we do. The first step is to develop a model in which technology differences across firms depend on investment decisions at the entry stage. Our point of departure is a multi-sector and multi-country static version Melitz (2003), which is the workhorse model of trade with heterogeneous firms. As it is customary, firms draw productivity upon paying an entry cost and exit if they cannot profitably cover a

[1] See for instance Syverson (2004, 2011).
[2] See Poschke (2015) and Bartelsman, Haltiwanger and Scarpetta (2009).
[3] See for instance Manova (2013), Beck (2003) and Svaleryd and Vlachos (2005).

fixed production cost. As in Bonfiglioli, Crinò and Gancia (2015), however, firms can affect the distribution from which technology is drawn. In particular, due to a complementarity between the (endogenous) size of the entry cost and the unknown quality of ideas, larger investments are associated to more spread-out realizations of productivity. As a result, the ex-post degree of heterogeneity in a sector depends on the ex-ante choice of the entry investment. In this framework, we introduce credit frictions, which raise the cost of financing the entry investment in financially vulnerable sectors, and both variable and fixed costs of selling to foreign markets.

A key feature of the model is that the possibility to exit insures firms from bad realizations and increases the value of drawing productivity from a more dispersed distribution.[4] This generates two main predictions. First, credit frictions lower the equilibrium degree of heterogeneity in a sector. The intuition for this result is as follows. Credit frictions raise the cost of investment and reduce entry, thereby lowering the minimum productivity needed to survive. But a lower exit cutoff reduces the value of drawing productivity from a more dispersed distribution. We also show that, by making firms smaller and more homogeneous, credit frictions hinder the volume of exports both along the intensive and the extensive margin, and that the effect is stronger in sectors that are more financially vulnerable. Second, as in Bonfiglioli, Crinò and Gancia (2015), export opportunities, by shifting expected profits to the tail and raising the exit cutoff, increase the value of drawing productivity from a more dispersed distribution thereby generating more heterogeneity.

In the second part of the paper, we take these predictions to the data. To guide the analysis, we use the model to show how the parameter measuring firm heterogeneity at the sector level can be computed from the dispersion of sales from any country and industry to a given destination market. We then empirically assess the predictions of the model using extremely detailed data on US imports of roughly 15,000 (10-digit) products from 119 countries and 365 manufacturing industries over 1989-2006. Starting from almost 4 million observations at the country-product-year level, we measure sale dispersion for each country, industry and year as the standard deviation of log exports across products. We thereby obtain a unique data set, which includes more than 230,000 comparable measures of sale dispersion across all countries and manufacturing industries, over a period that spans two decades.[5]

After documenting some interesting statistics on how sale dispersion varies across coun-

[4] Note that in our model risk is completely diversified so that investors seek to maximize expected returns. However, expected returns will depend on the variance of productivity draws.

[5] This would be impossible to do using firm-level data, which are unavailable for most countries. For instance, Berman and Hericourt (2010) in their study on finance and trade use a sample of only nine countries and around 5,000 firms overall.

tries, industries and time, we study how it depends on financial development and export opportunities. Following a large empirical literature, we identify the effect of credit frictions exploiting cross-country variation in financial development and cross-industry variation in financial vulnerability (Rajan and Zingales, 1998; Manova, 2013). We find two main results. First, consistent with our model, financial development increases sale dispersion, especially in more financially vulnerable industries. Export opportunities, proxied by country-sector measures of comparative advantage as in Romalis (2004), also make the distribution of sales more spread out. These results are robust to controlling for the number of exported products, to the inclusion of country-year and industry-year fixed effects, to the level of industry aggregation, to various changes in the sample such as excluding small exports, to the use of alternative proxies for financial frictions and financial vulnerability, and to instrumenting financial development with historical conditions of countries. Second, our mechanism is quantitatively important for explaining the effect of financial frictions on exports: when included as an additional regressor in specifications for total exports, number of exported products and exports per product, sale dispersion is always highly significant and reduces the coefficients on financial development by 20-60%.

Our theory of endogenous firm heterogeneity has been developed simultaneously in this paper and in Bonfiglioli, Crinò and Gancia (2015). In the latter, we use a simpler model and draw implications for wage inequality. We also provide evidence that export opportunities increase firm heterogeneity, innovation and wage inequality. In the present paper, instead, we introduce financial frictions and extend the model to multiple asymmetric countries. Regarding the evidence, the two papers use completely different data and approaches. In Bonfiglioli, Crinò and Gancia (2015) we use US firm-level data and individual wages; here instead, we use non-US product level data. Remarkably, the measures of sector-level heterogeneity computed in the different data sets are comparable in magnitudes, display similar trends and have similar positive correlations with export opportunities.

Besides the considerable amount of evidence consistent with the model presented in these two papers, our theory accords well with a number of additional observations. For instance, several papers show evidence suggesting that differences in productivity across firms appear to be related to investment in new technologies (e.g., Dunne et al., 2004, Doraszelski and Jaumandreu, 2009, and Faggio, Salvanes and Van Reenen, 2010). Moreover, the emphasis on the role of entry of new product innovation is empirically relevant, given that every year about 25 percent of consumer goods sold in US markets are new (Broda and Weinstein, 2010). It is also consistent with Midrigan and Xu (2014), who find that financial frictions distort more entry than the allocation of resources between existing firms. The entry margin is also an important driver of productivity growth, so much that promoting entry is often an important concern for policy-makers.

The trade-off between large/small innovation projects with more/less variable outcomes seems also to describe well some important aspects of the innovation strategies pursued by different firms. For instance, designing and assembling a new variety of laptop PCs, which mostly requires the use of established technologies, is safer and less costly than developing an entirely new product, such as the iPad. Yet, Apple's large investment was rewarded with the sale of more than 250 million units over a period of five years only, while the sales of manufacturers of traditional computers, such as Dell, stagnated.[6] Yet, the choice between innovations differing in the variance of outcomes and the implications for firm heterogeneity has received little attention in the literature. Notable exceptions are Caggese (2015), who shows that financial frictions, by shielding profit of existing firms from competition, can deter radical, high-risk, innovation and Gabler and Poschke (2013), who study how policy distortions affect experimentation. However, these papers focus on the implications for productivity and firm growth, while, to obtain testable predictions, we are interested in heterogeneity in a static setting.[7] Also, compared to models in which firms can choose between "complex" and "traditional" technologies, our approach has the advantage of yielding smooth comparative statics and simple analytical results thereby facilitating the mapping with the data.

This paper also sheds new light on the role of firm heterogeneity in the literature on trade and finance. The fact that financial constraints reduce foreign exports disproportionately more than domestic production has been documented in a series of recent contributions (see Manova and Chor 2012, Manova, 2013, Paravisini et al., 2015 and all the papers surveyed in Foley and Manova, 2015). This literature has provided robust evidence that financial development indeed hinders trade, both along the extensive and the intensive margin, and that this effect is stronger for sectors with higher external financial dependence. Yet, the theoretical underpinnings remain somewhat mysterious. In particular, it is not entirely clear why credit frictions should be more binding for exports than for domestic sales, especially since exporting firms are large and large firms are usually found to be the least financially constrained (e.g., Beck, Demirgüç-Kunt and Maksimovic, 2005). Our model overcomes these

[6] In a 1983 speech, Steve Jobs said: "Apple's strategy is really simple. What we want to do is we want to put an incredibly great computer in a book that you can carry around with you and learn how to use in 20 minutes... and we really want to do it with a radio link in it so you don't have to hook up to anything and you're in communication with all of these larger databases and other computers." Yet, inventing the iPad required 27 years of investment constellated with failures and unforeseen spin-offs, including the development of the iPhone.

[7] There is a vast literature on financial frictions and firm dynamics, with several paper studying how borrowing constraints distort resource allocation and growth (e.g., Khan and Thomas, 2013, and the survey in Buera, Kaboski and Shin, 2015). We focus instead on entry decisions and abstract altogether from firm dynamics. Although adding innovation by incumbents would certainly make the model more realistic, Cabral and Mata (2003) show that there is already considerable heterogeneity among new firms.

difficulties by assuming that credit constraints affect the entry cost paid by all firms when new products are introduced. This is appealing, because it is well-known that financing R&D-intensive projects by means of external credit is subject to relevant informational frictions (e.g., Hall and Lerner, 2010). Moreover, no asymmetry is required in the financial needs of domestic or export activities.

The remainder of the paper is organized as follows. In Section 2, we build a model where differences in the variance of firm-level outcomes originate from technological choices at the entry stage and show that financial development and export opportunities generate more heterogeneity in equilibrium. Section 3 derives a number of predictions on how observable measures of within-sector heterogeneity at the country-industry level depend on export opportunities and financial development and how firm heterogeneity affects the margins of trade. Section 4 tests the model's predictions. Section 5 concludes.

2 The Model

We now build a multi-sector, multi-country, static model of monopolistic competition between heterogeneous firms along the lines of Melitz and Redding (2014). After paying an entry cost, firms draw their productivity from some distribution and exit if they cannot profitably cover a fixed cost of production. As in Bonfiglioli, Crinò and Gancia (2015), we allow the variance of the productivity draws to depend on investment decisions. We then introduce a credit friction between firms, who must borrow to finance the entry investment, and external investors, and study how it affects firm-level heterogeneity.

2.1 Preferences and Demand

Country o is populated by a unit measure of risk-neutral households of size L_o. Preferences over consumption of goods produced in I industries are:

$$U_o = \prod_{i=1}^{I} C_{oi}^{\beta_i}, \quad \beta_i > 0, \quad \sum_{i=1}^{I} \beta_i = 1.$$

Each industry $i \in \{1, ..., I\}$ produces differentiated varieties and preferences over these varieties take the constant elasticity of substitution form:

$$C_{oi} = \left[\int_{\omega \in \Omega_{oi}} c_{oi}(\omega)^{\frac{\sigma_i}{\sigma_i+1}} \mathrm{d}\omega \right]^{\frac{\sigma_i+1}{\sigma_i}}, \quad \sigma_i > 0$$

where $c_{oi}(\omega)$ is consumption of variety ω, Ω_{oi} denotes the set of varieties available for consumption in country o in sector i, and $(\sigma_i + 1)$ is the elasticity of substitution between varieties within the industry i.

We denote by $p_{oi}(\omega)$ the price of variety ω in industry i and by P_{oi} the minimum cost of one unit of the consumption basket C_{oi} :

$$P_{oi} = \left[\int_{\omega \in \Omega_{oi}} p_{oi}(\omega)^{-\sigma_i} \, \mathrm{d}\omega \right]^{-1/\sigma_i}.$$

Then, demand for a variety can be written as:

$$c_{oi}(\omega) = \frac{\beta_i E_o P_{oi}^{\sigma_i}}{p_{oi}(\omega)^{\sigma_i + 1}},$$

where E_o is expenditure available for consumption.

2.2 Industry Equilibrium

We now focus on the equilibrium of a single industry $i \in \{1, ..., I\}$. In each industry, every variety ω is produced by monopolistically competitive firms which are heterogeneous in their labor productivity, φ. Since all firms with the same productivity behave symmetrically, we index firms by φ and we identify firms with products. We first describe the technological and financial constraints faced by the typical firm.

A firm is run by a manager, who owns the idea needed to produce a given variety. To implement the idea, the manager must choose how much to invest in innovation at the entry stage. As in Bonfiglioli, Crinò and Gancia (2015), this choice will affect the variance of the possible realizations of productivity φ. Managers have no wealth so that the entry cost, which is borne up-front, must be financed by external capital. Once the entry investment is paid, the manager draws productivity from a Pareto distribution, whose shape parameter will depend on the size of the investment.[8]

Next, the firm faces standard production and pricing decisions. There is a fixed cost of selling in a given market and a variable iceberg cost of exporting. Finally, investors need to be paid. We assume that with probability δ_o the manager returns the profit π_i to investors. With probability $(1 - \delta_o)$, instead, the manager can misreport the value of production and repay only a fraction $\kappa_i < 1$ of profit. The parameter κ_i, capturing how difficult it is to hide the cash flow, is an inverse measure of financial vulnerability which, following Rajan and Zingales (1998) and Manova (2013), is assumed to vary across industries for technological

[8] The Pareto distribution is widely used in the literature and has been shown to approximate well observed firm-level characteristics, especially among exporters (e.g., Helpman, Melitz and Yeaple, 2004). As in Chaney (2008), its convenient properties allow us to derive closed-form solutions useful for mapping the model to the data.

reasons. The parameter δ_o captures instead the strength of financial institutions and is associated to the level of financial development of the country.

2.2.1 Production, Prices and Profit

We solve the problem backwards. At the production stage, the manager will choose the price and in which markets to sell (if any) so as to maximize profit. As it is customary, the equilibrium price of a firm with productivity φ serving market d from country o is:

$$p_{doi}(\varphi) = \frac{\sigma_i + 1}{\sigma_i} \frac{\tau_{doi} w_o}{\varphi}$$

where w_o is the wage in country o and $\tau_{doi} \geq 1$ is the iceberg cost of shipping from o to d (with $\tau_{ooi} = 1$) in industry i. Revenues earned from selling to destination d are:

$$r_{doi}(\varphi) = \beta_i E_d P_{di}^{\sigma_i} p_{doi}(\varphi)^{-\sigma_i} .$$

Profit earned in destination d is a fraction $(\sigma_i + 1)$ of revenue minus the fixed cost of selling in market d, $w_o f_{doi}$. Hence:

$$\pi_{doi}(\varphi) = A_{di} \left(\frac{\varphi}{\tau_{doi} w_o} \right)^{\sigma_i} - w_o f_{doi}, \tag{1}$$

where the term $A_{di} = \frac{\beta_i E_d P_{di}^{\sigma_i}}{(\sigma_i+1)^{\sigma_i+1}(\sigma_i)^{-\sigma_i}}$ captures demand conditions in the destination market.

The firm will not find it profitable to serve market d whenever its productivity is below the cutoff

$$\varphi_{doi}^* = \tau_{doi} w_o \left(\frac{w_o f_{doi}}{A_{di}} \right)^{1/\sigma_i}, \tag{2}$$

corresponding to $\pi_{doi}(\varphi_{doi}^*) = 0$.

2.2.2 Entry Stage

We now consider the entry stage. As in Melitz (2003), firms pay a sunk innovation cost to be able to manufacture a new variety with productivity drawn from some distribution with c.d.f. $G_{oi}(\varphi)$. Hence, combining the pricing and exit decision, we can write *ex-ante* expected profit from market d:

$$\mathbb{E}[\pi_{doi}] = \int_0^\infty \pi_{doi}(\varphi) \, \mathrm{d}G_{oi}(\varphi) = w_o f_{doi} \int_{\varphi_{doi}^*}^\infty \left[\left(\frac{\varphi}{\varphi_{doi}^*} \right)^{\sigma_i} - 1 \right] \mathrm{d}G_{oi}(\varphi), \tag{3}$$

where the last equation makes use of (1) and (2). Expected profit from selling in all potential markets is $\mathbb{E}[\pi_{oi}] = \sum_d \mathbb{E}[\pi_{doi}]$.

We depart from the canonical approach by making the distribution $G_{oi}(\varphi)$ endogenous. To this end, we develop a simple model of investment in innovation projects generating a Pareto distribution for φ with mean and variance that depend on firms' decisions. The model formalizes the intuitive idea that firms can choose between smaller projects with less variable returns and larger projects with more spread-out outcomes.

Suppose that, in order to enter, the manger of the firm must invest in an innovation project. The outcome of the project is a technology allowing the firm to manufacture a new variety with productivity φ. The realization of this productivity depends both on the quality of the project q, which is uncertain, and the size s_{oi} of the investment, which is a choice variable and is normalized to be on the scale $(0,1]$. More specifically, assume that quality, q, of new projects is random and exponentially distributed:

$$\Pr[q > z] = \exp(-\alpha_i \sigma_i z),$$

with support $z \in [0, \infty)$ and rate $\alpha_i \sigma_i > 0$, with $\alpha_i > 1$. The rate $\alpha_i \sigma_i$ captures how "compressed" the distribution is. The assumption that this rate is a positive function of σ_i means that the quality of potential ideas is more dispersed in industries producing more differentiated varieties. This seems reasonable, given that the scope for technological differentiation is likely to be limited, almost by definition, for very homogeneous products. More importantly, as we will see shortly, this assumption is useful for technical reasons: together with $\alpha_i > 1$ and $s_{oi} \in (0,1]$, it guarantees that $\mathbb{E}[\pi_{oi}]$ converges to a finite value.

While quality is inherently uncertain, the manager can instead choose the size of the project, $s_{oi} \in (0,1]$. We assume that productivity depends both on the quality and the size of the project as follows:

$$\ln \varphi = s_{oi} q + \ln \varphi_{\min},$$

with $\varphi_{\min} > 0$. This equation embeds a complementarity between quality and size: resources invested in a bad project ($q = 0$) are wasted, in that they do not increase φ, while even a great idea is useless without some investment to implement it. Then, φ is Pareto distributed with minimum $\varphi_{\min}$ and shape parameter $\alpha_i \sigma_i / s_{oi}$, as can be seen from:

$$1 - G_{oi}(\varphi) = \Pr\left[q > \frac{\ln(\varphi/\varphi_{\min})}{s_{oi}}\right] = \left(\frac{\varphi}{\varphi_{\min}}\right)^{-\frac{\alpha_i \sigma_i}{s_{oi}}}. \tag{4}$$

Equation (4) illustrates that, by choosing the size of the project, the firm can draw φ from different Pareto distributions, identified by the new parameter $v_{oi} \equiv s_{oi}/(\alpha_i \sigma_i)$, with

$v_{oi} \in (0, 1/\alpha_i\sigma_i]$. Note that the standard deviation of the log of φ is equal to v_{oi}. Hence, v_{oi} can be interpreted as an index of the dispersion of the distribution. At the same time, v_{oi} also affects the expected value of φ, which is equal to $\varphi_{\min}(1 - v_{oi})^{-1}$.[9] Finally, we assume that the entry cost, which is in units of labor, is an increasing and convex function of the investment s_{oi}, satisfying the Inada-like condition that the cost tends to infinity as s_{oi} approaches the maximum size of one. Since $v_{oi} = s_{oi}/(\alpha_i\sigma_i)$, the problem of choosing s_{oi} can be reformulated as one of choosing v_{oi} at the cost $w_o F(v_{oi})$, with $F'(v_{oi}) > 0$, $F''(v_{oi}) > 0$, $F(0) = 0$ and $\lim_{v_{oi} \to 1/\alpha_i\sigma_i} F(v_{oi}) = \infty$.

How is the initial entry investment determined in equilibrium? Recall that $w_o F(v_{oi})$ must be financed externally and that investors expect to be repaid π_{oi} with probability δ_o and $\kappa_i\pi_{oi}$, with probability $(1 - \delta_o)$. For simplicity, we normalize the outside option of both managers and investors to zero. Then, competition for funds between managers implies that v_{oi} be set so as to maximize the expected returns of investors:

$$\max_{v_{oi}} \left\{ \mathbb{E}[\pi_{oi}] - w_o \lambda_{oi} F(v_{oi}) \right\}, \tag{5}$$

where $\lambda_{oi} \equiv [\delta_o + (1-\delta_o)\kappa_i]^{-1} > 1$ captures the additional cost of financing the entry investment in presence of credit frictions ($\kappa_i < 1$ and $\delta_o < 1$). Moreover, free-entry implies that investors must break-even, $\mathbb{E}[\pi_{oi}] = w_o\lambda_{oi}F(v_{oi})$, which is also their (binding) participation constraint.

To solve (5), we use $G_{oi}(\varphi)$ to express *ex-ante* expected profits (3) as a function of v_{oi}:

$$\mathbb{E}[\pi_{oi}] = \frac{\sigma_i w_o}{1/v_{oi} - \sigma_i} \left(\frac{\varphi_{\min}}{\varphi^*_{ooi}} \right)^{1/v_{oi}} \sum_d f_{doi} \rho_{doi}^{1/v_{oi}},$$

where:

$$\rho_{doi} \equiv \frac{\varphi^*_{ooi}}{\varphi^*_{doi}} = \tau^{-1}_{doi} \left(\frac{A_{di}}{f_{doi}} \frac{f_{ooi}}{A_{oi}} \right)^{1/\sigma_i} \tag{6}$$

is a measure of export opportunities in destination d. In particular, in a given industry i, $\rho_{doi}^{1/v_{oi}} \in (0, 1)$ is the fraction of country o firms selling to market d.

To make sure that the maximand in (5) is concave, the cost function $F(v_{oi})$ must be sufficiently convex. In particular, we define the elasticities of the entry cost and of profit as $\eta_F(v_{oi}) \equiv v_{oi}F(v_{oi})'/F(v_{oi})$ and $\eta_\pi(v_{oi}) \equiv \partial \ln \mathbb{E}[\pi_{oi}]/\partial \ln v_{oi}$, and assume $\eta'_F(v_{oi}) > \eta'_\pi(v_{oi})$.

[9] Although the positive relationship between mean and variance is realistic, our main results hold in an alternative model in which firms can choose between distributions that are a mean-preserving spread. See Bonfiglioli, Crinò and Gancia (2015).

Then, the first order condition for an interior v_{oi} is:

$$\frac{\mathbb{E}\left[\pi_{oi}\right]}{v_{oi}}\left[\frac{1}{1-v_{oi}\varsigma_i}+\ln\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}}+\frac{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}\ln\rho_{doi}^{-1/v_{oi}}}{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}}\right]=w_o\lambda_{oi}F'\left(v_{oi}\right). \tag{7}$$

The left-hand side of (7) is the marginal benefit of increasing v_{oi}, while the right-hand side represents its marginal cost. In particular, the terms in brackets, equal to the elasticity of expected profit to v_{oi}, capture the fact that a higher v increases expected profits for various reasons. First, it raises the unconditional mean of productivity draws. Second, it increases the probability of drawing a productivity above the cutoff needed to sell to any destination. Third, it increases the relative gains from high realization of φ when the profit function is convex, i.e., when $\sigma_i > 1$ (this can be seen from equation 1).

Note, however, that both $\mathbb{E}\left[\pi\right]$ and $\varphi^*_{ooi}/\varphi_{\min}$ are endogenous. To solve for them, we impose free entry, requiring that *ex-ante* expected profit be equal to the entry cost: $\mathbb{E}\left[\pi_{oi}\right] = w_o\lambda_{oi}F\left(v_{oi}\right)$. Replacing this into the first-order condition (7), we obtain the following expression:

$$\frac{1}{1-v_{oi}\sigma_i}+\ln\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}}+\frac{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}\ln\rho_{doi}^{-1/v_{oi}}}{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}}=\frac{v_{oi}F'\left(v_{oi}\right)}{F\left(v_{oi}\right)}, \tag{8}$$

where the left-hand side is the elasticity of expected profit, $\eta_\pi(v_{oi})$, while the right-hand side is the elasticity of the entry cost, $\eta_F(v_{oi})$. Under the assumptions that $\eta'_F(v_{oi}) > \eta'_\pi(v_{oi})$ and $\lim_{v_{oi}\to 1/\alpha_i\sigma_i}\eta_F(v_{oi}) = \infty$, there is a unique interior v_{oi} in equilibrium. Finally, we need to substitute for the equilibrium exit cutoff for productivity, which is pinned down again by the free-entry condition:

$$\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}}=\frac{\sigma_i}{1/v_{oi}-\sigma_i}\frac{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}}{\lambda_{oi}F\left(v_{oi}\right)}.$$

Note that the exit cutoff is decreasing in the cost of financing, λ_{oi}: higher financing costs deter entry, thereby reducing the degree of competition and the minimum productivity required to break even. In addition, the exit cutoff is increasing in export opportunities, ρ_{doi}: as it is well-known from Melitz (2003), export opportunities increase profit for more productive firms thereby inducing more entry and making survival more difficult.[10]

After replacing the cutoff in (8), it can be proved that, for given fixed costs, the left-hand side, i.e., the elasticity of expected profit, is increasing in export opportunities and decreasing in the cost of financing. Note also that, in an interior equilibrium, all parameters raising $\eta_\pi(v_{oi})$ also increase the optimal v_{oi}. Hence, we obtain the result that the equilibrium dispersion of firm productivity varies across sectors, countries and destination markets as

[10]We assume that f_{ooi} is sufficiently high to make sure that $\varphi^*_{ooi}/\varphi_{\min} > 1$ in equilibrium.

described by Proposition 1.

Proposition 1 *Assume that the solution to (5) is interior. Then, the equilibrium dispersion of firm productivity in sector i, as measured by the standard deviation of the log of φ, is increasing in export opportunities, ρ_{doi}, and in the financial development of the country of origin, δ_o, especially in sectors with high financial vulnerability (low κ_i).*

$$\frac{\partial v_{oi}}{\partial \rho_{doi}} > 0; \ \frac{\partial v_{oi}}{\partial \delta_o} > 0; \ \frac{\partial^2 v_{oi}}{\partial \delta_o \partial \kappa_i} < 0.$$

Proof. *See the Appendix* ■

A key insight to understand the results in Proposition 1 is that the possibility to exit insures firms from bad realizations and increases the value of drawing productivity from a more dispersed distribution. This generates two main predictions. First, credit frictions lower the equilibrium degree of heterogeneity in a sector. The intuition is as follows. Credit frictions raise the cost of investment and reduce entry, especially in financially vulnerable sectors. In turn, lower entry softens competition in the industry, thereby raising the minimum productivity needed to survive. But a higher surviving probability lowers the value of drawing productivity from a more dispersed distribution. Second, as in Bonfiglioli, Crinò and Gancia (2015), export opportunities, by shifting expected profits to the tail and raising the exit cutoff, also increase the value of drawing productivity from a more dispersed distribution thereby generating more heterogeneity.

3 Exports, Finance and Firm Heterogeneity

We now derive a number of predictions on how observable measures of within-sector heterogeneity at the country-industry level depend on export opportunities and financial development. We also study how heterogeneity affects the volume of export at the country-industry level. These predictions will be tested empirically in the next section.

3.1 Sale Dispersion per Destination Market

Revenue from market d of firms from country o operating in sector i is a power function of productivity, $r_{doi}(\varphi) = r_{doi}(\varphi^*_{doi}) \left(\varphi/\varphi^*_{doi}\right)^{\sigma_i}$. Then, from the properties of the Pareto distribution, it follows that $r_{doi}(\varphi)$ is also Pareto distributed with c.d.f. $G_r(r) = 1 - \left(r_{\min}/r\right)^{1/v_{oi}\sigma_i}$, for $r > r_{\min} = (\sigma_i + 1)\, w_o f_{doi}$.[11] This means that the standard deviation (SD) of the log of

[11] If φ follows a Pareto(φ^*, z), then $x \equiv \ln(\varphi/\varphi^*)$ is distributed as an exponential with parameter z. Then, any power function of φ of the type $A\varphi^B$, with A and B constant, is distributed as a Pareto$(A\,(\varphi^*)^B, z/B)$, since $A\varphi^B = A\,(\varphi^*)^B e^{Bx}$ with $Bx \sim Exp(z/B)$, by the properties of the exponential distribution.

sales in industry i is equal to $v_{oi}\sigma_i$ (the inverse of the shape parameter of the corresponding Pareto distribution), and for given demand elasticity at the sector level, σ_i, it is determined by v_{oi}. Hence, we can apply Proposition 1 to draw results for the determinants of sale dispersion across sectors, countries and destination markets:

Proposition 2 *Assume that the solution to (5) is interior. Then, the dispersion of sales from country o to destination d in sector i, as measured by the standard deviation of the log of r_{doi}, is increasing in export opportunities, ρ_{doi}, and in financial development, δ_o. The effect of financial development is stronger in sectors with higher financial vulnerability (low κ_i).*

$$\frac{\partial SD\left[\ln r_{doi}\right]}{\partial \rho_{doi}} > 0; \ \frac{\partial SD\left[\ln r_{doi}\right]}{\partial \delta_o} > 0; \ \frac{\partial^2 SD\left[\ln r_{doi}\right]}{\partial \delta_o \partial \kappa_i} < 0.$$

Proof. *This follows from Proposition 1 and from the distribution of revenues, which implies that $SD \ln r_{doi} = v_{oi}\sigma_i$.* ■

We now focus on the effects of financial variables on firm heterogeneity. To obtain more precise testable implications, we want to relate the financial vulnerability of a sector $(1-\kappa_i)$ to the observable measures, such as those used in Manova (2013). First, it is natural to argue that the fraction of profit that a misbehaving manger can steal is a negative function of asset tangibility, for example because tangible assets are more difficult to hide. Hence, defining asset tangibility in industry i as t_i, we assume $\partial\kappa_i/\partial t_i > 0$. Second, it is also plausible to postulate that the fraction of profit that the investors may lose is a positive function of the total investment. For example, this would be the case in the presence of a fixed cost of hiding profits. It is also a familiar result from models of costly state verification, where the cost of monitoring is typically increasing in the stake (e.g., Bernanke and Gertler, 1989). Hence, $\partial\kappa_i/\partial F < 0$. More in general, this assumption captures the notion that financial vulnerability is higher, the higher the need for external finance (high F in our model). Note also that, although F is endogenous, it is also affected by purely sector-specific components (such as α_i and σ_i). Hence, we can think of sectors with high financial needs for exogenous reasons (high F_i). Under these assumptions, Proposition 2 immediately yields the following predictions:

Corollary 1 *Financial development in country o increases the standard deviation of the log of sales in any destination d relatively more in sectors with higher external financial dependence, F_i, and lower asset tangibility, t_i.*

$$\frac{\partial^2 SD\left[\ln r_{doi}\right]}{\partial \delta_o \partial F_i} > 0; \ \frac{\partial^2 SD\left[\ln r_{doi}\right]}{\partial \delta_o \partial t_i} < 0.$$

We can also develop more testable predictions regarding the effect of export opportunities on equilibrium heterogeneity. Proposition 2 shows that the dispersion of sales is higher in sectors with higher ρ_{doi}. But how can we measure export opportunities in the data? From (6), it can be seen that ρ_{doi} is a negative function of variable trade costs, τ_{doi}. Hence, our results suggest that globalization, by lowering variable trade costs, increases the value of technologies with higher variance and leads to more heterogeneity. Second, there is another important determinant of export opportunities, A_{di}/A_{oi}, which capture relative demand conditions. As shown in Bernard, Redding and Schott (2007), this term may depend on comparative advantage. In particular, they show that, other things equal, A_{di}/A_{oi} will be higher in a country's comparative advantage industry. The intuition for this finding is that profits in the export market are larger relative to profits in the domestic market in comparative advantage industries. It follows that, even if we abstract from microfounding the differences in A_{di}/A_{oi} here, we can use existing results to conclude that the exit cutoff, export opportunities, and equilibrium sale dispersion will all be higher in a country's comparative advantage industries.

3.2 Export Volumes, Firm Heterogeneity and Finance

We now derive predictions for the volume of trade. The total value of exports to destination d from origin o in industry i can be written as

$$X_{doi} = \underbrace{M_{oi}\left(\frac{\varphi^*_{ooi}}{\varphi^*_{doi}}\right)^{1/v_{oi}}}_{\text{mass of exporters}} \underbrace{\frac{(\sigma_i+1)\, w_o f_{doi}}{1-v_{oi}\sigma_i}}_{\text{export per firm}},$$

where M_{oi} is the mass of country o firms operating in industry i and $\left(\varphi^*_{ooi}/\varphi^*_{doi}\right)^{1/v_{oi}}$ is the fraction of firm exporting to destination d. We now study how firm heterogeneity affects various components of the export volume.

Consider first the intensive margin of trade. Average sales to market d per firm from country o serving that destination, denoted as x_{doi}, is:

$$x_{doi} = \frac{(\sigma_i+1)\, w_o f_{doi}}{1-v_{oi}\sigma_i},$$

which is increasing in v_{oi}. The intuition for this result is that a higher v_{oi} increases average productivity and hence average revenue from any destination market.

Interestingly, note also that, for given v_{oi}, average exports per firm does not depend on the variable trade cost, τ_{doi}, due to a compositional effect. A fall in τ_{doi} induces existing exporters to export more. However, it also induces entry into exporting of less productive firms, which export smaller quantities. The combination of Pareto productivity and CES

(Constant Elasticity of Substitution) demand functions implies that these two effect exactly cancel out. Although this is certainly a special result, even in more general models these two effects will tend to offset each other. Hence, the net impact of τ_{doi} on the intensive margin of exports will depend on how strongly the data deviate from the case of Pareto productivity and CES demand. In our model, however, τ_{doi} affects exports per firm through an additional channel: by increasing export opportunities, a lower variable trade cost induces firms to invest in technologies with a higher v, which are more productive, thereby raising average exports per firm.

Consider then the extensive margin of trade. The fraction of country-o firms exporting to market d in industry i can be expressed as:

$$\left(\frac{\varphi_{ooi}^{*}}{\varphi_{doi}^{*}}\right)^{1/v_{oi}} = \left[\tau_{doi}\left(\frac{f_{doi}}{f_{ooi}}\frac{A_{oi}}{A_{di}}\right)^{1/\sigma_i}\right]^{-1/v_{oi}},$$

where, recall, A_{oi} summarizes demand conditions in market o. To better isolate the effect of v_{oi}, consider the case of symmetric countries, i.e., $A_{oi} = A_{di}$. Since $\tau_{doi}\left(f_{doi}/f_{ooi}\right)^{1/\sigma_i} > 1$ (so that not all existing firms export), it immediately follows that the fraction of exporters is increasing in v_{oi}. Intuitively, a higher v_{oi} increases the mass in the tail of the distribution and hence the probability that a firm is productive enough to export. In an asymmetric world, the fraction of exporters will also depend on relative demand conditions, A_{di}/A_{oi}. For example, in sectors of comparative advantage competition will tend to be tougher in the home market (higher A_{di}/A_{oi}) and more firms will export.

Finally, the volume of exports from o to d relative to production for the home market is also increasing in v_{oi} :

$$\frac{X_{doi}}{X_{ooi}} = \tau_{doi}^{-1/v_{oi}}\left(\frac{f_{doi}}{f_{ooi}}\frac{A_{oi}}{A_{di}}\right)^{-1/(\sigma_i v_{oi})}\frac{f_{doi}}{f_{ooi}}.$$

Together with Proposition 2, these results imply that credit frictions, by lowering v_{oi}, reduce the volume of trade, average sales per exporter and the fraction of exporting firms.

4 Empirical Evidence

In this section, we use a unique data set to document novel facts about the variation in sale dispersion across countries, industries and years. Then, we test the main predictions of our model. We start by studying how sale dispersion responds to financial development across industries with different financial vulnerability. Then, we explore how sale dispersion helps explaining the effects of financial development and export opportunities on countries' export flows.

4.1 Data and Stylized Facts

For our analysis, we need to construct reliable and comparable measures of sale dispersion across countries and industries. As is well known, firm-level data are unavailable for most countries in the world. Instead, we compute sale dispersion using extremely detailed trade data at the product level. In particular, we source from Feenstra, Romalis and Schott (2002) data on US imports from 171 countries over 1989-2006, across roughly 15,000 products defined at the 10-digit level of the Harmonized System (HS) classification.[12] These products can be uniquely mapped into 377 4-digit manufacturing industries, defined according to the 1987 Standard Industry Classification (SIC). Overall, we have approximately 4 million observations at the country-product-year level. Starting from these data, we construct sale dispersion for each country-industry-year triplet, as the standard deviation of log exports across all 10-digit products exported to the US in that triplet. The resulting data set is unique, in that it includes more than 230,000 comparable measures of sale dispersion across all countries in the world, all manufacturing industries and a period that spans two decades. In most of the analysis, we focus on a consistent sample of 119 countries and 365 industries for which we observe positive exports to the US in all years between 1989 and 2006.[13]

In using product-level data for measuring sale dispersion we assume, consistent with our model and previous studies (e.g., Manova, 2013), that each product exported by country o to the US coincides with a single country-o firm selling in the US market. While in reality the one-to-one relationship between firms and products does not hold perfectly, this assumption is less restrictive when working with a high level of product disaggregation, as we do. Indeed, the cross-industry variation in sale dispersion obtainable from trade data at the 10-digit product level reflects fairly closely the cross-industry variation in sale dispersion obtainable from available firm-level data. For instance, we have computed the standard deviation of log sales using 10-digit product-level export data from the US to the rest of the world (Feenstra, Romalis and Schott, 2002) and correlated this measure with the standard deviation of log sales computed with firm-level data from Compustat in 1997 (the midpoint of our sample). Despite the important differences between these two data sets, and the fact that sales do not include only exports, the correlation turned out to be positive, sizable and statistically significant (0.47, p-value 0.03).

[12] These are the most disaggregated trade data available at the moment. For instance, in other data sources, trade data are reported at the 6-digit (UN Comtrade) or 8-digit (Eurostat Comext) level of product disaggregation.

[13] Working with this sample ensures that our descriptive statistics are not driven by compositional effects, and reassures that our econometric results are not contaminated by the creation of new countries (e.g., the former members of the Soviet Union) or by the presence of small exporters and industries that trade with the US only occasionally. In a robustness check, we show however that our evidence is preserved when using the whole sample of countries and industries.

In Table 1, we report descriptive statistics on sale dispersion across countries, industries and years. In each panel, we focus on a different sample, and show the mean and standard deviation of sale dispersion for the year 2006 as well as the change in average sale dispersion over 1989-2006. We also show the same statistics for the number of 10-digit products used to construct the sale dispersion measures. In panel a), we focus on the consistent sample of countries and industries. Our measures of sale dispersion are constructed using 15 products on average, and their mean and standard deviation equal 1.94 and 0.88, respectively. This suggests that sale dispersion is large and varies greatly across both countries and industries. Over the sample period, sale dispersion has also substantially increased, by 6 percent on average. Panel b) and c) focus, respectively, on the whole sample and on a consistent sample of 8,518 products that are always present in the HS classification between 1989 and 2006. The numbers are very close to those reported in panel a), suggesting that our results are independent of sample size and unaffected by changes in product classifications over time.

Next, we study the cross-industry and cross-country variation in sale dispersion. In panel d), we focus on cross-industry variation. We compute the mean, standard deviation and change in sale dispersion across industries, separately for each country, and then report average statistics across the 119 economies in our sample. In panel e), we focus instead on cross-country variation. We compute the mean, standard deviation and change in sale dispersion across countries, separately for each industry, and then report average statistics across the 365 sectors in our sample. Sale dispersion varies greatly both geographically and across industries, with cross-country variation (1.95) being slightly larger than cross-industry variation (1.62). In both cases, sale dispersion has substantially increased over the sample period, by 11 percent on average. These numbers are remarkably close to those obtained by Bonfiglioli, Crinò and Gancia (2015) using completely different data, at the firm level, for the US over 1997-2007.

4.2 Sale Dispersion and Finance

4.2.1 Baseline Estimates

We now turn to regression analysis to test Proposition 2 and Corollary 1. In particular, we study how sale dispersion depends on financial development across industries with different financial vulnerability. To this purpose, we estimate variants of the following specification:

$$\begin{aligned} SD_{oit} &= \alpha_o + \alpha_i + \alpha_t + \beta_1 FD_{ot-1} + \beta_2 FD_{ot-1} \cdot EF_i + \beta_3 FD_{ot-1} \cdot AT_i + \\ &\quad + \beta_4 X_{ot-1} + \beta_5 X_{ot-1} \cdot Z_i + \varepsilon_{oit}, \end{aligned} \tag{9}$$

where SD_{oit} is the standard deviation of log exports from country o to the US in industry i and year t; α_o, α_i and α_t are country, industry and year fixed effects, respectively; FD_{ot-1} is a measure of financial development in country o and year $t-1$; EF_i and AT_i are measures of industry i's financial vulnerability; X_{ot-1} and Z_i are vectors of country characteristics and industry characteristics, respectively, which determine comparative advantage and thus proxy for export opportunities (details below); finally, ε_{oit} is an error term.

Following a well-established empirical literature, and in particular Manova (2013), our preferred measure of financial development (FD_{ot-1}) is private credit, the amount of credit (as a share of GDP) issued by commercial banks and other financial institutions to the private sector. We source this variable from the Global Financial Development Database. Private credit is a well-measured and cross-country comparable proxy for the size of the financial sector. As for financial vulnerability, we proxy for industries' external finance dependence (EF_i) and asset tangibility (AT_i) using, respectively, the share of capital expenditure not financed with cash flow from operations (Rajan and Zingales, 1998; Manova, 2013) and the share of net property, plant and equipment in total assets (Claessens and Laeven, 2003; Manova, 2013). As standard, we construct both variables using US firm-level data from Compustat.[14] Because the US has one of the most advanced financial systems in the world, using US data makes EF_i and AT_i more likely to reflect firms' actual credit needs and availability of tangible assets (Rajan and Zingales, 1998; Claessens and Laeven, 2003). At the same time, the ranking of industries in terms of EF_i and AT_i is likely to be preserved across countries, given that financial vulnerability mostly depends on technological factors (e.g., the cash harvest period or the type of production process) that are common across economies and largely stable over time (Rajan and Zingales, 1998). Finally, following Romalis (2004), Levchenko (2007) and Nunn (2007), we proxy for export opportunities using standard country-industry proxies for comparative advantage, namely, the interactions between a country's skill endowment, capital endowment and institutional quality (X_{ot-1}) with an industry's skill intensity, capital intensity and contract intensity (Z_i).[15]

We start by estimating equation (9) with fixed effects for origin countries (α_o), industries

[14] Following the conventional approach, we take the median value of asset tangibility and average external finance dependence across all firms in a given industry over 1989-2006. For 4-digit industries with no firms in Compustat, we use the value of a given variable in the corresponding 3-digit or 2-digit sector.

[15] Skill and capital endowments are the log index of human capital per person and the log real capital stock per person engaged, respectively. Both variables are sourced from the Penn World Table 8.1. Skill and capital intensity are the log ratio of non-production to production workers' employment and the log real capital stock per worker, respectively. Both variables are sourced from the NBER Manufacturing Industry Productivity Database and averaged over 1989-2006. Institutional quality is average rule of law over 1996-2006, sourced from the Worldwide Governance Indicator Database. Contract intensity is the indicator for the importance of relationship-specific investments in each industry, constructed by Nunn (2007).

(α_i) and years (α_t).[16] These fixed effects absorb all time-invariant determinants of sale dispersion at the country and industry level, as well as general time trends common to all economies and sectors. We then move to more demanding specifications, in which we use country-time (α_{ot}) and industry-time (α_{it}) effects in place of α_o, α_i and α_t. By doing so, we ensure that our parameters of interest are identified only from the combination of cross-country variation in financial development (endowments) and cross-industry variation in financial vulnerability (factor intensities), and are not contaminated by country and industry shocks.[17] We always correct the standard errors for two-way clustering by country-industry and industry-year, thereby accommodating both autocorrelated shocks for the same country-industry pair and industry-specific shocks correlated across countries.

The baseline results are reported in Table 2. In column (1) we start with a parsimonious version of equation (9) that only includes the financial variables. The results show that, consistent with Corollary 1, financial development increases sale dispersion, especially in more financially vulnerable industries, where firms are more dependent on external finance and have fewer tangible assets. In column (2), we add our proxies for export opportunities.[18] We find skill endowment, capital endowment and institutional quality to increase sale dispersion relatively more in industries that are more skill and capital intensive or dependent on relationship-specific investments. Hence, better export opportunities also make the distribution of sales more spread out, as predicted by Proposition 2. In column (3), we replace the country, industry and year fixed effects with country-year and industry-year effects. The interaction coefficients are largely unchanged. In column (4) we control for the number of products exported to the US within each country-industry-year triplet. While this variable has a positive coefficient, our main results do not change, suggesting that sale dispersion is not mechanically driven by the number of products. Finally, in column (5) we follow Manova (2013) and include a full set of interactions between countries' CPI and industry dummies, to control for country-industry specific changes in the price indexes. Our main evidence is unaffected also in this very demanding specification.

We can use the coefficients reported in column (5) to have a sense of the quantitative relevance of financial development in explaining variation in sale dispersion across countries and industries. In particular, the point estimates imply that a 1 standard deviation increase in private credit raises sale dispersion by 1 percent more in the industry at the third quartile of the distribution by external finance dependence (relative to the industry at the first

[16]The industry fixed effects subsume the linear terms in financial vulnerability and factor intensities.

[17]The country-time and industry-time effects absorb all country- and industry-specific determinants of sale dispersion, such as the elasticity of substitution or the country components (e.g., distance) and industry components (e.g., bulkiness) of variable trade costs.

[18]Because rule of law does not vary over time, its linear term is captured by the country fixed effects α_o.

quartile) and by 3.5 percent more in the industry at the first quartile of the distribution by asset tangibility (relative to the industry at the third quartile). A commensurate increase in institutional quality, skill and capital endowments raise sale dispersion by 1, 3.5 and 6.2 percent more, respectively, in the industry at the third quartile of the distribution by contract, skill and capital intensity (relative to the industry at the first quartile). Hence, the effects of financial development are in the same ballpark as those of standard determinants of export opportunities.

4.2.2 Robustness Checks

We now submit the baseline results (see column 5 of Table 2) to a large number of robustness checks. We start, in Table 3, by showing that our evidence is unchanged when using alternative samples. In particular, in column (1) we use the whole sample of countries and industries. The coefficients are very similar to the baseline estimates, suggesting that our results are independent of sample size. In column (2), we compute financial vulnerability (and all other industry-level variables) at the 3-digit rather than 4-digit level, to address the concern that financial vulnerability may be measured less precisely at higher levels of industry detail, as the number of firm-level observations is smaller for more disaggregated sectors. In practice, however, the results are similar to the baseline estimates. In column (3), we re-construct sale dispersion after restricting to the consistent sample of products that are always present in the HS classification. The results are unchanged, suggesting that our evidence is not driven by changes in product classifications. In columns (4)-(6) we finally show that our results do not depend on the existence of small exporters, observations for which SD_{oit} is computed with few products, and products with small exports to the US. In particular, in column (4) we estimate equation (9) using observations for which SD_{oit} is constructed with three or more products; in column (5) we re-compute SD_{oit} after excluding the bottom 25% of products (separately for each country-industry-year triplet) with the smallest value of exports to the US; and in column (6) we estimate equation (9) after excluding countries with less than 5 million people in 2006. The results are strikingly robust across the board.

In Table 4, we use alternative measures of financial development and financial vulnerability. We start by replacing private credit with other common proxies for the size of the financial sector: deposit money bank assets as a share of GDP (column 1); deposit money bank assets over the sum of deposit money bank assets and central bank assets (column 2); liquid liabilities and domestic credit as a share of GDP (columns 3 and 4, respectively).[19] The

[19] Bank assets are total assets held by commercial banks. As such, they also include credit to the public sector and assets other than credit. This feature makes bank assets a more comprehensive, but less precise,

results always show that financial development increases sale dispersion in more financially vulnerable industries. In column (5) we instead use the log lending rate, which measures the cost incurred by firms in obtaining credit and thus is an inverse proxy for the size and efficiency of the financial sector.[20] Consistently, we find the interactions involving the lending rate to have the opposite signs as those involving private credit and the other proxies for size. Finally, in column (6) we replace the financial vulnerability variables computed over the period 1989-2006 with equivalent measures based on data for the previous decade (1979-1988). Because financial vulnerability is constructed with US data, its past values may be a better proxy for countries at earlier stages of development. Reassuringly, the results are similar to the baseline estimates, consistent with cross-industry differences in financial vulnerability being mostly driven by technological factors, which tend to persist both across countries and over time.

In Table 5, we report cross-sectional results, replacing all time-varying variables with their long-run averages over 1989-2006. By doing so, we further ensure that the coefficients are identified only from cross-country variation in these variables, and are not contaminated by temporary shocks. In spite of a dramatic loss of observations, the results in column (1) are remarkably close to the baseline panel estimates. Next, we compare the results based on private credit (column 1) with those obtained when using indexes for the quality of institutions that affect business creation and credit access. These indexes get closer to our theoretical definition of financial development, but they are inherently time invariant and, thus, can be meaningfully used only in a cross-sectional set-up. Hence, in columns (2) and (3) we replace private credit with indexes for the ease of doing business and for the effectiveness of the legal system at resolving insolvencies, respectively.[21] Reassuringly, the results always confirm our baseline evidence.

Finally, we discuss remaining concerns with endogeneity. We start by noticing that, because the panel regressions control for country-year and industry-year fixed effects, our parameters of interest are identified by the differential effect of financial development across industries, and do not reflect shocks to specific countries and sectors. Moreover, our specifica-

proxy for the size of the financial sector. The ratio of commercial-to-central bank assets is a commonly used proxy for the relative importance of private financial institutions. Liquid liabilities include all liabilities of banks and other financial intermediaries. Thus, this variable may also include liabilities backed by credit to the public sector. Finally, domestic credit also includes credit issued by, and granted to, the public sector, and thus is a broader, but perhaps less precise, measure of the size of the financial system. See Crinò and Ogliari (2015) for more details.

[20] The lending rate is the rate charged by banks for loans to private firms. As such, it is a standard proxy for the cost of borrowing in a country (see, e.g., Chor and Manova, 2012). We source this variable from the IMF International Financial Statistics and from the OECD.

[21] We source both indexes from the World Bank Doing Business Database; we normalize them to range between 0 and 1, and so that higher values correspond to countries with a higher position in the ranking.

tions control for a wealth of country-industry variables (i.e., proxies for export opportunities and price indexes). Thus, the results do not pick up the effects of the main observable confounders at the country-industry level. Other features of the analysis mitigate the concern that our estimates may be driven by unobserved shocks specific to a given country-industry pair. In particular, the financial vulnerability measures are kept constant over time and are based on US data. Thus, they are conceivably unaffected by such shocks. Moreover, our results are unchanged when using financial vulnerability measures based on data for the previous decade which, by construction, do not reflect shocks occurring over the sample period. At the same time, our results are robust across a battery of proxies for financial development; we believe it is unlikely that an omitted shock could move all these variables equally and simultaneously. Finally, our results hold when using long-run averages of private credit and time-invariant indexes for the quality of financial institutions. Yet, we now show that our evidence is preserved when using instrumental variables (IV). The latter allow us to isolate the variation in financial development due to countries' historical conditions, while cleaning up the variation due to current economic conditions potentially correlated with sale dispersion.

The results are reported in columns (4)-(6) of Table 5. Following La Porta, Lopez-de-Silanes and Shleifer (2008), we instrument private credit, or the indexes of doing business and resolving insolvencies, using three dummy variables, which are equal to 1 if countries' legal systems have French, German or Scandinavian origins, respectively. The instruments have a strong predictive power, as indicated by the high values of the Kleibergen-Paap F-statistic for weak instruments reported at the bottom of the table. This confirms the result of La Porta, Lopez-de-Silanes and Shleifer (2008), according to which differences in financial development across countries to a large extent reflect historical differences in countries' legal origins. More importantly, the second stage coefficients maintain their signs, remain statistically significant, and are approximately of the same size as the OLS estimates.

4.3 Trade, Finance and Sale Dispersion

Our first result, documented in the previous sections, is that financial development increases sale dispersion, especially in more financially vulnerable industries. Better export opportunities also make the sale distribution more disperse. In turn, according to our model, higher sale dispersion should raise both the number of exported products (extensive margin) and exports per product (intensive margin), thereby leading to a larger volume of exports. It follows that sale dispersion provides a mechanisms through which financial development may affect export flows across countries and industries. We now provide evidence on this mechanism. To this purpose, we estimate a specification similar to equation (9), in which we replace the dependent variable with log total exports, log number of exported products and log exports per product. We report results with and without controlling for sale dispersion. If our mechanism is statistically relevant, sale dispersion should enter with a positive and precisely estimated coefficient. If our mechanism is also quantitatively important, the coefficients on financial development should substantially drop when controlling for sale dispersion.

The baseline results are reported in Table 6. In columns (1)-(4) we estimate specifications without controlling for sale dispersion. Columns (1) and (2) use log total exports as the dependent variable: column (1) includes country, industry and year fixed effects, while column (2) replaces these fixed effects with full sets of country-year and industry-year effects. The results confirm the well-known fact that financial development increases exports relatively more in financially vulnerable sectors (Beck, 2002; Manova, 2013). The results also support the standard view that countries with larger endowments of skilled labor and capital, or with better institutional quality, export relatively more in industries that are more skill and capital intensive, or more dependent on relationship-specific investments (Romalis, 2004; Levchenko, 2007; Nunn, 2007). Columns (3) and (4) decompose total exports into the extensive margin (number of exported products) and the intensive margin (exports per product). Financial development increases both margins relatively more in financially vulnerable industries. Export opportunities also increase both the extensive and the intensive margin of trade.

In columns (5)-(8), we repeat the previous specifications adding sale dispersion among the regressors. The coefficient on this variable is positive and very precisely estimated. Consistent with our model, this implies that countries and industries in which the sale distribution is more spread out export more products and have greater sales per product, thereby exhibiting higher volumes of exports in a given destination market. At the same time, the coefficients on financial development substantially drop in size when controlling for sale dispersion. In particular, by comparing the results in columns (6)-(8) with those in columns (2)-(4), note that the coefficients on financial development drop by 20-60%. The coefficients on export opportunities also drop by a similar amount, suggesting that our mechanism is not only statistically significant but also quantitatively relevant for explaining the effects of financial frictions and factor endowments on exports. Finally, in Tables 7 and 8 we submit these results to a large number of robustness checks, focusing on the intensive margin of trade, for which the model has clearer predictions. Our evidence is reassuringly unchanged when using cross-sectional variation, different proxies for financial development and IV regressions.

5 Conclusions

In this paper we have studied how financial development affects firm-level heterogeneity and trade in a model where productivity differences across monopolistically competitive firms are endogenous and depend on investment decisions at the entry stage. By increasing entry costs, financial frictions lower the exit cutoff and hence also the value of investing in bigger projects with more dispersed outcomes. As a result, credit frictions make firms more homogeneous and hinder the volume of exports both along the intensive and the extensive margin. Export opportunities, instead, shift expected profits to the tail and increase the value of technological heterogeneity.

We tested these predictions using comparable measures of sales dispersion within 365 manufacturing industries in 119 countries built from highly disaggregated US import data. Consistent with the model, financial development increases sale dispersion, especially in more financially vulnerable industries; sale dispersion is also increasing in measures of comparative advantage. These results are quantitatively important for explaining the effect of financial development and factor endowments on export sales.

The results in this paper have important implications. First, they help explaining why credit frictions restrain trade more than domestic production. To rationalize this finding, existing models typically assume that credit is relatively more important to finance foreign than domestic activities (e.g., Chaney, 2015, and Manova, 2013). The origin of this asymmetry is however not entirely clear. Existing explanations also face the challenge that exporter volumes are dominated by large firms, and large firms are typically less financially constrained. Our model overcomes both shortcomings. Second, this paper sheds new light on the relationship between trade volumes and finance. Our empirical results not only confirm and extend the finding in Manova (2013) that financial development increases the volume of export especially in financially vulnerable sectors using a larger sample and a finer level of industry aggregation. They also help identifying the mechanism, suggesting that a significant fraction of the overall effect works through the dispersion of sales.

Finally, it is well-known that the extent of firm-level heterogeneity is a key determinant of the size of the gains form trade (e.g., Arkolakis, Costinot and Rodriguez-Clare, 2012, Melitz and Redding, 2015). Then, our finding that credit frictions compress productivity differences across firms suggests that well-functioning financial markets are a precondition for countries to fully benefit from trade liberalization.[22] In light of this, the spectacular growth of the financial sector in the past decades may reflect an efficient reaction to globalization.[23]

[22] Similarly, Caggese and Cuñat (2013) show that financial frictions lower the gains from trade by distorting export (rather than innovation) decisions.

[23] Consistently, Braun and Raddaz (2008) and Do and Levchenko (2007) find that trade can promote

Since more productive firms pay higher wages, this paper also hints to an overlooked channel through which financial development may affect income inequality. More generally, our results contribute to explaining the empirical and theoretical determinants of productivity differences across firms, and how firm heterogeneity varies across countries and sectors.

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6 Appendix

6.1 Proof of Proposition 1

To prove that the equilibrium optimal v_{oi} is increasing in export opportunities and financial development, especially in more financially vulnerable sectors, we first use (8) to define

$$\begin{aligned} W &\equiv \frac{1}{1-v_{oi}\sigma_i} + \ln\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}} + \frac{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}}{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}} - \frac{v_{oi}F'(v_{oi})}{F(v_{oi})} \\ &= \eta_\pi(v_{oi}) - \eta_F(v_{oi}), \end{aligned}$$

and apply the implicit function theorem to obtain the generic expression for the derivative of v_{oi} with respect to variable y:

$$\frac{\partial v_{oi}}{\partial y} = -\frac{\partial W}{\partial y} \Big/ \frac{\partial W}{\partial v_{oi}}.$$

Under our assumption that $\eta'_F(v_{oi}) > \eta'_\pi(v_{oi})$, the denominator is negative: $\frac{\partial W}{\partial v_{oi}} = \frac{\partial \eta_\pi(v_{oi})}{\partial v_{oi}} - \frac{\partial \eta_F(v_{oi})}{\partial v_{oi}} < 0$. Next, we prove that $\frac{\partial v_{oi}}{\partial \rho_{doi}} > 0$ by computing

$$\begin{aligned} \frac{\partial W}{\partial \rho_{doi}} &= \frac{\partial \ln\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}}}{\partial \rho_{doi}} + \frac{\partial\left(\frac{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}}{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}}\right)}{\partial \rho_{doi}} \\ &= \frac{\sum_{d\neq o} \frac{f_{doi}\rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}}{\rho_{doi} v_{oi}}}{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}} - \frac{\left(\sum_{d\neq o} f_{doi}\rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}\right)\left(\sum_{d\neq o} \frac{f_{doi}\rho_{doi}^{1/v_{oi}}}{\rho_{doi} v_{oi}}\right)}{\left(\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}\right)^2}, \end{aligned}$$

and showing that it is positive. To this end, we set the following condition

$$\frac{\sum_{d\neq o} \frac{1}{\rho_{doi}} f_{doi}\rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}}{\sum_{d\neq o} f_{doi}\rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}} > \frac{\sum_{d\neq o} \frac{1}{\rho_{doi}} f_{doi}\rho_{doi}^{1/v_{oi}}}{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}},$$

take the terms for $d = o$ (with f_{ooi} and $\rho_{ooi} = 1$) out of the summations, and obtain

$$\frac{\sum_{d\neq o} \frac{1}{\rho_{doi}} f_{doi}\rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}}{\sum_{d\neq o} f_{doi}\rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}} > \frac{\sum_{d\neq o} \frac{1}{\rho_{doi}} f_{doi}\rho_{doi}^{1/v_{oi}}}{f_{ooi} + \sum_{d\neq o} f_{doi}\rho_{doi}^{1/v_{oi}}},$$

which holds for any $\rho_{doi} > 1$.

We then prove that $\frac{\partial v_{oi}}{\partial \delta_o} > 0$ by computing

$$\frac{\partial W}{\partial \delta_o} = \frac{\partial W}{\partial \lambda_{oi}} \frac{\partial \lambda_{oi}}{\partial \delta},$$

which is positive since

$$\frac{\partial W}{\partial \lambda_{oi}} = \frac{\partial \ln \left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}}}{\partial \lambda_{oi}} = \frac{\partial \ln \left(\frac{1}{\lambda_{oi}}\right)}{\partial \lambda_{oi}} = -\frac{1}{\lambda_{oi}} \text{ and } \frac{\partial \lambda_{oi}}{\partial \delta_o} = -\lambda^2_{oi} \left(1 - \kappa_i\right).$$

Finally, to prove that $\frac{\partial^2 v_{oi}}{\partial \delta_o \partial \kappa_i} < 0$, we first obtain

$$\frac{\partial^2 v_{oi}}{\partial \delta_o \partial \kappa_i} = \frac{\partial \left(-\frac{dW}{d\delta_o} / \frac{dW}{dv_{oi}}\right)}{\partial \kappa_i} = \frac{-\frac{\partial^2 W}{\partial \delta_o \partial \kappa_i}\frac{\partial W}{\partial v_{oi}} - \frac{\partial^2 W}{\partial v_{oi} \partial \kappa_i}\frac{\partial W}{\partial \delta_o}}{\left(\frac{\partial W}{\partial v_{oi}}\right)^2},$$

where the denominator is positive, $-\frac{\partial W}{\partial v_{oi}} > 0$, and $-\frac{\partial W}{\partial \delta_o} > 0$. We prove the numerator to be negative by computing

$$\frac{\partial^2 W}{\partial \delta_o \partial \kappa_i} = \frac{\partial \left(\lambda_{oi} \left(1 - \kappa_i\right)\right)}{\partial \kappa_i} = \lambda_{oi} \left[\delta_o \left(1 - \kappa_i\right) - 1\right] < 0,$$

since both δ_o and κ_i take values between 0 and 1, and

$$\frac{\partial^2 W}{\partial v_{oi} d\kappa_i} = \frac{\partial \frac{\partial \ln \left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}}}{\partial v_{oi}}}{\partial \kappa_i} = \frac{1}{v_{oi}} \frac{\partial \frac{\partial \ln \left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}}}{\partial \ln v_{oi}}}{\partial \kappa_i} = \frac{\delta_o}{v_{oi}} > 0,$$

where the elasticity of $\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}}$ with respect to v_{oi} is calculated imposing the equilibrium first order condition (8).[24] Hence, $\frac{\partial^2 (v_{oi})}{\partial \delta_o \partial \kappa_i} < 0$.

[24] In particular, it can be shown that $d \ln \left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}} / d \ln v_{oi} = \left(1 - v_{oi}\sigma_i\right)^{-1} + \left(\sum_d f_{doi} \rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}\right) / \left(\sum_d f_{doi} \rho_{doi}^{1/v_{oi}}\right) - v_{oi} F'\left(v_{oi}\right) / F\left(v_{oi}\right)$, which under (8) is equal to $-\ln \left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}}$.

Table 1 - Descriptive Statistics on Sale Dispersion

	Mean	Std. Dev.	Change	Mean	Std. Dev.	Change	Mean	Std. Dev.	Change
	a) Consistent Countries and Industries			*b) All Countries and Industries*			*c) Consistent Countries, Industries and Products*		
Sale Dispersion	1,94	0,88	0,06	1,91	0,89	0,05	1,92	0,92	0,07
N. Products	15	25	2	14	24	1	11	17	0
	d) Cross-Industry			*e) Cross-Country*					
Sale Dispersion	1,62	0,84	0,11	1,95	0,87	0,11			
N. Products	9	12	2	12	10	2			

Sale dispersion is the standard deviation of log exports, computed separately for each exporting country, 4-digit SIC manufacturing industry and year, using data on exports to the US at the product (10-digit) level. The number of products is the number of 10-digit product codes used to compute the measures of sale dispersion. Mean and standard deviation refer to the year 2006; changes are computed over 1989-2006 and are expressed in percentages for sale dispersion and in units for the number of products. Panel a) refers to a consistent sample of countries (119) and 4-digit industries (365) with positive exports to the US in all years between 1989 and 2006. Panel b) refers to the whole sample of countries (171) and 4-digit industries (377) with positive exports to the US in at least one year between 1989 and 2006. Panel c) uses the same sample of countries and industries as in panel a), but restricts to a consistent set of 10-digit product codes (8548) that are present in the HS classification in all years between 1989 and 2006. In panel a)-c), statistics are computed across all country-industry observations. The statistics in panel d) are computed across industries within a given country and then averaged across the 119 countries. The statistics in panel e) are computed across countries within a given industry and then averaged across the 365 industries.

Table 2 - Sale Dispersion and Finance: Baseline Estimates

	(1)	(2)	(3)	(4)	(5)
Financial Development	0.042*	0.061**			
	[0.024]	[0.024]			
Fin. Dev. * External Finance Dependence	0.075***	0.058***	0.056***	0.053***	0.037***
	[0.012]	[0.011]	[0.012]	[0.012]	[0.013]
Fin. Dev. * Asset Tangibility	-0.150**	-0.219***	-0.259***	-0.275***	-0.411***
	[0.076]	[0.078]	[0.079]	[0.079]	[0.085]
Skill Endowment		0.692***			
		[0.100]			
Capital Endowment		-0.247***			
		[0.033]			
Skill End. * Skill Intensity		0.350***	0.384***	0.374***	0.246***
		[0.037]	[0.039]	[0.038]	[0.044]
Cap. End. * Capital Intensity		0.067***	0.067***	0.061***	0.059***
		[0.006]	[0.006]	[0.006]	[0.009]
Institutional Quality * Contract Intensity		0.172*	0.107	0.058	0.109
		[0.104]	[0.105]	[0.105]	[0.139]
N. Products				0.003***	0.003***
				[0.000]	[0.000]
Obs.	234,112	229,128	229,114	227,568	227,568
R2	0,19	0,20	0,23	0,23	0,25
Country FE	yes	yes	no	no	no
Industry FE	yes	yes	no	no	no
Year FE	yes	yes	no	no	no
Country-Year FE	no	no	yes	yes	yes
Industry-Year FE	no	no	yes	yes	yes
Price indexes * Industry FE	no	no	no	no	yes

The dependent variable is the standard deviation of log exports, computed separately for each exporting country, 4-digit SIC manufacturing industry and year, using data on exports to the US at the product (10-digit) level. Financial development is proxied by private credit as a share of GDP. External finance dependence and asset tangibility are, respectively, the share of capital expenditure not financed with cash flow from operations and the share of net property, plant and equipment in total assets (industry-level averages over 1989-2006). Skill endowment is the log index of human capital per person. Capital endowment is log real capital stock per person engaged. Skill intensity is the log average ratio of non-production to production worker employment over 1989-2006. Capital intensity is the log average ratio of real capital stock per worker over 1989-2006. Institutional quality is average rule of law over 1996-2006. Contract intensity is an indicator for the importance of relationship-specific investments in each industry. The number of products is the number of 10-digit product codes exported by a given country to the US in a given industry and year. All time-varying regressors are lagged one period. All regressions are based on a consistent sample of countries (119) and 4-digit industries (365) with positive exports to the US in all years between 1989 and 2006. Standard errors are corrected for two-way clustering by country-industry and industry-year, and are reported in square brackets. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

Table 3 - Sale Dispersion and Finance: Alternative Samples

	Whole Sample	3-Digit Industries	Consistent Products	At Least 3 Products	No Small Products	No Small Countries
	(1)	(2)	(3)	(4)	(5)	(6)
Fin. Dev. * Ext. Fin. Dep.	0.040***	0.059***	0.054***	0.031**	0.035***	0.037***
	[0.012]	[0.017]	[0.020]	[0.013]	[0.012]	[0.013]
Fin. Dev. * Ass. Tang.	-0.423***	-0.208*	-0.279**	-0.381***	-0.185**	-0.393***
	[0.083]	[0.111]	[0.130]	[0.084]	[0.079]	[0.086]
Skill End. * Skill Int.	0.205***	0.156***	0.141**	0.240***	0.129***	0.258***
	[0.039]	[0.056]	[0.068]	[0.047]	[0.039]	[0.047]
Cap. End. * Cap. Int.	0.061***	0.051***	0.037**	0.060***	0.040***	0.061***
	[0.008]	[0.013]	[0.016]	[0.009]	[0.007]	[0.009]
Inst. Qual. * Contr. Int.	0.181	0.442**	0.379*	-0.126	0.056	0.063
	[0.135]	[0.185]	[0.213]	[0.143]	[0.127]	[0.146]
N. Prod.	0.003***	0.002***	0.002***	0.003***	0.001***	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Obs.	245,620	110,331	95,311	189,445	227,568	197,082
R2	0,25	0,32	0,28	0,28	0,16	0,26
Country-Year FE	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes	yes	yes	yes

The dependent variable is the standard deviation of log exports, computed separately for each exporting country, industry and year, using data on exports to the US at the product (10-digit) level. Column (1) uses the whole sample of countries (171) and 4-digit industries (377) with positive exports to the US in at least one year between 1989 and 2006. Columns (2) and (3) define industries at the 3-digit instead of 4-digit level; column (3) further constructs the dependent variable using a consistent set of 10-digit product codes (8548) that are present in the HS classification in all years between 1989 and 2006. Column (4) uses country-industry-year observations for which sale dispersion is calculated using at least three products. In column (5), sale dispersion is computed after excluding the bottom 25% of products (with the smallest value of exports) in each country-industry-year triplet. Column (6) excludes countries with less than 5 million people in 2006. All time-varying regressors are lagged one period. Standard errors are corrected for two-way clustering by country-industry and industry-year, and are reported in square brackets. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 4 - Sale Dispersion and Finance: Alternative Proxies

	Bank Assets	Bank/Central Bank Assets	Liquid Liabilities	Domestic Credit	Lending Rate	Lagged Financial Vulnerability
	(1)	(2)	(3)	(4)	(5)	(6)
Fin. Dev. * Ext. Fin. Dep.	0.043***	0.162***	0.026**	0.031***	-0.042***	0.049***
	[0.013]	[0.044]	[0.013]	[0.012]	[0.007]	[0.010]
Fin. Dev. * Ass. Tang.	-0.527***	-1.178***	-0.639***	-0.401***	0.171***	-0.296***
	[0.080]	[0.269]	[0.081]	[0.077]	[0.048]	[0.098]
Skill End. * Skill Int.	0.250***	0.260***	0.240***	0.253***	0.185***	0.247***
	[0.044]	[0.044]	[0.044]	[0.044]	[0.047]	[0.044]
Cap. End. * Cap. Int.	0.061***	0.068***	0.061***	0.058***	0.035***	0.060***
	[0.009]	[0.009]	[0.009]	[0.009]	[0.010]	[0.009]
Inst. Qual. * Contr. Int.	0.064	0.261*	0.093	0.121	0.325**	0.142
	[0.139]	[0.140]	[0.137]	[0.139]	[0.146]	[0.139]
N. Prod.	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Obs.	226,866	213,613	229,098	230,826	216,026	227,281
R2	0,25	0,25	0,25	0,25	0,26	0,25
Country-Year FE	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes	yes	yes	yes

The dependent variable is the standard deviation of log exports, computed separately for each exporting country, industry and year, using data on exports to the US at the product (10-digit) level. Financial development is proxied by: deposit money bank assets as a share of GDP in column (1); deposit money bank assets over the sum of deposit money bank assets and central bank assets in column (2); liquid liabilities as a share of GDP in column (3); domestic credit to the private sector as a share of GDP in column (4); and the log lending rate in column (5). In column (6), external finance dependence and asset tangibility are averages over 1979-1988. All time-varying regressors are lagged one period. All regressions are based on a consistent sample of countries (119) and 4-digit industries (365) with positive exports to the US in all years between 1989 and 2006. Standard errors are corrected for two-way clustering by country-industry and industry-year, and are reported in square brackets. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 5 - Sale Dispersion and Finance: Cross-Sectional Results

	OLS			IV		
	Private Credit	Doing Business	Resolving Insolvencies	Private Credit	Doing Business	Resolving Insolvencies
	(1)	(2)	(3)	(4)	(5)	(6)
Fin. Dev. * Ext. Fin. Dep.	0.071***	0.110***	0.101***	0.089***	0.180***	0.188***
	[0.015]	[0.030]	[0.034]	[0.030]	[0.042]	[0.050]
Fin. Dev. * Ass. Tang.	-0.320***	-0.509**	-0.368*	-0.589**	-0.734*	-0.862*
	[0.120]	[0.211]	[0.211]	[0.251]	[0.407]	[0.497]
Skill End. * Skill Int.	0.262***	0.232***	0.241***	0.245***	0.208***	0.203***
	[0.052]	[0.051]	[0.052]	[0.055]	[0.041]	[0.057]
Cap. End. * Cap. Int.	0.055***	0.052***	0.051***	0.057***	0.053***	0.053***
	[0.008]	[0.009]	[0.009]	[0.008]	[0.006]	[0.009]
Inst. Qual. * Contr. Int.	0.436**	0.448**	0.493***	0.333*	0.383***	0.369**
	[0.172]	[0.178]	[0.169]	[0.180]	[0.138]	[0.183]
N. Prod.	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]
Obs.	20,716	20,952	20,952	20,716	20,952	20,952
R2	0,36	0,36	0,36	0,29	0,29	0,29
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
First Stage Results						
Kleibergen-Paap F-Statistic	-	-	-	467,2	600,0	194,4

The dependent variable is the standard deviation of log exports for each exporting country and industry, computed with data on exports to the US at the product (10-digit) level and averaged over 1989-2006. Financial development is proxied by: private credit in columns (1) and (4); an index of doing business in columns (2) and (5); and an index of resolving insolvencies in columns (3) and (6). Private credit, factor endowments, and number of products are averaged over 1989-2006. The indexes of doing business and resolving insolvencies are normalized between 0 and 1, and take higher values for countries occupying higher positions in the ranking. In columns (4)-(6), the financial variables are instrumented using the interactions between the two measures of financial vulnerability and three dummies for whether countries' legal systems have French, German or Scandinavian origins. All regressions are based on a consistent sample of countries (119) and 4-digit SIC industries (365) with positive exports to the US in all years between 1989 and 2006. Standard errors are corrected for clustering by industry, and are reported in square brackets. The F-statistics are reported for the Kleibergen-Paap test for weak instruments. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 6 - Trade, Finance and Sale Dispersion: Panel Estimates

	Total Exports	Total Exports	Number of Products	Exports per Product	Total Exports	Total Exports	Number of Products	Exports per Product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fin. Dev.	0.612***				0.510***			
	[0.095]				[0.072]			
Fin. Dev. * Ext. Fin. Dep.	0.207***	0.141***	0.040***	0.101**	0.110***	0.076**	0.033***	0.043
	[0.042]	[0.049]	[0.012]	[0.041]	[0.030]	[0.035]	[0.011]	[0.027]
Fin. Dev. * Ass. Tang.	-2.040***	-3.153***	-0.368***	-2.786***	-1.672***	-2.504***	-0.295***	-2.209***
	[0.332]	[0.348]	[0.098]	[0.290]	[0.251]	[0.265]	[0.093]	[0.213]
Skill End.	3.733***				2.570***			
	[0.286]				[0.210]			
Cap. End.	-0.733***				-0.317***			
	[0.126]				[0.096]			
Skill End. * Skill Int.	2.372***	1.460***	0.442***	1.018***	1.785***	1.043***	0.395***	0.648***
	[0.150]	[0.177]	[0.049]	[0.145]	[0.107]	[0.126]	[0.046]	[0.098]
Cap. End. * Cap. Int.	0.313***	0.235***	0.035***	0.201***	0.200***	0.135***	0.024**	0.111***
	[0.023]	[0.035]	[0.010]	[0.028]	[0.017]	[0.026]	[0.009]	[0.019]
Inst. Qual. * Contr. Int.	2.439***	1.847***	0.858***	0.989**	2.149***	1.579***	0.828***	0.751**
	[0.396]	[0.536]	[0.146]	[0.439]	[0.283]	[0.388]	[0.138]	[0.301]
Sale Dispersion					1.680***	1.632***	0.183***	1.449***
					[0.015]	[0.015]	[0.004]	[0.012]
Obs.	229,128	229,114	229,114	229,114	229,128	229,114	229,114	229,114
R2	0,50	0,55	0,73	0,48	0,69	0,73	0,75	0,70
Country FE	yes	no	no	no	yes	no	no	no
Industry FE	yes	no	no	no	yes	no	no	no
Year FE	yes	no	no	no	yes	no	no	no
Country-Year FE	no	yes	yes	yes	no	yes	yes	yes
Industry-Year FE	no	yes	yes	yes	no	yes	yes	yes
Price indexes * Industry FE	no	yes	yes	yes	no	yes	yes	yes

The dependent variables are indicated in columns' headings and are all expressed in logs. Sale dispersion is the standard deviation of log exports, computed separately for each exporting country, 4-digit SIC manufacturing industry and year, using data on exports to the US at the product (10-digit) level. All time-varying regressors are lagged one period. All regressions are based on a consistent sample of countries (119) and 4-digit SIC industries (365) with positive exports to the US in all years between 1989 and 2006. Standard errors are corrected for two-way clustering by country-industry and industry-year, and are reported in square brackets. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 7 - Trade, Finance and Sale Dispersion: Cross-Sectional OLS Estimates

	Private Credit	Doing Business	Resolving Insolvencies	Private Credit	Doing Business	Resolving Insolvencies
	(1)	(2)	(3)	(4)	(5)	(6)
Fin. Dev. * Ext. Fin. Dep.	0.147***	0.247**	0.215**	0.007	0.030	0.016
	[0.051]	[0.098]	[0.099]	[0.036]	[0.062]	[0.063]
Fin. Dev. * Ass. Tang.	-1.959***	-2.520***	-1.939***	-1.319***	-1.429**	-1.174**
	[0.424]	[0.720]	[0.704]	[0.352]	[0.568]	[0.509]
Skill End. * Skill Int.	1.203***	1.121***	1.159***	0.698***	0.679***	0.696***
	[0.167]	[0.164]	[0.166]	[0.101]	[0.104]	[0.103]
Cap. End. * Cap. Int.	0.175***	0.167***	0.163***	0.062***	0.059***	0.057***
	[0.027]	[0.027]	[0.027]	[0.016]	[0.016]	[0.016]
Inst. Qual. * Contr. Int.	2.154***	2.372***	2.556***	1.283***	1.487***	1.570***
	[0.545]	[0.559]	[0.535]	[0.332]	[0.333]	[0.331]
Sale Dispersion				1.920***	1.928***	1.929***
				[0.034]	[0.034]	[0.034]
Obs.	20,716	20,952	20,952	20,716	20,952	20,952
R2	0,50	0,50	0,50	0,77	0,77	0,77
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes

The dependent variable is log average exports per product over 1989-2006. Financial development is proxied by: private credit in columns (1) and (4); the index of doing business in columns (2) and (5); and the index of resolving insolvencies in columns (3) and (6). Sale dispersion is the standard deviation of log exports for each exporting country and industry, computed with data on exports to the US at the product (10-digit) level and averaged over 1989-2006. All regressions are based on a consistent sample of countries (119) and 4-digit SIC industries (365) with positive exports to the US in all years between 1989 and 2006. Standard errors are corrected for clustering by industry, and are reported in square brackets. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 8 - Trade, Finance and Sale Dispersion: Cross-Sectional IV Estimates

	Private Credit	Doing Business	Resolving Insolvencies	Private Credit	Doing Business	Resolving Insolvencies
	(1)	(2)	(3)	(4)	(5)	(6)
Fin. Dev. * Ext. Fin. Dep.	0.235*	0.450**	0.474**	0.055	0.090	0.096
	[0.130]	[0.186]	[0.195]	[0.089]	[0.122]	[0.129]
Fin. Dev. * Ass. Tang.	-4.421***	-5.736***	-6.212***	-3.284***	-4.253***	-4.488***
	[0.853]	[1.631]	[1.740]	[0.732]	[1.239]	[1.287]
Skill End. * Skill Int.	1.062***	0.931***	0.919***	0.592***	0.537***	0.534***
	[0.181]	[0.197]	[0.200]	[0.114]	[0.129]	[0.130]
Cap. End. * Cap. Int.	0.194***	0.188***	0.189***	0.078***	0.079***	0.078***
	[0.026]	[0.026]	[0.026]	[0.017]	[0.017]	[0.016]
Inst. Qual. * Contr. Int.	1.224**	1.545***	1.532***	0.547	0.780**	0.791**
	[0.594]	[0.599]	[0.584]	[0.383]	[0.387]	[0.376]
Sale Dispersion				1.915***	1.924***	1.924***
				[0.034]	[0.034]	[0.034]
Obs.	20,716	20,952	20,952	20,716	20,952	20,952
R2	0,43	0,43	0,43	0,73	0,73	0,73
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
First Stage Results						
Kleibergen-Paap F-Statistic	461,8	164,6	191,8	463,7	167,3	191,2

The dependent variable is log average exports per product over 1989-2006. Financial development is proxied by: private credit in columns (1) and (4); the index of doing business in columns (2) and (5); and the index of resolving insolvencies in columns (3) and (6). Sale dispersion is the standard deviation of log exports for each exporting country and industry, computed with data on exports to the US at the product (10-digit) level and averaged over 1989-2006. The financial variables are instrumented using the interactions between the two measures of financial vulnerability and three dummies for whether countries' legal systems have French, German or Scandinavian origins. All regressions are based on a consistent sample of countries (119) and 4-digit SIC industries (365) with positive exports to the US in all years between 1989 and 2006. Standard errors are corrected for clustering by industry, and are reported in square brackets. The F statistics are reported for the Kleibergen-Paap test for weak instruments. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.