Trade, Finance and Endogenous Firm Heterogeneity*

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Abstract

We study how financial frictions affect firm-level heterogeneity and trade. We build 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 the value of investing in bigger projects with more dispersed outcomes. As a result, credit frictions make firms smaller and more homogeneous, and hinder the volume of exports. Export opportunities, instead, shift expected profits to the tail and increase the value of technological heterogeneity. We test 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 sales dispersion, especially in more financially vulnerable industries; sales dispersion is also increasing in measures of comparative advantage. These results help 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 shed new light on these hypotheses. We start by introducing financial frictions 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. Instead, we consider 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 sales dispersion across a large set of 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 sales 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 of 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 fixed production cost. As in Bonfiglioli, Crinò and Gancia (2016), however, firms can affect the distribution from which technology is drawn. In particular, investments in bigger innovation

[1] See for instance Syverson (2011).

[2] See Poschke (2015) and Bartelsman, Haltiwanger and Scarpetta (2009).

[3] See for instance Manova (2013), Beck (2002) and Svaleryd and Vlachos (2005).

projects are associated to more dispersed 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 insight 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. This generates two main predictions. First, credit frictions lower the equilibrium degree of heterogeneity in a sector. The intuition for this result is that credit frictions reduce entry, which in turn lowers the minimum productivity needed to survive. But a higher surviving probability lowers the value of drawing from a more dispersed distribution.[4] We then 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 the effect is stronger in sectors that are more financially vulnerable. Second, as in Bonfiglioli, Crinò and Gancia (2016), 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.

At a first glance, this mechanism seems to capture important real-world phenomena. It is widely documented that entry barriers, financial frictions and trade costs allow unproductive firms to survive. Limited export opportunities also lower the payoffs of successful products. Our theory suggests that these frictions have additional effects on incentives: they discourage investment in large-scale projects and the use of advanced technologies with high upside potential. As a consequence, in equilibrium firms are small, the resulting distribution of revenue has a low dispersion, and there are few exporters. This picture does not seem far from the reality in many financially underdeveloped countries.

Our next step is to test these predictions using highly disaggregated 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 across products 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 sales dispersion for each country, industry and year as the standard deviation of log exports across products. We thereby obtain a unique dataset, which includes more than 230,000 comparable measures of

[4] Note that in our model risk is completely diversified. However, expected returns depend on the variance of productivity draws. In a more general model, financial frictions may deter entry also by lowering diversification opportunities as in Michelacci and Schivardi (2013).

sales dispersion across countries and manufacturing industries, over a period that spans two decades.

The dataset we use has several advantages and some limitations. For our purposes, its most important feature is that it allows us to construct measures of the dispersion of sales to a single market for a large set of countries which differ greatly in the level of financial development and for a large set of sectors which differ greatly in financial vulnerability. This would be hard to do using firm-level data, which are unavailable for most countries and often do not separate sales by destination.[5] Moreover, although in the model firms and products coincide, it is not *a priori* obvious whether its predictions should be tested preferably using firm- or product-level data. In practice, however, measures of heterogeneity across firms or products are highly correlated, as we show using US data. The impossibility to control for firm characteristics is also mitigated by the fact that the mechanism in the model works through an adjustment of the exit cutoff which affects indiscriminately all firms in a sector and by the inclusion of a host of fixed effects.

After documenting some interesting statistics on how sales dispersion varies across countries, 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). Our main result is that, consistent with our model, financial development increases sales 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, to alternative estimation approaches and measures of sales dispersion, and to instrumenting financial development with historical conditions of countries. We also find that sales dispersion is important for explaining trade flows and the well-known effect of financial frictions on exports (Manova, 2013, Beck, 2002).

Finally, we provide some more direct evidence on the mechanism at work in the model, which operates through changes in the innovation strategies of firms. To this end, we show that our proxies for financial frictions at the country-sector-year level are a significant determinant of major innovations, as measured by the number of utility patents applied for at the US Patent Office, computed separately for each foreign country, industry and application

[5] 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.

year. In turn, patent applications are positively correlated with sales dispersion, as in our theory.

Our model of endogenous firm heterogeneity has been developed in this paper and in Bonfiglioli, Crinò and Gancia (2016). In the latter, we abstract from financial frictions 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. This allows us to derive novel empirical implications. Regarding the evidence, the two papers use completely different data and approaches. In Bonfiglioli, Crinò and Gancia (2016) we use US firm-level data; 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 magnitude, display similar trends and have similar correlations with export opportunities.

Compared to Bonfiglioli, Crinò and Gancia (2016), an important advantage of the data used in this paper is also that it enables us to document new empirical patterns. Among these, we extend to a much broader sample the little-known fact that the dispersion of firm size increases with per capita income. For comparison, Poschke (2015) uses survey data from less than 50 countries, and Bartelsman, Haltiwanger and Scarpetta (2009) uses data for 24 countries only. We also document that the dispersion of sales has increased on average by 6% between 1989 and 2006. More importanly, we establish the result that financial frictions have a satistically significant and quantitatively large effect on sales dispersion. For instance, our estimates implies that the average increase in private credit over the sample period could explain 59% of the observed increase in sales dispersion.

Besides the evidence 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, Faggio, Salvanes and Van Reenen, 2010, and Doraszelski and Jaumandreu, 2013). Moreover, the emphasis on the role of entry and 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). Furthermore, as shown for instance in Cabral and Mata (2003), there is already considerable heterogeneity among new firms.

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. Nevertheless, the choice between innovations differing in the variance of outcomes and the implications for firm heterogeneity has received so far little attention in the literature. An exception is Caggese (2015), who has developed a dynamic model where firms with low profitability invest in radical, high-risk, innovation because they have less to lose in case innovation fails.[6] Financial frictions increase the rents of these firms and hence reduce their willingness to take on risk. Our mechanism differs in that it applies to all firms and does not depend on their profit level. Our focus is also entirely different: we study and test the implications for the dispersion of sales and the volume of trade.

From a theoretical perspective, the effect of financial frictions of the size distribution of firms is not *a priori* obvious. Existing models do not focus explicitly on the dispersion of the size distribution and often study how credit constraints distort the allocation of resources across firms.[7] Whether these misallocations amplify or dampen the dispersion of sales depends on several factors, and most of all on whether credit constraints bind more for less or more productive firms. For instance, Arellano, Bai and Zhang (2012) argue that small firms are more likely to be inefficient in scale because they are closer to their borrowing limits, although other results are possible. Hence, the effect of financial frictions on sales dispersion is ultimately an empirical question on which this paper sheds some light. Our approach is instead motivated by Midrigan and Xu (2014), who find that financial frictions can distort entry more than the allocation of resources between existing firms. They find that misallocation generated by financial frictions are fairly small because more efficient producers accumulate internal funds over time and quickly grow out of their borrowing constraints (see also the survey by Buera, Kaboski and Shin, 2015). Our evidence that financial frictions hinder patenting, which in turn is associated with lower sales dispersion, lends additional support to a channel based on endogenous innovation decisions.

This paper is closely related to the literature on trade with heterogenous firms. In particular, our findings shed new light on the role of financial frictions in affecting export decisions. The fact that financial constraints reduce exports disproportionately more than domestic production has been documented in a series of recent contributions (see Chor and Manova, 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 hinders trade and that this effect is stronger for sectors with higher external financial dependence. Yet, the theoretical underpinnings remain somewhat mysterious. Existing explanations typically assume that credit frictions should be more binding for exports than for domestic sales.[8]

[6] Gabler and Poschke (2013) study instead how policy distortions affect experimentation by firms. Adding firm dynamics would be an interesting exercise, which however goes beyond the scope of this paper.

[7] A growing literature studies distorsions generating dispersion in the marginal product of factors, but this is a very different question.

[8] For instance, in Manova (2013) and Chaney (2016) firms only face liquidity constraints for accessing

But the foundation for this assumption is not entirely clear, especially since export volumes are overwhelmingly driven by large firms which are usually less financially constrained (e.g., Beck, Demirgüç-Kunt and Maksimovic, 2005). Our model overcomes these difficulties. Through their effect on the exit cutoff at the sector level, financial frictions affect all firms, including those that are not credit constrained. Their negative effect on the introduction of new products is also easy to justify, 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, in our model there is no need to impose any asymmetry on the financial needs of domestic or export activities.

Finally, this paper is also part of the broader and growing literature studying the effect of trade on technology choices, such as Bustos (2011). We depart from previous works by focusing on the dispersion rather than the level of productivity and studying a mechanism that does not rely on scale effects. Yet, our result that entry can foster the use of better technologies accords well with recent findings that pro-competitive forces appear to have increased firm-level productivity (Khandelwal and Topalova, 2011).

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 these predictions. Section 5 concludes.

2 The Model

We 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 (2016), 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.

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foreign markets; in Kohn, Leibovici and Szkup (2016) exporters face relatively higher working capital needs than non-exporters; in Caggese and Cuñat (2013) exporting increases volatility and hence the risk of a costly bankruptcy, which is higher for more productive firms. The results can also be sensitive to assumptions on the credit frections. For instance, Brooks and Dovis (2015) find that when debt limits of firms respond to profit opportunities, which they argue is the empirically relevant case, credit frictions do not hamper reallocation and do not reduce the gains from trade.

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:

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

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 σ_i 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} :

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

Then, demand for a variety can be written as:

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

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 (2016), 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.[9]

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 is an inverse measure of financial vulnerability which, following Rajan and Zingales (1998) and Manova (2013), is assumed to vary across industries for technological 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:

$$p_{doi}\left(\varphi\right)=\frac{\sigma_i}{\sigma_i-1}\frac{\tau_{doi}w_o}{\varphi}$$

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:

$$r_{doi}(\varphi)=\beta_i E_d P_{di}^{\sigma_i-1} p_{doi}\left(\varphi\right)^{1-\sigma_i}.$$

Profit earned in destination d is a fraction σ_i of revenue minus the fixed cost of selling in market d, $w_o f_{doi}$. Hence:

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

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

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

[9] 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.

the cutoff

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

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:

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

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 follow Bonfiglioli, Crinò and Gancia (2016) in using a simple model of investment in new products generating a Pareto distribution for φ with mean and variance that depend on firms' decisions. The model formalizes the idea that firms can choose between smaller projects with less variable returns and larger projects with more spread-out outcomes. In particular, in order to enter, the manager of the firm can choose between a menu of projects of size $s_{oi} \in (0, 1]$ which allows the firm to manufacture a new variety with productivity drawn from the distribution

$$G_{oi}(\varphi) = 1 - \left(\frac{\varphi_{\min}}{\varphi} \right)^{1/v_{oi}}, \tag{4}$$

where

$$v_{oi} = \frac{s_{oi}}{\alpha_i \sigma_i}, \qquad \alpha_i > 1. \tag{5}$$

Hence, by choosing the size s_{oi} of the project, the firm is selecting to draw φ from a family of Pareto distributions differing in the parameter $v_{oi} = s_{oi}/(\alpha_i \sigma_i)$ (i.e., the inverse of the shape parameter of the Pareto distribution).[10]

The choice of v_{oi} affects positively the dispersion of φ. To see this, note that the standard deviation of the log of φ is equal to v_{oi}, which can therefore be interpreted as an index of

[10] A simple microfoundation can be built on the idea that the realization of productivity depends both on quality of the project q, which is unknown and uncertain, and the size s_{oi} of the investment. In particular, assume that $\ln \varphi = s_{oi} q + \ln \varphi_{\min}$, which implies that quality and resources are complements. Then, if quality, q, is exponentially distributed with $\Pr[q > z] = \exp(-\alpha_i \sigma_i z)$, it follows that φ is Pareto distributed with

dispersion of the distribution. At the same time, v_{oi} also affects the expected value of φ, which is equal to $\varphi_{\min}(1-v_{oi})^{-1}$.[11] This positive relationship between mean and variance is realistic: Bonfiglioli, Crinò and Gancia (2016) find strong evidence of a positive correlation between the average and the dispersion of sales across US firms. Yet, as we show in the appendix, our main results hold in an alternative model in which firms can choose between distributions that are a mean-preserving spread.

How is the initial entry investment determined in equilibrium? To answer this question we turn to the cost of entry. First, we assume that the entry cost, expressed 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.[12] 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 $\lim_{v_{oi}\to 1/\alpha_i\sigma_i} F(v_{oi}) = \infty$. Next, recall that $w_o F(v_{oi})$ must be financed externally and that with probability $(1-\delta_o)$ managers can hide a fraction $(1-\kappa_i)$ of profit. For simplicity, we normalize the outside option of both managers and investors to zero. Hence, investors expect to be repaid π_{oi} with probability δ_o and $\kappa_i \pi_{oi}$, with probability $(1-\delta_o)$. Then, competition for funds between managers implies that v_{oi} be set so as to maximize the expected returns of investors:

$$\max_{v_{oi}} \left\{ \mathbb{E}\left[\pi_{oi}\right] - w_o \lambda_{oi} F\left(v_{oi}\right) \right\}, \tag{6}$$

where $\lambda_{oi} \equiv [\delta_o + (1-\delta_o)\kappa_i]^{-1} > 1$ captures the additional cost of financing the entry investment in the presence of credit frictions ($\kappa_i < 1$ and $\delta_o < 1$). Moreover, free-entry implies that investors must break even, $\mathbb{E}\left[\pi_{oi}\right] = w_o \lambda_{oi} F\left(v_{oi}\right)$, which is also their (binding) participation constraint.[13]

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minimum $\varphi_{\min}$ and shape parameter $\alpha_i\sigma_i/s_{oi}$, as can be seen from:

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

[11] The assumptions $\alpha_i > 1$, $s_{oi} \in (0,1]$ and $v_{oi} = s_{oi}/(\alpha_i\sigma_i)$ imply that $v_{oi} < 1/\sigma_i < 1$, which guarantees that productivity is drawn from a distribution with a finite mean and that $\mathbb{E}\left[\pi_{oi}\right]$ converges to a finite value. The condition $v_{oi} < 1/\sigma_i$ can be relaxed if the number of firms is finite or if there is an upper bound to the support of the Pareto distribution for φ. Yet, the assumption that productivity is less dispersed in industries producing more homogeneous varieties is consistent with Syverson (2004).

[12] Equivalently, we could have modified (5) so that the dispersion parameter is a concave function of the entry investment.

[13] This is a simple way to obtain the general result that financial frictions raise the cost of borrowing and that the friction has both a country-level component and an industry-level component. Similar assumptions are made by Manova (2013). See for instance Tirole (2005) for a textbook treatment of agency problems in corporate finance.

To solve (6), we use $G_{oi}(\varphi)$ to express *ex-ante* expected profits (3) as a function of v_{oi}:

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

where:

$$\rho_{doi} \equiv \frac{\varphi^*_{ooi}}{\varphi^*_{doi}} = \tau_{doi}^{-1} \left(\frac{A_{di}}{f_{doi}} \frac{f_{ooi}}{A_{oi}}\right)^{1/(\sigma_i - 1)} \tag{7}$$

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 (6) 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 $\eta_\pi(v_{oi}) \equiv \partial \ln \mathbb{E}\left[\pi_{oi}\right] / \partial \ln v_{oi}$, respectively. We then assume $\eta'_F(v_{oi}) > \eta'_\pi(v_{oi})$. The first order condition for an interior v_{oi} is:

$$\frac{\mathbb{E}\left[\pi_{oi}\right]}{v_{oi}} \left[\frac{1}{1 - v_{oi}(\sigma_i - 1)} + \ln\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}} + \frac{\sum_d f_{doi} \rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}}{\sum_d f_{doi} \rho_{doi}^{1/v_{oi}}}\right] = w_o \lambda_{oi} F'(v_{oi}). \tag{8}$$

The left-hand side of (8) is the marginal benefit of increasing v_{oi}, while the right-hand side is 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 a high realization of φ when the profit function is convex, i.e., when $\sigma_i > 2$ (as can be seen from equation 1).

Yet, both $\mathbb{E}[\pi]$ 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: $\mathbb{E}\left[\pi_{oi}\right] = w_o \lambda_{oi} F(v_{oi})$. Replacing this into the first-order condition (8), we obtain the following expression:

$$\frac{1}{1 - v_{oi}(\sigma_i - 1)} + \ln\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}} + \frac{\sum_d f_{doi} \rho_{doi}^{1/v_{oi}} \ln \rho_{doi}^{-1/v_{oi}}}{\sum_d f_{doi} \rho_{doi}^{1/v_{oi}}} = \frac{v_{oi} F'(v_{oi})}{F(v_{oi})}, \tag{9}$$

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} satisfying (9). Finally, we need to substitute for the equilibrium exit cutoff for productivity, which is pinned down again by the free-entry condition:

$$\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}} = \frac{\sigma_i - 1}{1/v_{oi} - (\sigma_i - 1)} \frac{\sum_d f_{doi} \rho_{doi}^{1/v_{oi}}}{\lambda_{oi} F(v_{oi})}. \tag{10}$$

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 since Melitz (2003), export opportunities increase profit for more productive firms thereby inducing more entry and making survival more difficult.[14]

After replacing the cutoff in (9), 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}. We are then in the position to draw predictions on the equilibrium dispersion of productivity, which is Pareto with minimum φ^*_{ooi} and shape parameter $1/v_{oi}$. Hence, the log of φ is exponential with standard deviation equal to v_{oi}.[15] Using this result, we can show how the equilibrium dispersion of firm productivity varies across sectors, countries and destination markets as described by Proposition 1.

Proposition 1 *Assume that the solution to (6) 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 (or, more in general, to discard failed innovations) 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. This lowers the minimum productivity needed to survive, which in turn reduces the value of drawing productivity from a

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

[15] The standard deviation of the log of φ is a common measure of dispersion which has the convenient property of being scale invariant. If φ is Pareto, this measure is also invariant to truncation from below.

more dispersed distribution. Second, as in Bonfiglioli, Crinò and Gancia (2016), 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.

Note that the problem studied so far is simplified by the assumption that all firms entering a given sector in a given country are *ex-ante* identical and therefore end up choosing the same v_{oi}. An alternative case would be one in which firms differ in their exposure to financial frictions before the innovation decision is made. Even though more complex, this case is interesting because in reality new products are introduced by firms, some of which have more internal funds (e.g., older and larger firms) than others (e.g., startups and small firms). To see how this *ex-ante* heterogeneity affects our main results, in the appendix we sketch a version of the model in which in each industry there is an exogenous mass of entering firms which are not subject to the financial friction (i.e., for them $\lambda_{oi} = 1$). We then show that, while financially constrained firms behave exactly as in the baseline model, financially unconstrained firms choose a higher v_{oi}. Yet, the choice of v_{oi} by any firms is still affected by the exit cutoff as in the baseline model.

The additional difficluty is that, with different firms making heterogeneous choices, the overall productivity distribution is not Pareto anymore. Nevertheless, its dispersion can still be characterized analytically using the Theil index, which can be decomposed into within- and between-group components. Factoring in the compositional effects, we then show that the average dispersion in an industry is increasing in the exogenous fraction of financially unconstrained firms, the more so the higher the index of financial vulnerability λ_{oi}. Hence, adding *ex-ante* heterogeneity does not alter the main predictions of the model. On the contrary, it suggests that the financial vulnerability of a sector may also be proxied by firm characteristics, such as average size or age, that typically correlate with the presence of financial constraints.

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 exports at the country-industry level. These predictions will be tested empirically in the next section.

3.1 Sales Dispersion per Destination Market

Revenue from market d of firms from country o operating in sector i is a power function of productivity, $r_{doi}(\varphi) = r_{doi}(\varphi^*_{doi}) \left(\varphi/\varphi^*_{doi}\right)^{\sigma_i - 1}$. Then, from the properties of the

Pareto distribution, it follows that $r_{doi}(\varphi)$ is also Pareto distributed with c.d.f. $G_r(r) = 1 - (r_{\min}/r)^{1/(v_{oi}(\sigma_i - 1))}$, for $r > r_{\min} = \sigma_i w_o f_{doi}$.[16] This means that the standard deviation (SD) of the log of sales in industry i is equal to $v_{oi}(\sigma_i - 1)$, 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 sales dispersion across sectors, countries and destination markets:

Proposition 2 *Assume that the solution to (6) 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 $SD\left[\ln r_{doi}\right] = v_{oi}(\sigma_i - 1)$.* ■

We can also develop 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 (7), 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 captures relative demand conditions. As shown in Bernard, Redding and Schott (2007), this term in general depends 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 because 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 sales dispersion will all be higher in a country's comparative advantage industries.

[16] 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.

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

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

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

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

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

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 export 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 constant-elasticity-of-substitution demand functions implies that these two effects cancel out. Although this is certainly a special result, even in more general models these two effects will tend to offset each other. 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:

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

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 $\tau_{doi}\left(f_{doi}/f_{ooi}\right)^{1/(\sigma_i-1)} > 1$ (so that not all 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} :

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

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

The main result of the model is that financial development and export opportunities increase the value of investing in bigger innovation projects with more variable outcomes, thereby generating more heterogeneity across firms and a higher volume of trade. In this section, we test these predictions. We start by describing the data and the measures of sales dispersion, and documenting some new facts about how this measure varies across countries, industries and years. Next, we study how sales dispersion responds to financial development across industries with different financial vulnerability. We then explore how sales dispersion mediates the effects of financial development and export opportunities on countries' export flows. Finally, we use patent data to provide some evidence on the mechanism at work in the model, namely that financial development affects sales dispersion by fostering major innovations.

4.1 Data and Measures of Sales Dispersion

Our main measure of dispersion is the standard deviation of log sales in a single destination market. Besides being consistent with Proposition 2, this measure has the convenient property of being scale invariant. To construct it across countries and industries, we use highly detailed product-level data on international trade. In particular, we source data on US imports of roughly 15,000 products - defined at the 10-digit level of the Harmonized System (HS) classification - from all countries in the world over 1989-2006 (Feenstra, Romalis and Schott, 2002). These data contain approximately 4 million observations at the country-product-year level.[17] We map products into manufacturing industries - defined at the 4-digit

[17] 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.

level of the 1987 Standard Industry Classification (SIC) - and then construct measures of sales dispersion separately for each country-industry-year triplet. We define sales dispersion as the standard deviation of log exports across the 10-digit products exported to the US in a given triplet. To ensure that our results are not driven by sample composition, we focus on a consistent sample of 119 countries and 365 industries for which we observe exports to the US in all years between 1989 and 2006.[18]

Sales dispersion is observed for triplets that have two or more products exported to the US. In the remaining triplets, the standard deviation of log exports is unobserved (i.e., it is missing), because either no or a single product is shipped to the American market. Since the US is the main export destination for most countries in our sample, triplets with two or more exported products are numerous and relatively large.[19] Table 1 makes this point by providing details on the structure of our data set in 2006. Note that almost 40% of triplets have at least two products exported to the US, and that this number rises to 52% when industries are aggregated at the 3-digit level. Moreover, triplets with two or more exported products are large in terms of export value, which equals 85 (178 at the 3-digit level) million dollars on average. At the same time, Table 1 also shows that the measures of sales dispersion are generally based on a large number of products. In particular, the average triplet contains 15 (31 at the 3-digit level) products exported to the US.

The most important and innovative feature of our data set is that it includes approximately 230,000 measures of sales dispersion in a single and large market, across many countries and industries which differ greatly in financial frictions and financial vulnerability. It would be hard to assemble a similar data set using firm-level data, which are difficult to obtain for most countries, and often do not distinguish sales by destination. While in reality the one-to-one correspondence between firms and products postulated in the model does not hold perfectly, it is not *a priori* obvious whether the predictions should be tested preferably using firm- or product-level data, given that the theory applies more directly to product innovation rather than firm creation. Fortunately, however, this distinction is not too relevant when working with a high level of product disaggregation, as we do.

To see this, note that the number of products exported to the US across countries and

[18] In particular, each of the 119 countries has exported to the US in at least one industry during all years between 1989 and 2006. By analogy, in each of the 365 industries at least one country has exported to the US over the same period. Focusing on this consistent sample ensures that our stylized facts are not driven by compositional effects, and that our econometric results are not contaminated by the creation of new countries (e.g., the former members of the Soviet Union) and by the presence of small exporters that trade with the US only occasionally. Nevertheless, the results obtained for the entire sample of countries (171) and industries (377) are very similar (available upon request).

[19] For these reasons, we find below that our results are essentially unchanged when using different approaches for accommodating the presence of triplets with missing observations on sales dispersion (see Section 4.3.3 for details).

industries is typically not far from the number of foreign firms selling in the US. In particular, while we do not have information on firm-level sales, we were able to obtain data on the number of foreign firms that have exported to the US in the year 2002, separately for each foreign country and manufacturing industry. This information comes from the PIERS database, and was provided to us by IHS Markit. PIERS covers the universe of maritime trade transactions of the US, and accounts for 83% of total US imports in 2002. Using this information, we have found that, across all foreign countries and manufacturing industries, the median number of firms exporting to the US is equal to 8 when defining industries at the 4-digit level, and to 13 when defining industries at the 3-digit level. The corresponding numbers of 10-digit products exported to the US are 7 and 12, respectively (see Table 1). Hence, the number of units on which our sales dispersion measures are constructed is not far from the one that we would have used if we had access to export data at the firm level.

The overall similarity between the number of products and firms is perhaps not too surprising, given that for the average country in our sample it is not very likely that more than one firm exports the same 10-digit product to the US. Yet, a concern may remain that in large countries the mapping between firms and products may be less accurate. However, the cross-industry variation in sales dispersion obtained from trade data at the 10-digit product level reflects fairly closely the cross-industry variation in sales dispersion obtained from US firm-level data. To check this, we have computed the standard deviation of log sales using 10-digit product-level data on exports 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 important differences between the two data sets, and the fact that firms' sales do not include only exports, the correlation turned out to be positive, sizable and statistically significant (0.47, p-value 0.03).

4.2 Stylized Facts

We now present some new facts about how sales dispersion varies across countries, industries and years. In Table 2, we report descriptive statistics. In each panel, we consider a different sample, and show the mean and standard deviation of sales dispersion for the year 2006, as well as the change in sales dispersion over 1989-2006. We also show statistics on the number of 10-digit products used to construct the measures of sales dispersion in a given panel. In panel a), we focus on our baseline sample of 119 countries and 365 industries. The mean and standard deviation of sales dispersion, computed across countries and industries, equal 1.94 and 0.88, respectively. Between 1989 and 2006, sales dispersion has increased on average by 6 percent. Hence, sales dispersion is large, varies greatly both geographically and across sectors, and has risen over the last two decades. In panel b), we report the same statistics computed on a restricted sample of products, which consist of the 8,548 10-digit codes that are present in HS classification in each year between 1989 and 2006. The numbers are very close to those reported in panel a), suggesting that our results do not depend on the changes that have occurred over time in the product classification (Schott and Pierce, 2012).

Next, we study how sales dispersion varies across countries and industries. In panel c), we focus on cross-industry variation. To this purpose we first compute, separately for each country, the mean and standard deviation of sales dispersion across the 365 industries, as well as the change in sales dispersion over the sample period. Then, we report average statistics across the 119 economies in our sample. In panel d), we focus instead on cross-country variation. To this purpose we first compute, separately for each industry, the mean and standard deviation of sales dispersion across the 119 countries, as well as the change in sales dispersion over the sample period. Then, we report average statistics across the 365 industries in our sample. Note that sales dispersion varies greatly both geographically and across industries, with the cross-country variation being slightly larger than the cross-industry variation. In both cases, sales dispersion has increased over the sample period, by 11 percent on average. These numbers are comparable to those obtained by Bonfiglioli, Crinò and Gancia (2016) using US firm-level data over 1997-2007.

Finally, we show that the variation in sales dispersion is not random, but correlates strongly with a number of country characteristics that are relevant for our theory. To this end we first compute, separately for each country, average sales dispersion across the 365 industries in 2006. Then, we plot this variable against different country characteristics. The results are displayed in Figure 1. The first graph studies how sales dispersion correlates with economic development, as proxied by real per-capita GDP.[20] It shows that sales are significantly more dispersed in richer countries. This result confirms, using product-level trade data instead of firm-level data, the evidence from recent work on the firm size distribution, according to which the dispersion in firm size is increasing in countries' level of development (e.g., Poschke, 2015, Bartelsman, Haltiwanger and Scarpetta, 2009). The second graph plots average sales dispersion against a standard proxy for countries' financial development, namely the amount of credit (over GDP) issued by commercial banks and other financial institutions to the private sector. Note that sales dispersion is larger in countries where financial markets are more developed, and the relationship between the two measures is tight. The third graph shows how sales dispersion varies across countries with different levels of regulatory barriers affecting entry costs. In particular, we use an inverse proxy for entry barriers, given by the ranking of countries in terms of an index of doing business: countries occupying a higher position in the ranking have more friendly business regulations.[21] Note

[20] We use data on real per-capita GDP from the Penn World Table 8.1.

[21] We source the index of doing business from the World Bank Doing Business Database.

that sales dispersion is increasing in the index of doing business and, thus, it is higher in countries with lower entry barriers. Finally, in the fourth graph we plot sales dispersion against average exports to the US per product. The relationship is strong and positive, suggesting that countries with greater sales dispersion export more to a given market.

Overall, Figure 1 shows that sales dispersion is higher in countries that are richer, have less harsh financial frictions and exhibit lower entry costs. In turn, greater sales dispersion is associated with greater exports. In the next sections, we exploit highly disaggregated data and variation across countries, industries and years, to identify the causal effect of financial development on sales dispersion and the effect of sales dispersion on exports.

4.3 Sales Dispersion and Finance

4.3.1 Empirical Specification and Variables

According to Proposition 2, the dispersion of sales from an origin country to a destination market, as measured by the standard deviation of log exports, should be increasing in the country's level of financial development, especially in industries with higher financial vulnerability. Moreover, better export opportunities should also raise sales dispersion.

To test Proposition 2, we estimate variants of the following specification:

$$\begin{aligned} SD_{oit} &= \alpha_o + \alpha_i + \alpha_t + \beta_1 FD_{ot-1} + \beta_2 FD_{ot-1} \cdot FV_i + \\ &\quad + \beta_3 X_{ot-1} + \beta_4 X_{ot-1} \cdot Z_i + \varepsilon_{oit}, \end{aligned} \tag{11}$$

where SD_{oit} is the standard deviation of log exports to the US from country o 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 $t-1$; FV_i is a measure of industry i's financial vulnerability; X_{ot-1} and Z_i are, respectively, vectors of country and industry characteristics that determine comparative advantage, and thus proxy for export opportunities; finally, ε_{oit} is an error term.[22]

Our coefficient of interest is β_2, which captures the differential effect of financial development on sales dispersion, across industries characterized by different degrees of financial vulnerability. As discussed in Rajan and Zingales (1998) and Manova (2013), this coefficient is identified by exploiting the asymmetric impact that financial frictions exert on industries, depending on technological characteristics that make industries more or less reliant on the financial system. The advantage of this strategy over a simple cross-country regression is the

[22] We lag all time-varying controls by one period because the effects of financial development on sales dispersion need not fully unfold within a year. Our main results are however robust to using contemporaneous values (available upon request).

possibility to control for time-varying country characteristics potentially correlated with financial development.[23] We are also interested in the vector of coefficients β_4, which measure the impact of export opportunities and are identified similarly.

Following, among others, Manova (2013), our preferred proxy for financial development (FD_{ot-1}) is private credit, which is a well-measured and internationally comparable indicator of the size of the financial system. In our main specifications, we use two variables for measuring the degree of financial vulnerability of an industry. The first proxy is external finance dependence (EF_i), defined as the share of capital expenditure not financed with cash flow from operations (Rajan and Zingales, 1998, Manova, 2013). This variable is a direct proxy for financial vulnerability, because in sectors where EF_i is higher, firms rely more on outside capital to finance their operations. The second proxy is asset tangibility (AT_i), defined as the share of net property, plant and equipment in total assets (Claessens and Laeven, 2003, Manova, 2013). This variable is an inverse proxy for financial vulnerability, because in sectors where AT_i is higher, firms have more tangible assets to pledge as collateral when borrowing. Accordingly, we expect the coefficient β_2 in equation (11) to be positive when using EF_i and negative when using AT_i.[24]

To construct EF_i and AT_i, we use firm-level data for the US, sourced from Compustat for the period 1989-2006.[25] Because the US has one of the most advanced financial systems in the world, using US data makes it more likely that EF_i and AT_i 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 obtained with US data is likely to be preserved across countries and time periods, because financial vulnerability mostly depends on technological factors - such as the cash harvest period or the type of production process - that are common across economies and largely stable over time (Rajan and Zingales, 1998).[26]

Finally, following Romalis (2004), Levchenko (2007), Nunn (2007) and Chor (2010), we proxy for export opportunities using different country-industry proxies for comparative advantage. These are 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 con-

[23] We discuss these controls and other endogeneity concerns below and in Section 4.3.3.

[24] In Section 4.3.3, we show that our results are robust to the use of alternative measures of financial development and financial vulnerability.

[25] Following the conventional approach, we take the median value of asset tangibility and average external finance dependence across all firms in an 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.

[26] Consistently, in some robustness checks we show that our results are unchanged when using lagged values of EF_i and AT_i (computed over the decade before the beginning of our sample) or the rankings of industries in terms of these two variables.

tract intensity (Z_i), respectively.[27]

4.3.2 Baseline Estimates

The baseline estimates of equation (11) are reported in Table 3. Standard errors are corrected for two-way clustering by country-industry and industry-year, in order to accommodate both autocorrelated shocks for the same country-industry pair and industry-specific shocks correlated across countries. In column (1), we start with a parsimonious specification that only includes the financial variables and full sets of fixed effects for origin countries (α_o), industries (α_i) and years (α_t). These fixed effects absorb all time-invariant determinants of sales dispersion at the country and industry level, as well as general time trends common to all countries and sectors.[28] Consistent with Proposition 2, the results show that sales dispersion is increasing in financial development, especially in financially vulnerable industries, where firms are more dependent on external finance or have fewer tangible assets. In column (2), we add the proxies for export opportunities.[29] We find skill endowment, capital endowment and institutional quality to raise sales dispersion relatively more in industries that are skill and capital intensive, or dependent on relationship-specific investments. Hence, sales dispersion is also greater in the presence of better export opportunities, consistent with Proposition 2.

In column (3), we replace the country, industry and year fixed effects with country-year (α_{ot}) and industry-year (α_{it}) fixed effects. The latter soak up all shocks hitting a given country or sector in a year.[30] Hence, to identify the coefficients, in this specification we exploit the combination of cross-country variation in financial development and endowments within a year, and cross-industry variation in financial vulnerability and factor intensities. Reassuringly, the interaction coefficients are largely unchanged. In column (4), we augment the previous specification by including a full set of interactions between countries' Consumer Price Indexes and industry dummies. These variables are meant to control for country-industry specific changes in the price indexes (see, e.g., Manova, 2013). Our main evidence is unaffected. Finally, in column (5) we control for the number of products exported to the

[27] 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 investment in each industry, sourced from Nunn (2007).

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

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

[30] The country-time and industry-time effects also absorb all country- and industry-specific determinants of sales dispersion. These include the elasticity of substitution, as well as the country and industry components of variable trade costs (e.g., distance and bulkiness).

US within each country-industry-year triplet. This variable has a positive but very small coefficient, and its inclusion does not make any noteworthy change in our main results. This suggests that sales dispersion is not mechanically driven by the number of products on which it is constructed. Furthermore, to make sure that the effect of financial development is not confounded by any correlation with the number of exported products, from now on we control for the latter variable in most of the specifications.

4.3.3 Robustness Checks

In this section, we submit the baseline estimates to a large number of robustness checks. We focus on the richest specification reported in column (5) of Table 3.

Alternative samples In Table 4, we address a number of potential concerns with the composition of the estimation sample. We start by showing that our evidence is not driven by the sample of 10-digit HS products used to construct the measures of sales dispersion. In particular, in column (1) we find similar results when excluding country-industry-year triplets with only two products exported to the US. In column (2), we instead confirm the main evidence by re-computing SD_{oit} after excluding products with limited exports to the US, i.e., products that fall in the bottom 25 percent of exports within each country-industry-year triplet.[31]

In columns (3)-(6), we use different approaches for accommodating observations with missing sales dispersion, which correspond to triplets that have either zero or one product exported to the US. A possible concern is that, if the missing values are not random, our evidence might be driven by sample selection bias. We start by addressing this issue with a two-step model à la Heckman (1979). In particular, in column (3) we estimate a Probit model for the probability of observing a triplet with non-missing sales dispersion. The results show that sales dispersion is more likely to be observed in financially developed countries, especially in industries with greater financial vulnerability.[32] Then, using predicted values from column (3), we construct the inverse Mills ratio and include it as an additional control in the main equation (column 4).[33] The coefficient on the inverse Mills ratio is positive

[31] In unreported specifications, we have also estimated the baseline regression after excluding countries with extreme values of private credit (Japan an Sierra Leone) and industries with extreme values of financial vulnerability (SIC 2111, 2836, 3844 and 2421). The coefficients (available upon request) were very close to the baseline estimates, suggesting that our main results are not driven by outliers.

[32] Helpman et al. (2008) and Manova (2013) use a similar two-step model for correcting the estimates of gravity equations from sample selection bias. Consistently, the Probit results in column (3) are similar to those in Manova (2013), who finds the probability of observing a trade flow to be increasing in the exporter's financial development, the more so in financially vulnerable industries.

[33] We omit the number of products from columns (3) and (4), because this variable creates convergence problems when estimating the Probit model. The reason is that the number of products is zero for most

and precisely estimated, indicating that the errors of the two equations are correlated, but it is also small in size. Accordingly, correcting the estimates for sample selection yields coefficients that are practically identical to the baseline ones reported in column (4) of Table 3.[34] In column (5), we instead exclude small countries (those with less than 5 million people in 2006) and concentrate on large exporters, for which we observe sales dispersion in the vast majority of industries and years. Alternatively, in column (6) we re-define industries at the 3-digit level, since triplets with missing sales dispersion are less numerous when industries are more aggregated, as shown in Table 1. Despite the drop in sample size, our evidence is unchanged also in these specifications.

Finally, in column (7) we further restrict the sample to a consistent set of 8,548 products that are present in the HS classification during all years between 1989-2006, and we re-construct the measures of sales dispersion using these products only. While the HS classification has been partly restructured over the sample period (Schott and Pierce, 2012), the main results are unchanged, suggesting that they are not driven by the modifications occurred over time in the product classification.

Alternative proxies In Table 5, 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 system, namely, deposit money bank assets, liquid liabilities and domestic credit as a share of GDP (columns 1-3).[35] The results always show that financial development increases sales dispersion especially in financially vulnerable industries. In column (4) we use instead the log lending rate, which measures the cost incurred by firms for obtaining credit, and is therefore an inverse proxy for the size and efficiency of the

of the triplets in which the dependent dummy variable is also zero (see Table 1 for details). This creates nonconcavities in the log-likelyhood function, and prevents convergence. The estimates in column (4) should thus be compared with those reported in column (4) of Table 3, which excludes as well the number of products.

[34] The coefficients reported in columns (3) and (4) of Table 4 are identified through the implicit assumption that the errors of the two equations are jointly normal. In untabulated regressions (available upon request), we have estimated the Probit model using the lagged dependent variable as an additional regressor, which is excluded from the main equation in column (4) (see Johnson, 2012). This variable has strong predicted power, consistent with the existence of fixed export costs. At the same time, our coefficients of interest were very close to those reported in column (4). One caveat with this specification is that past participation in trade may be correlated with some unobserved determinant of sales dispersion.

[35] 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, proxy for the size of the financial sector. 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 (2017) for more details.

financial system.[36] Consistent with this interpretation, we find the interactions involving the lending rate to have the opposite signs as those involving private credit or other proxies for size.

Next, we porform robustness checks using alternative proxies for financial vulnerability. In column (5), we replace our main measures with equivalent indicators based on data for the pre-sample decade (1979-1988). In column (6), we instead replace the actual values of EF_i and AT_i with the rankings of industries in terms of these two variables.[37] The results are similar to the baseline estimates, consistent with the idea that cross-industry differences in financial vulnerability are mostly driven by technological factors, which tend to persist both across countries and over time. Finally, in column (7) we use the age of firms in an industry as an alternative proxy for financial vulnerability, as younger firms typically rely more on external funding than more established ones. We proxy for firm age using the log median number of years in which firms in an industry are listed in the US stock market, based on data from Compustat. Remarkably, we find the interaction of financial development with firm age to be negative and very precisely estimated, implying that financial frictions have stronger effects on sales dispersion in industries that are populated by younger firms. Hence, our evidence is remarkably robust across different proxies for financial vulnerability.

Alternative estimation approaches We now show that our main evidence holds when using alternative ways of measuring sales dispersion and alternative strategies for estimating the baseline specification. The results are reported in Table 6. We start by running weighted regressions, which give more weight to triplets with a larger number of products, for which sales dispersion may be measured more precisely. In particular, in column (1) we weight the regression with the log number of products; taking logs avoids giving excessive weight to a few, exceptionally large, triplets. In column (2), we instead weight the regression using industries' shares in the total number of products exported by a given country to the US in each year; using shares accommodates differences in the number of products sold by different countries in the US. In both cases, the coefficients on the financial variables are close to our baseline estimates.

Next, we use an alternative estimate of sales dispersion. As a baseline measure, we have chosen the standard deviation of log sales both because it is easy to build and interpret, and because it is consistent with the theoretical model. However, under the assumption that sales are Pareto distributed, as in our model, the same measure of dispersion can be estimated as the inverse of the shape parameter. To check that the results are indeed robust

[36] 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 the OECD.

[37] To ease the interpretation of the coefficients, we normalize the rankings between 0 and 1.

to these alternative measures of dispersion, we estimate a separate shape parameter for each country-industry-year triplet, by running regressions of log sales rank on log sales across 10-digit products; the shape parameters are the absolute values of the coefficients on log sales obtained from these regressions.[38] It is reassuring that the correlation between the two measures of sales dispersion is extremely high (0.97).

In column (3), we use the new measures of sales dispersion in place of the standard deviation of log sales. We bootstrap the standard errors by re-sampling observations within country-industry pairs, to account for the estimation of the shape parameters in the first stage. Using the inverse of the Pareto shape parameter we obtain coefficients that are very close to our baseline estimates for the standard deviation of log exports. An additional advantage of the Pareto shape parameters is that, since they are estimated, they come with a measure of fit. We exploit this information in column (4), where we repeat the previous specification, but we now weight the observations with the inverse of the standard errors of the Pareto shape parameters. This allows us to give less weight to triplets for which sales dispersion is estimated less precisely. We find no noteworthy change in the main coefficients. Finally, in column (5) we re-estimate the weighted regression using firm age as an alternative proxy for financial vulnerability. We continue to find strong evidence that financial development raises sales dispersion more in financially vulnerable industries.

Additional controls A possible concern with our baseline results is that the coefficients on financial development may pick up the effects of omitted variables, which are correlated with financial frictions and may also influence sales dispersion. Our identification strategy partly allays this concern. Indeed, our specifications control for country-year and industry-year fixed effects, so the estimated coefficients do not reflect shocks hitting specific countries and sectors in a given year.

Hence, in this section we focus on factors that vary both across countries and over time, and that may have differential effects on sales dispersion across sectors. It is important to note that many such factors (i.e., export opportunities and price indexes) are already controlled for in all our specifications, and that their inclusion does not cause any significant change in our main results. Nevertheless, we now add further variables and study how they affect our coefficients of interest.

The results are reported in Table 7. In column (1), we include the interactions between real per-capita GDP and the two proxies for financial vulnerability, in order to account for the fact that richer countries are more financially developed. The coefficients on the new

[38] We exclude triplets with only two products exported to the US, as for these triplets there are fewer observations than parameters to be estimated. Moreover, following Gabaix and Ibragimog (2011), we adjust sales rank by subtracting 0.5, in order to correct for possible small-sample biases.

interactions are small and not very precisely estimated, suggesting that the effect of economic development on sales dispersion is not heterogeneous across industries. At the same time, our coefficients of interest are largely unchanged, suggesting that the baseline estimates are not contaminated by the correlation of financial development with per-capita income.

In columns (2)-(4), we add interactions between the measures of financial vulnerability and variables reflecting the degree of international integration and exposure to foreign competition of a country: import penetration and export intensity (column 2); the real exchange rate (column 3); and the ratio of outward FDI to GDP (column 4).[39] Including these variables does not make any noteworthy change in the main coefficients, suggesting that our estimates are not picking up the effects of different forms of international integration.

In column (5), we interact financial development with the total number of HS codes that belong to a 4-digit SIC industry in a given year. One may worry that this number, which is determined by an administrative convention and has little intrinsic meaning, may mechanically drive the measures of sales dispersion. Yet, including the new interaction leaves our main results unaffected. In column (6) we include all these controls in the same specification. Our main evidence is unchanged also in this demanding exercise. Finally, in column (7) we re-estimate the last specification using firm age to proxy for financial vulnerability. Our conclusions continue to hold.

Other issues The previous sections suggest that our results are unlikely to reflect time-varying shocks occurring in a given country or industry, or the effects of many confounders that vary at the country-industry level. In this section, we discuss other potential identification issues. The first concern is that even the large set of controls used in Table 7 might fail to fully account for time-varying shocks hitting specific country-industry pairs. While we cannot control for country-industry-year effects, in column (1) of Table 8 we introduce a full set of fixed effects for triplets of broad geographical areas, 3-digit industries and years.[40] These fixed effects soak up all time-varying shocks hitting a certain 3-digit sector within a region. As a result, identification now only comes from the remaining variation in financial development across nearby countries, as well as from the remaining variation in financial vulnerability across narrow industries with similar technological content. Reassuringly, the coefficients remain similar to the baseline estimates also in this case.

[39] Import penetration and export intensity are, respectively, the ratio of imports over apparent consumption (GDP plus imports minus exports) and the export share of GDP; both variables are constructed with data from the World Development Indicators. The real exchange rate and the FDI share of GDP are sourced from the Penn World Table 8.1 and UNCTAD FDI Statistics, respectively.

[40] Geographical areas are seven regions defined by the World Bank: East Asia and Pacific; Europe and Central Asia; Latin America and the Caribbean; Middle East and North Africa; North America; South Asia; and Sub-Saharan Africa.

The second concern is that our estimates may be driven by differential trends across country-industry pairs. In columns (2)-(4), we therefore control for underlying trends based on pre-existing characteristics of each pair. To this purpose, we interact the time dummies with the first-year value of the characteristic indicated in each column. The coefficients are stable across the board.

The third concern is that our results may be contaminated by unobserved, time-invariant, heterogeneity across country-industry pairs. In columns (5) and (6), we address this concern by exploiting the panel structure of the data and including country-industry fixed effects in place of the country-year effects. Compared to previous specifications, we therefore exploit a different source of variation, which is provided by changes in financial development and factor endowments over time within a country, rather than by differences in these variables across countries. Accordingly, this approach is not well-suited to study the effects of export opportunities, because a proper test of comparative advantage requires comparing different countries, as we do in our main specifications. On the contrary, this alternative approach is still well-suited to test the effect of financial frictions, as our theoretical mechanism predicts that sales dispersion should increase after an improvement in financial conditions within a country. We report results for both the whole sample of countries (column 5) and the subsample of economies that have experienced a banking crisis during the sample period (column 6).[41] For the latter countries, changes in private credit have been larger, thereby providing us with greater time variation for identification. Reassuringly, our evidence is unchanged also in these very demanding specifications.

Cross-sectional and IV estimates Finally, we present a set of cross-sectional results, which are obtained by replacing all time-varying variables with their long-run mean over 1989-2006. These regressions further ensure that our main coefficients are not contaminated by temporary shocks hitting a given country-industry pair. The results are reported in Table 9. In spite of a dramatic loss of observations, the coefficients shown in column (1) are similar to the baseline panel estimates. In column (2), we compare the results based on private credit with those obtained using an index for the quality of institutions that affect credit access. In particular, we use an index for the effectiveness of the legal system at resolving insolvencies.[42] This index is time invariant, and can thus be meaningfully used only in a cross-sectional set-up. The results confirm our baseline evidence. In column (3), we re-run the regression reported in column (1), but we esclude the country fixed effects. Unlike the previous specifications, this one allows us to identify the linear term in financial development,

[41] We use information on systemic banking crises from Laeven and Valencia (2012).

[42] We source this index from the World Bank Doing Business Database; we normalize it to range between 0 and 1, and so that higher values correspond to countries with a higher position in the ranking (i.e., better institutions).

and can thus be used to quantify the overall effect of financial frictions on sales dispersion, besides their differential effect across industries (see the next section). The results are close to those reported in column (1).

Finally, we discuss possibly remaining concerns with endogeneity. As previously shown, our coefficients are robust to controlling for a wide range of factors, suggesting that our evidence is unlikely to reflect simultaneity bias due to omitted variables. Other features of the empirical set-up help allay concerns with reverse causality. The latter would occur if sales dispersion increased in a given country and industry for reasons unrelated to financial development, and if this, in turn, affected the financial variables in a way that could explain the specific pattern of our coefficients. Note, however, that the financial vulnerability measures are based on US data and kept constant over time. Thus, these measures are unlikely to respond to changes in sales dispersion occurring in specific countries and industries. Second, we have shown that our results are unchanged across alternative financial vulnerability measures, and when using proxies based on data for the previous decade. It is unlikely that changes in sales dispersion over the sample period could drive the variation in all of these alternative indicators. Third, 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 a time-invariant index for the quality of financial institutions, which are unlikely to respond to changes in sales dispersion in a given year.

Yet, we now show that our evidence is also 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 sales dispersion. The results are reported in columns (4)-(6) of Table 9. Following La Porta, Lopez-de-Silanes and Shleifer (2008), we instrument the proxies for financial development using dummies for whether countries' legal systems are of civil law (French, German or Scandinavian origins). Consistent with La Porta, Lopez-de-Silanes and Shleifer (2008), we find the nature of countries' legal systems to be a strong predictor of financial development, suggesting that differences in financial frictions across countries to a large extent reflect historical differences in countries' legal origins. More importantly, our main evidence is preserved also in these specifications.

4.3.4 Economic Magnitude

We now quantify the effect of financial development on sales dispersion. To this purpose, we use the estimates reported in column (3) of Table 9 and study by how much sales dispersion would change following a certain increase in private credit. We start from the average effect, i.e., the effect on the industry with the average levels of financial vulnerability. Our estimates imply that an increase in private credit from the $25th$ percentile of the distribution (17%, roughly the level of Peru) to the $75th$ percentile (68%, approximately the level of South Korea) would raise sales dispersion by 12.9% on average. For comparison, a commensurate increase in skill (capital) endowment would raise sales dispersion by 8% (15%) in the average industry. The effects of financial development are therefore in the same ballpark as those of export opportunities. These estimates also imply that the observed increase in private credit over the sample period (15 p.p.) could explain 59% of the increase in sales dispersion between 1989 and 2006.

Next, we turn to the differential effect of financial development across industries with different levels of financial vulnerability. Our estimates imply that an increase in private credit from the $25th$ to the $75th$ percentile would raise sales dispersion by 11.7% in the industry at the first quartile of the distribution by external finance, and by 13.5% in the industry at the third quartile. The same increase in private credit would raise sales dispersion by 11.4% in the industry at the third quartile of the distribution by asset tangibility, and by 14.5% in the industry at the first quartile.

4.4 Trade, Finance and Sales Dispersion

The previous sections have shown that financial development increases sales dispersion especially in financially vulnerable industries. In turn, according to our model, higher sales dispersion should raise both the number of exported products (extensive margin) and exports per product (intensive margin), thereby increasing overall exports. It follows that sales dispersion provides a mechanisms through which financial development could affect export flows across countries and industries. We now provide some evidence on this mechanism.

The results are reported in Table 10. In columns (1)-(3), we start by studying how sales dispersion correlates with overall exports and the two margins of trade. To this purpose, we regress log total exports, log number of exported products and log exports per product, respectively, on sales dispersion, controlling for country-year and industry-year effects, as well as for the interactions between countries' CPI and industry dummies. All coefficients are positive and very precisely estimated. Consistent with our model, greater sales dispersion in a given country and industry is associated with larger exports to the US, more exported products and greater exports per product. In columns (4)-(6) we replace sales dispersion with its main determinants according to our model and previous empirical results; namely, with the interaction between financial development and financial vulnerability, as well as with export opportunities. The results confirm the well-known fact that financial development increases exports relatively more in financially vulnerable sectors (Beck, 2002, Manova, 2013), as well as 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 skill and capital intensive, or dependent on relationship-specific investments (Romalis, 2004, Levchenko, 2007, Nunn, 2007, Chor, 2010). Finally, in columns (7)-(9) we include all variables simultaneously. The coefficients on sales dispersion remain unchanged, while those on financial development and export opportunities drop in size, suggesting that part of the effect of these variables on exports works through the dispersion of sales.

4.5 Sales Dispersion, Finance and Innovation

In this final section, we provide some evidence on the mechanism through which financial development affects sales dispersion. In the model, firm heterogeneity depends on the innovation strategies chosen by firms. Financial development induces firms to invest in bigger projects with more dispersed outcomes. This translates into a larger share of revenue invested in innovation (as shown in Bonfiglioli, Crinò and Gancia, 2016) and also a higher incidence of "major" innovations: for any cutoff x, $\Pr(\varphi > x)$ increases with v. Are these predictions consistent with the data?

To answer this question, we need comparable measures of investment in major innovations across countries, sectors and time, which are not easy to come by. Once again, however, we can overcome the challenge relying on high-quality US data. In particular, we use the number of utility patents applied for at the US Patent Office (USPTO), computed separately for each foreign country, industry and application year. We source the raw patent data from the NBER Patent Data Project. Between 1989 and 2006, a total of 898,589 patents were applied for by foreign entities at the USPTO. These patents belong to 2,183 technology classes, defined according to the International Patent Classification. We map these technology classes into SIC industries using a correspondence table developed by Silverman (1999). Patenting is a relatively rare activity, which is typically concentrated in few countries. For instance, only 49 of the 119 countries in our sample have applied for a patent in at least one of the 365 manufacturing industries between 1989 and 2006. As a consequence, approximately 80% of the country-industry-year triplets in our sample have zero patent count.[43] On the other hand, a unique feature of the USPTO data is that they provide a measure of innovation that is easy to compute and comparable across countries and industries. Another advantage of this measure is that, since only significant innovations are patented in the US, foreign patent applications can be taken as a reasonable proxy for the outcome of major innovation projects.

We start by showing that sales dispersion is positively correlated with innovation, as predicted by the model. To this purpose, we regress sales dispersion on patent count across country-industry-year triplets, controlling for country-year fixed effects, industry-year fixed

[43] We consider various ways for dealing with the zeros in the regression analysis below.

effects and the interactions between countries' CPI and industry dummies. The results are reported in Table 11. In column (1), we use the whole sample, while in column (2) we restrict to the sub-sample of observations with positive patent count. Finally, in column (3) we replace the country-year effects with country-industry effects, in order to exploit time variation within country-industry pairs for identification. In all cases, the coefficient on patent count is positive and precisely estimated. While we cannot make any claim regarding causality, this evidence is nevertheless consistent with the model.

Next and more importantly, we study how financial frictions affect innovation. To this purpose, we estimate the baseline specification (see column 5 of Table 3) using patent count instead of sales dispersion as the dependent variable. The results are reported in Table 12. In column (1), we use the whole sample of observations. Consistent with the model, we find that financial development increases innovation relatively more in financially vulnerable industries. In column (2), we restrict to the sub-sample of observations with positive patent count. The coefficients have the same sign as in column (1), and are now even larger. While one coefficient is marginally insignificant (p-value 0.135), this reflects the reduced sample size. Indeed, when the two interactions are included individually rather than jointly (columns 3 and 4), both coefficients regain significance and maintain their size. In column (5), we alternately deal with the presence of zeros in the patent count variable by using a zero-inflated Poisson model. The coefficients have the same sign as before and are both highly significant. In columns (6) and (7), we use firm age as a proxy for financial vulnerability, focusing on the whole sample and on the sub-sample of observations with positive patent count, respectively. The results confirm that financial development raises innovation relatively more in financially vulnerable industries.

Finally, in Table 13 we re-estimate the previous specifications by replacing time-varying variables with their long-run averages. This reduces the incidence of zero patent counts, because our innovation variable is now positive as long as at least one patent was registered at the USPTO within a country-industry pair between 1989 and 2006. We also report results for IV specifications, estimated on the whole sample (column 8) or on the sub-sample of observations with positive patent count (column 9). The main results are preserved, and our coefficients of interest are similar in size to those of the panel 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 allow less productive firms to survive and hence lower 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 have 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 sales dispersion, especially in more financially vulnerable industries; sales dispersion is also increasing in measures of comparative advantage. Moreover, sales dispersion is important for explaining the effects 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 for financing foreign than domestic activities. The origin of this asymmetry is however not entirely clear. Existing explanations also face the challenge that export 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. In particular, our empirical results help identifying the mechanism through which financial development increases the volume of exports especially in financially vulnerable sectors, suggesting that part of the overall effect works through the dispersion of sales. Third, our results also contribute to understanding why firms are smaller and relatively more homogeneous in less developed countries. Finally, since more productive firms also pay higher wages, this paper also hints to an overlooked channel through which financial development may affect wage inequality.[44] Exploring more in detail this mechanism seems an interesting avenue for future research.

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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 (9) to define

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

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. 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

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

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 (9).[45] Hence, $\frac{\partial^2(v_{oi})}{\partial\delta_o\partial\kappa_i}<0$.

[45] In particular, $d\ln\left(\frac{\varphi_{ooi}^*}{\varphi_{\min}}\right)^{1/v_{oi}}/d\ln v_{oi}=\left(1-v_{oi}(\sigma_i-1)\right)^{-1}+\left(\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}\ln\rho_{doi}^{-1/v_{oi}}\right)/\left(\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}\right)-v_{oi}F'\left(v_{oi}\right)/F\left(v_{oi}\right)$, which under (9) is equal to $-\ln\left(\frac{\varphi_{ooi}^*}{\varphi_{\min}}\right)^{1/v_{oi}}$.

6.2 Mean-Preserving Spreads

We now consider the case in which $\varphi_{\min} = \bar{\varphi}(1 - v_{oi})$ so that the mean $\mathbb{E}[\pi_{oi}] = \bar{\varphi}$ is constant, while an increase in v_{oi} is still associated to a higher variance, $SD[\ln\varphi] = v_{oi}$. Thus, an increase in v corresponds to a mean-preserving spread. Although the evidence in Bonfiglioli, Crinò and Gancia (2016) suggests that the mean and the variance of productivity are likely to be linked, we nevertheless want to show that the main results in the paper still hold if firms can only choose the dispersion of the productivity draw.

Assuming $\varphi_{\min} = (1 - v_{oi})\bar{\varphi}$, *ex-ante* expected profits become:

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

The first order condition for an interior v_{oi} is:

$$\frac{\mathbb{E}[\pi_{oi}]}{v_{oi}} \left[\frac{1}{1 - v_{oi}(\sigma_i - 1)} - \frac{1}{1 - v_{oi}} + \ln\left(\frac{\varphi^*_{ooi}}{\varphi_{\min}}\right)^{1/v_{oi}} + \frac{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}} \ln\rho_{doi}^{-1/v_{oi}}}{\sum_d f_{doi}\rho_{doi}^{1/v_{oi}}}\right] = w_o\lambda_{oi}F'(v_{oi}). \tag{12}$$

Clearly, the fact that the mean of φ is constant lowers the marginal benefit of v_{oi}, as captured by the new term $-1/(1-v_{oi})$ in the left-hand side. Notice that $\varphi^*_{ooi}/\varphi_{\min}$ is still pinned down by the exit condition (10) as in the baseline model. Comparing (12) to (9) it is easy to see that the comparative statics for v_{oi} are qualitatively unchanged, provided that σ is high enough ($\sigma > 2$ is a sufficient condition). Yet, the degree of dispersion chosen in equilibrium is lower in the case of mean-preserving spreads.

We now show that the implications for the distribution of revenues, conditional on v_{oi}, are also identical. Since revenue from market d of firms from country o operating in sector i is $r_{doi}(\varphi) = r_{doi}(\varphi^*_{doi})(\varphi/\varphi^*_{doi})^{(\sigma_i - 1)}$, it follows that $r_{doi}(\varphi)$ is Pareto distributed with c.d.f. $G_r(r) = 1 - (r_{\min}/r)^{1/(v_{oi}(\sigma_i - 1))}$, for $r > r_{\min} = \sigma_i w_o f_{doi}$. Note that revenue of the marginal firm is independent of the productivity distribution because it is pinned down by the exit condition. It then follows that the formulas for the volume of trade are also unchanged. Even if the unconditional average of the productivity distribution does not change with dispersion, since the level of sales of the marginal firm is constant, average sales of operating firms still increase with dispersion. This does not mean that the volume of trade is the same in the two versions of the model. The volume of export is lower relative to the baseline case because the equilibrium v_{oi} is lower, but the way in which it varies with v_{oi} is unchanged.

6.3 Adding Financially Unconstrained Firms

We now sketch a version of the model in which in each industry there is an exogenous mass of entering firms which are not subject to the financial friction, i.e., for them $\lambda_{oi} = 1$. We denote these firms with the superscript u for "unconstrained" and assume that their measure is fixed exogenously. When entering, these firms will choose v^u_{oi} so as to maximize:

$$\max_{v^u_{oi}} \left\{\mathbb{E}[\pi^u_{oi}] - w_o F(v^u_{oi})\right\}.$$

Besides the entry stage, all firms with a given productivity are however identical. Hence, the first-order condition of unconstrained firms is:

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

Note that the left-hand side is identical for all firms. This is so because, after the entry cost is paid, all firms with a given productivity are identical. Moreover, the exit cutoff is the same for all firms. Thus, the value of drawing productivity from any distribution does not depend on whether the firm is constrained or not. The right-hand side is however different: unconstrained firms face a lower cost of financing the entry investment. Then, the assumption that F is sufficiently convex to make the maximand concave immediately implies that unconstrained firms choose a larger entry investment: $v_{oi}^{u} > v_{oi}$.

Given that unconstrained firms face a lower entry cost, they have a strictly stronger incentive to enter. However, the number of potential unconstrained entrants is fixed (we assume that a firm is a technology, so that an unconstrained firm with an unsuccessful product cannot re-enter). We then focus on the most interesting case in which unconstrained firms are so few that, after they have all drawn their productivity, entry is still profitable for financially constrained firms.[46] Under this assumption, constrained firms, denoted by a superscript c, will continue entering until the free-entry condition $\mathbb{E}\left[\pi_{oi}^{c}\right]=w_o\lambda_{oi}F\left(v_{oi}^{c}\right)$ is satisfied for them. This implies that the exit cutoff $\varphi_{ooi}^{*}/\varphi_{\min}$ is determined as in the baseline model. The choice of v_{oi}^{c} is also identical to the baseline model.

One key difference now is that in equilibrium there are two types of firms, with different distributions of revenues. On average, financially unconstrained firms are larger and make positive profits. The revenue of unconstrained firms selling to market d from country o in sector i is distributed as a Pareto with c.d.f. $G_r(r)=1-\left(r_{\min}/r\right)^{1/(v_{oi}^{u}(\sigma_i-1))}$, for $r > r_{\min}=\sigma_i w_o f_{doi}$. The distribution of revenues of constrained firm is also Pareto, it has the same minimum, $r_{\min}$, but a different shape parameter: $v_{oi}^{c}(\sigma_i-1) < v_{oi}^{u}(\sigma_i-1)$. The overall distribution is not Pareto anymore. However, its dispersion can still be characterized analytically using as a measure the Theil index, which has the advantage of being a weighted average of inequality within subgroups, plus inequality between those subgroups. In particular, denote $T\left(r_{doi}\right)$ as the Theil index of overall inequality of revenues in the destination country d in industry i for firms selling from the country of origin o, and denote the groups of constrained and unconstrained firms with the superscript $k\in\{u,c\}$. Then:

$$T\left(r_{doi}\right)=\int_0^{\infty}\frac{r_{doi}}{\bar{r}_{doi}}\ln\left(\frac{r_{doi}}{\bar{r}_{doi}}\right)\mathrm{d}\Phi(r_{doi})=\textstyle\sum_k\theta_{doi}^{k}T(r_{doi}^{k})+\sum_k\theta_{doi}^{k}\ln\frac{\bar{r}_{doi}^{k}}{\bar{r}_{doi}},\quad k\in\{u,c\}$$

where $\bar{r}_{doi}$ is average revenue, $\Phi(r_{doi})$ is the cumulative revenue distribution, $\bar{r}_{doi}^{k}$ is average revenue in group k, $T(r_{doi}^{k})$ is the Theil index of dispersion within group k and θ_{doi}^{k} is the revenue share of group k firms.

[46] The other case is trivial, in that it coincides with the equilibrium of an industry not subject to any financial friction.

Given that within each group revenues follow a Pareto distribution we have:

$$T(r_{doi}^{k}) = \ln(1 - v_{doi}^{k}) + \frac{v_{doi}^{k}}{1 - v_{doi}^{k}}.$$

It is easy to show that this within-group Theil index is increasing in the dispersion of the Pareto distribution as measured by the parameter v_{doi}^{k}:

$$\frac{\partial T(r_{doi}^{k})}{\partial v_{doi}^{k}} > 0.$$

Since $T(r_{doi}^{u}) > T(r_{doi}^{c})$ and $\bar{r}_{doi}^{u} > \bar{r}_{doi}^{c}$, it follows that the overall Theil index is increasing in the share of financially unconstrained firms:

$$\frac{\partial T\left(r_{doi}\right)}{\partial \theta_{doi}^{u}} = \left[T(r_{doi}^{u}) - T(r_{doi}^{c})\right] + \ln \frac{\bar{r}_{doi}^{u}}{\bar{r}_{doi}^{c}} > 0.$$

Moreover, since the difference between v_{doi}^{u} and v_{doi}^{c} in increasing in the level of financial frictions, λ_{oi}, we also have:

$$\frac{\partial^2 T\left(r_{doi}\right)}{\partial \theta_{doi}^{u} \partial \lambda_{oi}} > 0.$$

In sum, revenue is more dispersed the higher the share of financially unconstrained firms, and the effect is stronger in countries or sectors in which firm-level financial frictions are more severe.

Table 1 - Sample Composition

	Country-Industry Pairs		Number of HS-10 Products				Imports ($ '000)			
	Number	% of Total Number	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.
a) Sample: 119 Countries and 365 (4-Digit) Industries. Year: 2006										
All Country-Industry Pairs	43435	1.00	6	0	0	608	33083	0	0	47181989
Pairs w/no HS-10 Product Exported to the US	21809	0.50	0	0	0	0	0	0	0	0
Pairs w/1 HS-10 Product Exported to the US	4830	0.11	1	1	1	1	563	11	0.3	201813
Pairs w/2+ HS-10 Products Exported to the US	16796	0.39	15	7	2	608	85393	1727	0.5	47181989
b) Sample: 119 Countries and 131 (3-Digit) Industries. Year: 2006										
All Country-Industry Pairs	15589	1.00	16	2	0	804	92545	29	0	62961319
Pairs w/no HS-10 Product Exported to the US	5876	0.38	0	0	0	0	0	0	0	0
Pairs w/1 HS-10 Product Exported to the US	1614	0.10	1	1	1	1	797	9	0.3	115469
Pairs w/2+ HS-10 Products Exported to the US	8099	0.52	31	12	2	804	177972	2484	0.5	62961319

All statistics use product-level data on exports to the US at the 10-digit level of the Harmonized System (HS) classification (Feenstra, Romalis and Schott, 2002). The sample consists of 119 countries that have exported to the US in at least one industry during all years between 1989-2006. Industries are defined at the 4-digit level of the Standard Industrial Classification (SIC) in panel a) and at the 3-digit SIC level in panel b); in each panel, the sample includes industries in which at least one country has exported to the US during all years between 1989-2006. The standard deviation of log exports (used in subsequent tables) can be defined for country-industry pairs that have at least two HS-10 products exported to the US; it is instead undefined (i.e., missing) for the other country-industry pairs.

Table 2 - Descriptive Statistics on Sales Dispersion

	Mean	Std. Dev.	Change	Mean	Std. Dev.	Change
	a) Consistent Countries and Industries			***b) Consistent Countries, Industries and Products***		
Sales Dispersion	1.94	0.88	0.06	1.92	0.92	0.07
N. Products	15	25	2	11	17	0
	c) Cross-Industry			***d) Cross-Country***		
Sales Dispersion	1.62	0.84	0.11	1.95	0.87	0.11
N. Products	9	12	2	12	10	2

Sales 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 10-digit product level. The number of products is the number of 10-digit product codes used to compute the measures of sales dispersion. Mean and standard deviation refer to the year 2006; changes are computed over 1989-2006, and are expressed in percentages for sales 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) uses the same sample 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. The statistics in panels a) and b) are computed across all country-industry observations. The statistics in panel c) are computed across industries within a given country, and are then averaged across the 119 countries. The statistics in panel d) are computed across countries within a given industry, and are then averaged across the 365 industries.

Table 3 - Sales 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***	0.040***	0.037***
	[0.012]	[0.011]	[0.012]	[0.013]	[0.013]
Fin. Dev. * Asset Tangibility	-0.150**	-0.219***	-0.259***	-0.398***	-0.411***
	[0.076]	[0.078]	[0.079]	[0.085]	[0.085]
Skill Endowment		0.692***			
		[0.100]			
Capital Endowment		-0.247***			
		[0.033]			
Skill End. * Skill Intensity		0.350***	0.384***	0.256***	0.246***
		[0.037]	[0.039]	[0.044]	[0.044]
Cap. End. * Capital Intensity		0.067***	0.067***	0.062***	0.059***
		[0.006]	[0.006]	[0.009]	[0.009]
Institutional Quality * Contract Intensity		0.172*	0.107	0.164	0.109
		[0.104]	[0.105]	[0.139]	[0.139]
N. Products					0.003***
					[0.000]
Obs.	234,112	229,128	229,128	229,128	227,583
R2	0.19	0.12	0.23	0.25	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	yes	yes

The dependent variable is sales dispersion (the standard deviation of log exports), computed separately for each exporting country, industry and year, using data on exports to the US at the 10-digit product 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 that are 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 (reported in square brackets) are corrected for two-way clustering by country-industry and industry-year. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively.

Table 4 - Sales Dispersion and Finance: Alternative Samples

	At Least 3 Products	No Small Products	Probit	Heckman Correct.	No Small Countries	3-Digit Ind.	Consist. Prod.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fin. Dev. * Ext. Fin. Dep.	0.031**	0.035***	0.060***	0.041***	0.037***	0.059***	0.054***
	[0.013]	[0.012]	[0.005]	[0.013]	[0.013]	[0.017]	[0.020]
Fin. Dev. * Ass. Tang.	-0.381***	-0.185**	-0.693***	-0.384***	-0.393***	-0.208*	-0.282**
	[0.084]	[0.079]	[0.028]	[0.085]	[0.086]	[0.111]	[0.130]
Skill End. * Skill Int.	0.240***	0.129***	0.288***	0.266***	0.258***	0.156***	0.131*
	[0.047]	[0.039]	[0.007]	[0.044]	[0.047]	[0.056]	[0.068]
Cap. End. * Cap. Int.	0.060***	0.040***	0.017***	0.064***	0.061***	0.051***	0.036**
	[0.009]	[0.007]	[0.001]	[0.008]	[0.009]	[0.013]	[0.016]
Inst. Qual. * Contr. Int.	-0.126	0.056	2.380***	0.242*	0.063	0.442**	0.379*
	[0.143]	[0.127]	[0.025]	[0.140]	[0.146]	[0.185]	[0.213]
N. Prod.	0.003***	0.001***			0.003***	0.002***	0.002***
	[0.000]	[0.000]			[0.000]	[0.000]	[0.000]
Inverse Mills Ratio				0.101***			
				[0.021]			
Obs.	189,522	227,583	566,020	229,128	197,095	110,346	95,502
R2	0.28	0.16		0.25	0.26	0.32	0.28
Country-Year FE	yes	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes	yes	yes	yes	yes

Except for column (3), the dependent variable is sales dispersion (the standard deviation of log exports), computed separately for each exporting country, industry and year, using data on exports to the US at the 10-digit product level. In column (3), the dependent variable is instead a dummy, which takes the value of 1 for country-industry-year triplets with two or more products exported to the US (i.e., triplets for which sales dispersion is defined) and the value of 0 for the remaning triplets (for which sales dispersion is not defined). Column (1) uses country-industry-year observations for which sales dispersion is based on at least three products exported to the US. In column (2), sales dispersion is computed after excluding the bottom 25% of products (with the smallest value of exports) in each country-industry-year triplet. In column (4), the inverse Mills ratio is constructed as in Heckman (1979), using predicted values from the first-stage Probit regression reported in column (3). Column (5) excludes countries with less than 5 million people in 2006. Column (6) defines industries at the 3-digit (instead of 4-digit) level. Column (7) further constructs sales dispersion using a consistent set of 10-digit product codes (8548) that are present in the HS classification in all years between 1989 and 2006. All time-varying regressors are lagged one period. Standard errors (reported in square brackets) are corrected for two-way clustering by country-industry and industry-year, except in column (3), where they are corrected for clustering at the industry-year level. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 5 - Sales Dispersion and Finance: Alternative Proxies

	Bank Assets	Liquid Liabilities	Domestic Credit	Lending Rate	Lagged Fin. Vuln.	Rankings of Fin. Vuln.	Firm Age
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fin. Dev. * Ext. Fin. Dep.	0.043***	0.026**	0.031***	-0.042***	0.049***	0.111***	
	[0.013]	[0.013]	[0.012]	[0.007]	[0.010]	[0.032]	
Fin. Dev. * Ass. Tang.	-0.527***	-0.639***	-0.401***	0.171***	-0.296***	-0.176***	
	[0.080]	[0.081]	[0.077]	[0.048]	[0.098]	[0.035]	
Fin. Dev. * Firm Age							-0.118***
							[0.030]
Skill End. * Skill Int.	0.250***	0.240***	0.253***	0.185***	0.247***	0.247***	0.252***
	[0.044]	[0.044]	[0.044]	[0.047]	[0.044]	[0.044]	[0.044]
Cap. End. * Cap. Int.	0.061***	0.061***	0.058***	0.035***	0.060***	0.060***	0.059***
	[0.009]	[0.009]	[0.009]	[0.010]	[0.009]	[0.009]	[0.009]
Inst. Qual. * Contr. Int.	0.064	0.093	0.121	0.325**	0.142	0.090	0.270**
	[0.139]	[0.137]	[0.139]	[0.146]	[0.139]	[0.140]	[0.136]
N. Prod.	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Obs.	226,881	229,112	230,843	216,037	227,296	227,583	228,192
R2	0.25	0.25	0.25	0.26	0.25	0.25	0.25
Country-Year FE	yes	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes	yes	yes	yes	yes

The dependent variable is sales dispersion (the standard deviation of log exports), computed separately for each exporting country, industry and year, using data on exports to the US at the 10-digit product level. Financial development is proxied by deposit money bank assets as a share of GDP in column (1), liquid liabilities as a share of GDP in column (2), domestic credit to the private sector as a share of GDP in column (3), and the log lending rate in column (4). In column (5), external finance dependence and asset tangibility are computed as averages over the pre-sample period, 1979-1988. In column (6), the actual values of external finance dependence and asset tangibility are replaced by the rankings of industries in terms of these variables; the rankings are based on data for 1989-2006 and are normalized between 0 and 1. In columns (7), firm age is the log median number of years in which firms in an industry are listed in the US stock market, based on data from Compustat. 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 (reported in square brackets) are corrected for two-way clustering by country-industry and industry-year. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 6 - Sales Dispersion and Finance: Alternative Estimation Approaches

	Weighted Regr.	Weighted Regr.	Pareto Shape Par.	Pareto Shape Par.	Pareto Shape Par.
	(1)	(2)	(3)	(4)	(5)
Fin. Dev. * Ext. Fin. Dep.	0.026**	0.037**	0.033***	0.025***	
	[0.012]	[0.017]	[0.007]	[0.006]	
Fin. Dev. * Ass. Tang.	-0.397***	-0.591***	-0.506***	-0.480***	
	[0.079]	[0.135]	[0.037]	[0.034]	
Fin. Dev. * Firm Age					-0.133***
					[0.005]
Skill End. * Skill Int.	0.260***	0.055	0.257***	0.196***	0.201***
	[0.045]	[0.065]	[0.008]	[0.008]	[0.009]
Cap. End. * Cap. Int.	0.063***	0.034***	0.077***	0.066***	0.065***
	[0.009]	[0.010]	[0.002]	[0.001]	[0.002]
Inst. Qual. * Contr. Int.	-0.299**	-0.455**	-0.275***	-0.353***	-0.154***
	[0.136]	[0.195]	[0.031]	[0.028]	[0.029]
N. Prod.	0.002***	0.001***	0.003***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Obs.	227,583	227,583	189,522	189,522	189,912
R2	0.29	0.41	0.25	0.44	0.44
Country-Year FE	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes	yes	yes

The dependent variable is sales dispersion. In columns (1) and (2), it is defined as the standard deviation of log exports, computed separately for each exporting country, industry and year, using data on exports to the US at the 10-digit product level. In columns (3)-(5), sales dispersion is instead constructed as the inverse of the shape parameter of the Pareto distribution. To estimate the shape parameter for each exporting country, industry and year, a regression of log sales rank on log sales is run for each triplet, using data on exports to the US at the 10-digit product level; only triplets with at least three products are considered. Sales rank is adjusted by subtracting 0.5 as in Gabaix and Ibragimov (2011). The shape parameters are the absolute values of the coefficients on log sales obtained from these regressions. The regression in columns (1) is weighted using the log number of 10-digit products that are exported to the US in each country-industry-year triplet. The regression in column (2) is weighted using each industry's share in the total number of 10-digit products that are exported to the US by each country in each year. The regressions in columns (4) and (5) are weighted using the inverse of the standard errors of the Pareto shape parameters. All time-varying regressors are lagged one period. Standard errors (reported in square brackets) are corrected for two-way clustering by country-industry and industry-year (in columns 1-2) or bootstrapped (100 replications, with observations sampled within country-industry pairs, in columns 3-5). ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 7 - Sales Dispersion and Finance: Additional Controls

	Per-Capita GDP	Imp. Pen. and Exp. Int.	Real Exch. Rate	Foreign Direct Invest.	Number of HS Codes	All Controls	All Controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fin. Dev. * Ext. Fin. Dep.	0.035***	0.032**	0.037***	0.038***	0.039***	0.037***	
	[0.013]	[0.013]	[0.013]	[0.014]	[0.013]	[0.014]	
Fin. Dev. * Ass. Tang.	-0.484***	-0.355***	-0.416***	-0.378***	-0.351***	-0.389***	
	[0.089]	[0.086]	[0.085]	[0.088]	[0.084]	[0.091]	
Fin. Dev. * Firm Age							-0.101***
							[0.030]
Skill End. * Skill Int.	0.261***	0.249***	0.247***	0.257***	0.227***	0.253***	0.248***
	[0.045]	[0.044]	[0.044]	[0.045]	[0.044]	[0.046]	[0.046]
Cap. End. * Cap. Int.	0.053***	0.057***	0.059***	0.061***	0.060***	0.054***	0.057***
	[0.009]	[0.009]	[0.009]	[0.009]	[0.008]	[0.009]	[0.009]
Inst. Qual. * Contr. Int.	0.185	0.057	0.113	0.123	0.090	0.146	0.222
	[0.145]	[0.140]	[0.140]	[0.140]	[0.138]	[0.145]	[0.144]
N. Prod.	0.003***	0.003***	0.003***	0.003***	0.004***	0.004***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
GDP * Ext. Fin. Dep.	0.003					-0.002	0.002
	[0.011]					[0.012]	[0.012]
GDP * Ass. Tang.	0.126*					0.108	0.050
	[0.065]					[0.068]	[0.066]
Imp. Pen. * Ext. Fin. Dep.		-0.205**				-0.229***	-0.230***
		[0.089]				[0.086]	[0.086]
Imp. Pen. * Ass. Tang.		-3.311***				-3.329***	-3.293***
		[0.550]				[0.561]	[0.561]
Exp. Int. * Ext. Fin. Dep.		0.225**				0.262***	0.261***
		[0.087]				[0.085]	[0.085]
Exp. Int. * Ass. Tang.		2.656***				2.598***	2.548***
		[0.545]				[0.559]	[0.559]
Exch. Rate * Ext. Fin. Dep.			0.007			0.017	0.022
			[0.024]			[0.024]	[0.024]
Exch. Rate * Ass. Tang.			0.257			0.127	0.081
			[0.160]			[0.162]	[0.164]
FDI * Ext. Fin. Dep.				0.000		-0.021	-0.010
				[0.016]		[0.017]	[0.017]
FDI * Ass. Tang.				-0.184*		0.133	0.029
				[0.103]		[0.115]	[0.113]
Fin. Dev. * Numb. HS					-0.001***	-0.001***	-0.001***
					[0.000]	[0.000]	[0.000]
Obs.	227,583	227,194	227,583	223,381	227,583	222,992	222,992
R2	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Country-Year FE	yes	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes	yes	yes	yes	yes

The dependent variable is sales dispersion (the standard deviation of log exports), computed separately for each exporting country, industry and year, using data on exports to the US at the 10-digit product level. GDP is the real per-capita GDP of each country in each year. Import penetration and export intensity are the ratios of imports over apparent consumption (production plus imports minus exports) and of exports over GDP, respectively, in each country and year. The exchange rate is the PPP real exchange rate of each country, relative to the US dollar, in each year. FDI is the ratio of outward FDI over GDP in each country and year. The number of HS codes is the total number of 10-digit codes that belong to each 4-digit SIC industry according to the HS classification in each 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 (reported in square brackets) are corrected for two-way clustering by country-industry and industry-year. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 8 - Sales Dispersion and Finance: Other Issues

	Contemporaneous Shocks	Underlying Trends			Country-Industry Fixed Effects	
	Area-SIC3-Year Effects	Based on Initial Dispersion	Based on Initial Exports	Based on Initial N. of Products	All Countries	Countries with Banking Crises
	(1)	(2)	(3)	(4)	(5)	(6)
Fin. Dev.					0.040	0.045
					[0.032]	[0.042]
Fin. Dev. * Ext. Fin. Dep.	0.030**	0.027**	0.036***	0.038***	0.026*	0.042*
	[0.014]	[0.012]	[0.013]	[0.013]	[0.015]	[0.022]
Fin. Dev. * Ass. Tang.	-0.307***	-0.369***	-0.393***	-0.413***	-0.259**	-0.257*
	[0.100]	[0.076]	[0.084]	[0.085]	[0.121]	[0.155]
Skill End.					0.281*	0.134
					[0.152]	[0.223]
Cap. End.					-0.136	-0.087
					[0.108]	[0.117]
Skill End. * Skill Int.	0.216***	0.199***	0.251***	0.242***	-0.045	-0.129
	[0.048]	[0.040]	[0.044]	[0.044]	[0.135]	[0.196]
Cap. End. * Cap. Int.	0.053***	0.048***	0.058***	0.059***	0.039	0.022
	[0.009]	[0.007]	[0.009]	[0.009]	[0.025]	[0.028]
Inst. Qual. * Contr. Int.	-0.654***	0.133	0.113	0.107		
	[0.191]	[0.125]	[0.139]	[0.139]		
N. Prod.	0.003***	0.002***	0.003***	0.004***	0.003***	0.003***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.001]
Obs.	227,583	227,583	227,583	227,583	227,583	148,940
R2	0.31	0.32	0.25	0.25	0.57	0.59
Country-Year FE	yes	yes	yes	yes	no	no
Industry-Year FE	yes	yes	yes	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes	yes	yes	yes
Country-Industry Trends	no	yes	yes	yes	no	no
Area-SIC3-Year FE	yes	no	no	no	no	no
Country-Industry FE	no	no	no	no	yes	yes

The dependent variable is sales dispersion (the standard deviation of log exports), computed separately for each exporting country, industry and year, using data on exports to the US at the 10-digit product level. Column (1) controls for contemporaneous shocks. To this purpose, it includes a full set of interactions between the year dummies, dummies for 3-digit SIC industries, and seven dummies for geographical areas, as defined by the World Bank: East Asia and Pacific; Europe and Central Asia; Latin America and the Caribbean; Middle East and North Africa; North America; South Asia; and Sub-Saharan Africa. Columns (2)-(4) control for underlying trends based on pre-existing characteristics of each country-industry pair. To this purpose, each column includes a full set of interactions between the year dummies and the initial (first year) value of the characteristic indicated in the column's heading. Columns (5) and (6) control for time-invariant country-industry characteristics. To this purpose, each column includes country-industry fixed effects: column (5) uses the whole sample of countries, whereas column (6) uses the sub-sample of countries that have experienced at least one banking crisis over 1989-2006. All time-varying regressors are lagged one period. Except for column (6), the 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 (reported in square brackets) are corrected for two-way clustering by country-industry and industry-year. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 9 - Sales Dispersion and Finance: Cross-Sectional Results

	OLS			IV		
	Private Credit	Resolving Insolvencies	Private Credit	Private Credit	Resolving Insolvencies	Private Credit
	(1)	(2)	(3)	(4)	(5)	(6)
Fin. Dev.			0.342***			0.567***
			[0.052]			[0.092]
Fin. Dev. * Ext. Fin. Dep.	0.071***	0.101***	0.066***	0.089***	0.188***	0.078***
	[0.015]	[0.034]	[0.016]	[0.030]	[0.050]	[0.030]
Fin. Dev. * Ass. Tang.	-0.320***	-0.368*	-0.345**	-0.589**	-0.862*	-0.835***
	[0.120]	[0.211]	[0.145]	[0.251]	[0.497]	[0.263]
Skill End.			0.453***			0.425***
			[0.065]			[0.067]
Cap. End.			-0.103***			-0.126***
			[0.033]			[0.033]
Inst. Qual.			-0.413***			-0.414***
			[0.105]			[0.117]
Skill End. * Skill Int.	0.262***	0.241***	0.216***	0.245***	0.203***	0.189***
	[0.052]	[0.052]	[0.051]	[0.055]	[0.057]	[0.053]
Cap. End. * Cap. Int.	0.055***	0.051***	0.039***	0.057***	0.053***	0.043***
	[0.008]	[0.009]	[0.008]	[0.008]	[0.009]	[0.008]
Inst. Qual. * Contr. Int.	0.436**	0.493***	0.365**	0.333*	0.369**	0.188
	[0.172]	[0.169]	[0.166]	[0.180]	[0.183]	[0.173]
N. Prod.	0.003***	0.003***	0.010***	0.003***	0.003***	0.009***
	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]
Obs.	20,716	20,952	20,716	20,716	20,952	20,716
R2	0.36	0.36	0.22	0.29	0.29	0.14
Country FE	yes	yes	no	yes	yes	no
Industry FE	yes	yes	yes	yes	yes	yes
First-Stage Results						
Kleibergen-Paap F-Statistic	-	-	-	467.2	194.4	555.3

The dependent variable is sales dispersion (the standard deviation of log exports) for each exporting country and industry, computed with data on exports to the US at the 10-digit product level, and averaged over 1989-2006. Financial development is proxied by private credit in columns (1), (3), (4), and (6), and by an index of insolvencies resolutions in columns (2) and (5). Private credit, factor endowments, and the number of products are averaged over 1989-2006. The index of insolvencies resolutions is normalized between 0 and 1, and takes higher values for countries occupying higher positions in the ranking. In columns (4)-(6), financial development is instrumented using dummies for whether countries' legal systems are of civil law (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 (reported in square brackets) are corrected for clustering by industry. The F-statistics are reported for the Kleibergen-Paap test for weak identification. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 10 - Trade, Finance and Sales Dispersion

	Total Exp.	N. of Prod.	Exp. per Prod.	Total Exp.	N. of Prod.	Exp. per Prod.	Total Exp.	N. of Prod.	Exp. per Prod.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sales Dispersion	1.635***	0.185***	1.450***				1.632***	0.183***	1.449***
	[0.014]	[0.004]	[0.012]				[0.015]	[0.004]	[0.012]
Fin. Dev. * Ext. Fin. Dep.				0.141***	0.040***	0.101**	0.076**	0.033***	0.043
				[0.049]	[0.012]	[0.041]	[0.035]	[0.011]	[0.027]
Fin. Dev. * Ass. Tang.				-3.153***	-0.368***	-2.786***	-2.504***	-0.295***	-2.209***
				[0.348]	[0.098]	[0.290]	[0.265]	[0.093]	[0.213]
Skill End. * Skill Int.				1.460***	0.442***	1.018***	1.043***	0.395***	0.648***
				[0.177]	[0.049]	[0.145]	[0.126]	[0.046]	[0.098]
Cap. End. * Cap. Int.				0.235***	0.035***	0.201***	0.135***	0.024**	0.111***
				[0.035]	[0.010]	[0.028]	[0.026]	[0.009]	[0.019]
Inst. Qual. * Contr. Int.				1.847***	0.858***	0.989**	1.579***	0.828***	0.751**
				[0.536]	[0.146]	[0.439]	[0.388]	[0.138]	[0.301]
Obs.	259,309	259,309	259,309	229,128	229,128	229,128	229,128	229,128	229,128
R2	0.72	0.75	0.69	0.55	0.73	0.48	0.73	0.75	0.70
Country-Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes

The dependent variables are indicated in columns' headings and are all expressed in logs. Sales dispersion 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 10-digit product 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 (reported in square brackets) are corrected for two-way clustering by country-industry and industry-year. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 11 - Sales Dispersion and Innovation

	(1)	(2)	(3)
Patent Count	0.516***	0.409***	0.201**
	[0.104]	[0.099]	[0.080]
Obs.	259,309	54,884	259,309
R2	0.25	0.38	0.56
Country-Year FE	yes	yes	no
Industry-Year FE	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes
Country-Industry FE	no	no	yes

The dependent variable is sales dispersion (the standard deviation of log exports), computed separately for each exporting country, industry and year, using data on exports to the US at the 10-digit product level. Patent count is the number of patents registered at the USPTO in thousands, computed separately for each country, industry and application year. The 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. Columns (1) and (3) use the whole sample of observations, whereas column (2) restricts to the sub-sample of observations with positive patent count. Standard errors (reported in square brackets) are corrected for two-way clustering by country-industry and industry-year. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 12 - Determinants of Innovation: Panel Regressions

	Baseline	Baseline	Baseline	Baseline	Zero-Infl. Poisson	Firm Age	Firm Age
	Whole Sample	Positive Pat. Count.	Positive Pat. Count.	Positive Pat. Count.	Whole Sample	Whole Sample	Positive Pat. Count.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fin. Dev. * Ext. Fin. Dep.	0.006***	0.007	0.013**		0.189***		
	[0.002]	[0.005]	[0.005]		[0.008]		
Fin. Dev. * Ass. Tang.	-0.054***	-0.283***		-0.305***	-0.690***		
	[0.011]	[0.064]		[0.067]	[0.110]		
Fin. Dev. * Firm Age						-0.011**	-0.059***
						[0.004]	[0.022]
Skill End. * Skill Int.	0.007***	0.069***	0.082***	0.068***	0.585***	0.008***	0.080
	[0.002]	[0.013]	[0.015]	[0.013]	[0.025]	[0.002]	[0.050]
Cap. End. * Cap. Int.	0.000	-0.001	0.001	-0.002	0.070***	0.000	0.000
	[0.000]	[0.002]	[0.002]	[0.002]	[0.004]	[0.000]	[0.005]
Inst. Qual. * Contr. Int.	-0.034***	-0.319***	-0.331***	-0.316***	1.675***	-0.012***	-0.326***
	[0.008]	[0.056]	[0.060]	[0.056]	[0.146]	[0.004]	[0.059]
N. Prod.	0.000***	0.000***	0.000**	0.000***	0.005***	0.000***	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]
Obs.	227,583	46,864	46,864	46,864	227,583	228,192	46,951
R2	0.28	0.43	0.41	0.43		0.26	0.41
Country-Year FE	yes	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes	yes
Price indexes * Industry FE	yes	yes	yes	yes	yes	yes	yes

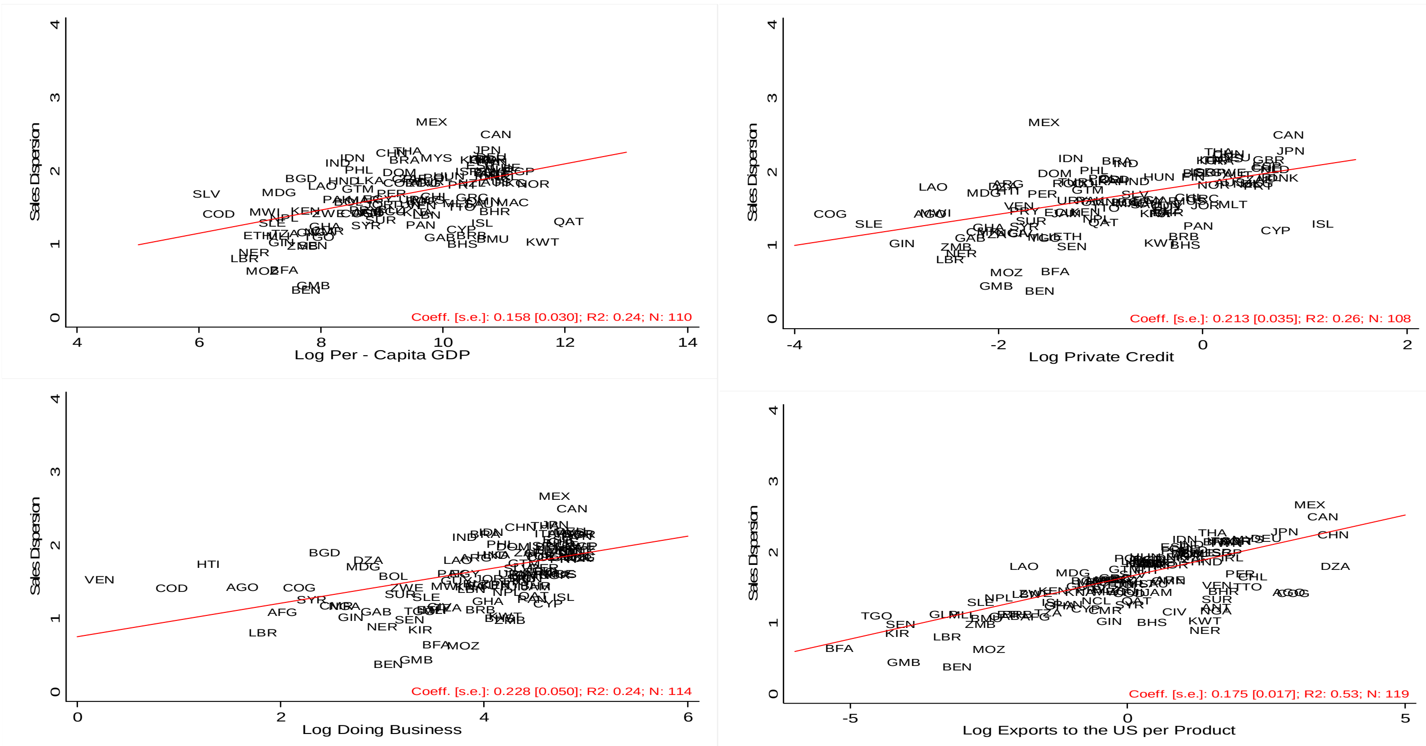
The dependent variable is the number of patents registered at the USPTO in thousands, computed separately for each country, industry and application year. All time-varying regressors are lagged one period. The regressions are based on a consistent sample of countries (119) and 4-digit industries (365) with positive exports to the US in all years between 1989 and 2006. Columns (1), (5) and (6) use the whole sample of observations, whereas columns (2)-(4) and (7) restrict to the sub-sample of observations with positive patent count. Standard errors (reported in square brackets) are corrected for two-way clustering by country-industry and industry-year, except in column (5), where they are clustered by industry-year. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Table 13 - Determinants of Innovation: Cross-Sectional Regressions

	Baseline	Baseline	Baseline	Baseline	Zero-Infl. Poisson	Firm Age	Firm Age	IV	IV
	Whole Sample	Positive Pat. Count.	Positive Pat. Count.	Positive Pat. Count.	Whole Sample	Whole Sample	Positive Pat. Count.	Whole Sample	Positive Pat. Count.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fin. Dev. * Ext. Fin. Dep.	0.006***	0.006	0.010**		0.315***			0.006***	0.012*
	[0.002]	[0.005]	[0.005]		[0.029]			[0.002]	[0.007]
Fin. Dev. * Ass. Tang.	-0.044***	-0.197***		-0.212***	-1.222***			-0.053***	-0.241***
	[0.010]	[0.041]		[0.044]	[0.352]			[0.013]	[0.049]
Fin. Dev. * Firm Age						-0.009**	-0.035**		
						[0.004]	[0.014]		
Skill End. * Skill Int.	0.009***	0.033***	0.042***	0.036***	1.097***	0.011***	0.043***	0.008***	0.026**
	[0.002]	[0.011]	[0.012]	[0.010]	[0.129]	[0.002]	[0.010]	[0.002]	[0.010]
Cap. End. * Cap. Int.	0.001***	0.003**	0.001	0.003**	0.162***	0.001***	0.001	0.001***	0.003***
	[0.000]	[0.001]	[0.001]	[0.001]	[0.013]	[0.000]	[0.001]	[0.000]	[0.001]
Inst. Qual. * Contr. Int.	0.002	-0.057***	-0.019*	-0.063***	3.478***	0.019***	-0.025**	-0.001	-0.063***
	[0.004]	[0.016]	[0.011]	[0.016]	[0.367]	[0.004]	[0.010]	[0.005]	[0.018]
N. Prod.	0.000**	0.000***	0.000**	0.000**	0.005***	0.000**	0.000**	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Obs.	20,716	5,008	5,008	5,008	20,716	20,771	5,016	20,716	5,008
R2	0.23	0.33	0.31	0.33		0.22	0.30	0.21	0.29
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
First-Stage Results									
Kleibergen-Paap F-Statistic	-	-	-	-	-	-	-	467.2	409.3

The dependent variable is the number of patents registered at the USPTO in thousands, computed separately for each country and industry, and averaged over 1989-2006. Private credit, factor endowments, and the number of products are also averaged over 1989-2006. The 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. Columns (1), (5), (6) and (8) use the whole sample of observations, whereas columns (2)-(4), (7) and (9) restrict to the sub-sample of observations with positive patent count. In columns (8) and (9), financial development is instrumented using dummies for whether countries' legal systems are of civil law (French, German or Scandinavian origins). Standard errors (reported in square brackets) are corrected for clustering by industry. The F-statistics are reported for the Kleibergen-Paap test for weak identification. ***, **, *: indicate significance at the 1, 5 and 10% level, respectively. See also notes to previous tables.

Figure 1 - Sales Dispersion and Country Characteristics



Sales 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 10-digit product level (Feenstra, Romalis and Schott, 2002). Each graph plots average sales dispersion in a given country (across 4-digit industries) against the country characteristic indicated on the horizontal axis. Per-capita GDP is real per-capita GDP from the Penn World Table 8.1. Private credit is the amount of credit issued by commercial banks and other financial institutions to the private sector over GDP, sourced from the Global Financial Development Database. Doing business is the ranking of countries in terms of the corresponding index of business regulation sourced from the World Bank Doing Business Database. Exports to the US are expressed in million of US dollars. Standard errors (reported in square brackets) are robust to heteroskedasticity. All graphs refer to the year 2006.