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RISKY GRAVITY

Luciana Juvenal
International Monetary Fund

Paulo Santos Monteiro
University of York

Abstract
We consider the canonical trade model with heterogeneous firms, love for variety and trade costs, and integrate it in the consumption CAPM model. This yields a structural gravity equation that includes an additional factor related to risk premia. Empirical evidence based on firm-level data confirms the importance of cross-sectional heterogeneity in risk and time-varying risk premia to shape bilateral trade flows. The structural gravity model augmented to account for fluctuations in risk premia offers a compelling explanation for trade collapses during abrupt economic downturns. (JEL: D81, E32, F10)

Keywords: risk premia, gravity equation, trade collapse.

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E-mail: ljuvenal@imf.org (Juvenal); paulo.santosmonteiro@york.ac.uk (Santos Monteiro)

1. Introduction

Large and countercyclical risk premia are widely viewed as an important source of business cycle fluctuations and, in particular, play a predominant role during large economic downturns. At the same time, in the presence of abrupt negative economic shocks such as those experienced during the global financial and COVID-19 crises, international trade often contracts sharply leading to trade collapses. However, the models which are used to predict the size and direction of international trade flows do not include a role for risk and risk pricing since they are perfect foresight models. We claim this is an important omission, and propose a simple extension of the canonical structural gravity model (as developed by Chaney, 2008), to overcome it.

We consider the canonical trade model with heterogeneous firms, love for variety and trade costs, and integrate it in the consumption Capital Asset Pricing Model (CAPM) with risk-averse agents. Thus, investment opportunities must be priced using an equilibrium discount factor obtained from the intertemporal marginal rate of substitution of the representative consumer. Selecting into an export market is a risky investment. Since firms are owned by risk averse households, this risk must be priced using the household's stochastic discount factor (SDF). As a result, selecting into a new export destination is more attractive if the demand from that destination acts as a hedge for the household's aggregate consumption growth risk. Through the lens of an intertemporal asset pricing model, the choice to export to a new destination is influenced by the comovement between the domestic investor's consumption growth and the importer-country's demand.

The key novel theoretical prediction we establish is the following: an increase in the riskiness of a given export destination lowers the probability of exporting to that destination. Risk affects trade through a mechanism which is analogous to Chaney's (2008) extensive margin trade elasticity. In particular, the extensive margin "risk-elasticity" is (in absolute value) decreasing with the elasticity of substitution across differentiated varieties, meaning that sectors in which firms have more market power (high markups) are more risk sensitive. The intuition for this result is closely related to the extensive margin elasticity of trade in Chaney (2008). If a firm can exert large market power in a given market, it is able to capture a substantial market share regardless of variations in productivity, and exert a significant impact on the overall profits of the representative investor's portfolio. But if the demand originating from that same market is very risky (comoves strongly with the investor's SDF), then that market contribution to the riskiness of the investor's portfolio will be large as well.

Our baseline model delivers predictions about how aggregate risk affects bilateral trade flows in a homoskedastic world without time-varying risk premia. Subsequently, we extend the analysis to consider the role of time-varying risk premia in shaping bilateral trade flows over the business cycle and the cross-section of export destinations chosen by exporters. Heightened risk premia is found to discourage firms' exports on the extensive margin and, as predicted by our model, this effect is stronger for riskier export destinations.

Risk affects directly the extensive margin of trade (the choice to export to a given destination), but not the intensive margin of trade. However, fluctuations in risk premia affect the intensive margin of trade indirectly, through the heterogeneous effect of risk premia shocks across different sized firms. An increase in risk premia will discourage exports in high "risk-elasticity" sectors. These are the sectors in which firms enjoy greater markups and market-shares. If those sectors are associated with larger firms, the upshot is that the extensive margin response to higher risk premia will, indirectly, also lower the average value of exports conditional on exporting (average intensive margin) due to the heterogeneous effect of heightened risk premia across firms. Therefore, when decomposing trade into its extensive and intensive margins, it is important to recognise that the two margins are intertwined.

To test the model predictions we rely on Argentinean firm-level export data. For each transaction between 2002 and 2009 we observe the name of the exporting firm, the Free on Board (FOB) export value (in US dollars), the date of the shipment, the country of destination, and the firms' Standard Industrial Classification (SIC). We compute the risk measure guided by our model, combining macroeconomic time series on aggregate consumption for each country in the global economy, and the corresponding bilateral trade flows. The measure obtained is based on imposing a factor structure to firm-destination sales growth rates (following an approach similar to Di Giovanni et al., 2014), and computing the covariance between the systemic component of aggregate sales growth and the aggregate Argentinean consumption growth rate. The resulting risk factor varies across sectors and import destinations. Thus, its inclusion still allows us to set up a baseline econometric specification containing both destination-specific and firm-specific time-effects to account for time-varying multilateral resistance (Anderson and Van Wincoop, 2003; Head and Mayer, 2014).

Consistent with the theoretical predictions, risk is found to affect directly the extensive margin of trade. The probability of exporting to a given destination decreases with risk. The probability of exporting to riskier markets (in the top-quartile of the risk distribution) is, depending on the empirical specification, estimated to be 0.4 to 1.4 percentage points lower compared to less risky markets (in the bottom-quartile of the risk distribution). These effects are economically substantial, since only a small subset of firms are exporters and, conditional on having exported at least once between 2002 and 2009, the probability of exporting to a given destination in a given year is around 32%. Thus, moving a market (defined by the sector and the importing country) from the bottom quartile to the top quartile of the risk distribution lowers the probability of market selection by the typical exporting firm between 1.3% and 4.4%.

Turning to the intensive margin, the baseline theoretical model predicts there should be no direct relation between the FOB value of exports (intensive margin) and risk.[1] However, testing this proposition is fraught with selection issues and other confounding factors, and therefore the empirical evidence is less clear. To try to better understand the relationship between the intensive margin and risk, we consider two alternative approaches. First, we follow the procedure proposed by Fitzgerald and Haller (2018) who argue that the intensive margin elasticities should be estimated on a restricted sample of firms which, based on their exporting histories, are well established and have a very high probability of serving the corresponding market. While for the full sample of firms risk lowers the intensive margin of trade, on the selected subsample of well established exporters, the intensive margin is not affected by risk. This empirical result is fully in line with the predictions of the dynamic extension of our baseline model, which predicts that for young exporters the intensive margin of trade is affected by risk, while for mature exporters, with an already well-established customer base, risk does not affect the intensive margin.

Second, instead of focusing on firm- level data alone, we consider aggregation directly (in a model consistent way) and look at the average value of exports conditional on exporting to a given market (the average intensive margin). This aggregation explicitly tackles the selection problem and, thus, eliminates firm-specific unobservables. Given the predicted direction of selection, the model implies that the average intensive margin is positively correlated with risk. This is because high risk markets are only chosen by the most productive firms. Thus, conditional on selection we expect average exports to be high in risky markets (this is exactly the underlying selection mechanism in Chaney, 2008). Consistent with this prediction, average exports conditional on selection is found to be higher in riskier markets.

Finally, to test the predictions regarding the impact of risk premium shocks on bilateral trade flows over the business cycle, we consider the 2008 Great Recession and concurrent trade collapse (Baldwin, 2009). This business cycle episode is widely recognised as a period of heightened uncertainty and elevated risk premia. Hence, we set-up a difference-in-difference specification to investigate the impact of time-varying risk premia on the extensive and intensive margins of trade. We find that during the trade collapse (which heavily

1. At any rate, there are theoretical mechanisms able to reconnect risk and the intensive margin of trade. For example, in a dynamic extension of our baseline model (outlined in Section 3.1 and discussed in detail in the Appendix B), we show that if the firm's life-cycle features realistic growth dynamics with endogenous customer base accumulation, then risk may directly affect the intensive margin of trade for young exporters. When we consider the dynamic model of exporter's growth, we show that this relationship is important for young exporters but not for established exporters, consistent with our empirical findings.

affected Argentinean exporters) the cross-section of export destinations served by exporting firms was tilted away from the most risky destinations, consistent with the model's prediction. The detrimental effect of risk premium shocks is shown to be stronger for larger firms, consistent with the heterogeneous risk-elasticities across sectors discussed above. We further extend our analysis to disentangle the impact of persistently high risk premium and a time-varying component of risk premium. Our findings are consistent with the risk-based explanation of exporters behavior and, in particular, the detrimental impact of risk on the extensive margin of trade.

Our paper contributes to the literature that investigates the importance of risk and uncertainty for shaping the internationalization of the firm and, in particular, international trade and foreign direct investment (FDI). Early work in this area focused on FDI and the firm's choice of production location. For example, Ramondo and Rappoport (2010) study how production location affects risk diversification in an environment with complete markets but risk averse consumers who require compensation for holding aggregate consumption risk. They show that it is optimal for firms owned by risk averse consumers to open affiliates in economies least correlated with world risk. Ramondo et al. (2013) study the firm's choice between serving a foreign market through exports or through FDI, in an environment with risk neutral agents and complete financial markets. They show that even under risk neutrality, the covariances of the country specific shocks affect the international strategies of firms: the firm's choice between exporting and FDI aims to achieve high market shares in states of the world in which local demand in those markets is high. The focus of the paper by Ramondo et al. (2013) is on production and sales efficiency in a risk neutral environment.

There is some recent work examining how international trade affects aggregate risk. For example, Caselli et al. (2020) show the importance of international trade as a vehicle to diversify the sources of demand and supply faced by firms in the global economy, when shocks are both country and sector specific. Conversely, Di Giovanni and Levchenko (2009) establish empirically the role of trade specialization as an amplifier of volatility. There is also a large literature investigating the association between bilateral trade and business cycle comovement (for example, Clark and Van Wincoop, 2001; Juvenal and Santos Monteiro, 2017; Kose and Yi, 2006). However, these papers do not study how risk affects the internationalization of the firm.

A related strand of the literature (see Handley and Limão, 2017), investigates directly how uncertainty affects the internationalisation strategy of the firm, in a set-up in which serving foreign markets requires a sunk investment that generates an option value of waiting. Their study differs substantially from ours, in its focus on domestic trade policy uncertainty and their assumption that the exporting country is large, such that changes in trade policy uncertainty confronting the exporting firms affects the importer's price index generating additional welfare gains from trade integration. Handley and Limão (2017) argue that the Chinese membership of the World Trade Organization boosted Chinese firms' investment and exports to the United States not so much by lowering the level of barriers confronting exporters but, instead, by lowering the trade policy uncertainty confronted by firms.

Our analysis is related to recent studies that examine firms' decision to export in the face of demand uncertainty. For example, Esposito (2020) considers firms with sunk entry costs, but our framework differs in that firms have access to capital markets and hold diversified portfolios. De Sousa et al. (2020) shows that uncertainty affects firms' exports decisions, both in terms of quantity and destination, and is measured using volatility in expenditure growth rates. More productive firms are found to be more affected, and the uncertainty channel affects mostly the extensive margin (consistent with results in this paper). But like Esposito (2020), the measure of risk used by De Sousa et al. (2020) does not distinguish between diversifiable and non-diversifiable risk resulting from assuming well functioning financial markets. Instead, we assume well functioning markets and firms owned by a risk-averse representative investor holding a well diversified portfolio. The upshot is that in our set-up fluctuations in capital markets' risk premia affect the cross-sectional profile of bilateral trade flows. This allows us to investigate how periods of high uncertainty and elevated risk premia are associated with trade collapses.[2]

Finally, our paper is related to the literature on the trade collapse during the 2008–2009 Great Recession (Baldwin, 2009). One of the striking features of the Great Recession was the magnitude of the trade decline, and its synchronisation across the world. Several papers have analyzed the collapse in trade through different angles (Bems et al., 2013, provide a comprehensive survey). These studies have typically focused either on the import demand adjustments or, like us, the behavior of exporting firms. Examples of the latter include Behrens et al. (2013) who looks at exporting firms in Belgium and assign a predominant role to the intensive margin of trade, and Bricongne et al. (2012) who study French exporters, and find that very large exporters adjusted mostly the intensive margin (the top 1% largest firms contributed to

2. The relationship between investment and uncertainty is complex and depends on various factors, including the investment technology and investment horizon, and how assets are priced, as shown, for example, in the studies by Abel (1983), Dixit and Pindyck (1994), McDonald and Siegel (1986), Pindyck (1991), and Bloom et al. (2007). If the firm's profits are distributed independently of the discount factor (the traditional assumption), an increase in the volatility of future demand has a positive effect on investment if the marginal revenue product of capital is a convex function of the shock, and a negative impact if it is a concave function of the shock (an application of Jensen's inequality). But in our framework, firms are priced with an equilibrium stochastic discount factor (SDF) and, thus, uncertainty only matters for investment if it affects the covariance of variable profits with the SDF (Craine, 1989; Leahy and Whited, 1996). An investment (adopting a new export market) that raises the covariance of variable profits with the SDF is riskier and requires a higher rate of return, while one that lowers it requires a lower rate of return. Therefore, in our setting, uncertainty lowers investment if and only if it raises risk.

75% of the overall intensive margin fall), but small exporters adjusted mostly the extensive margin (serving fewer products, to fewer destinations). Chen and Juvenal (2018) study the heterogeneous effects of the global financial crisis on international trade flows differentiated by quality. They find that volumes, prices, and also markups of higher quality exports contracted more sharply during the crisis. Looking specifically at the extensive margin, Chen and Juvenal (2018) also find that during the crisis, higher quality products were more likely to exit from exports. Because exporters of high quality products charge higher markups (Chen and Juvenal, 2022), their finding is consistent with our prediction that the risk elasticity of trade is larger for high markup sectors. Other important contributions include Amiti and Weinstein (2011) and Chor and Manova (2012), who emphasize the role of financial frictions and the decline of trade credit.

Uncertainty has been shown to sharply affect the behavior of the firm over the business cycle. Bloom (2009) shows how a temporary uncertainty shock generates a rapid drop, rebound, and overshoot in the hiring and investment choices made by the firm. At any rate, the internationalization strategy of firms should therefore be affected by such uncertainty shocks. Despite the massive spike in uncertainty coinciding with the trade collapse, little attention has been paid to heightened risk premia and uncertainty shocks as a contributing factor to the collapse. One important exception is offered by Novy and Taylor (2020), who propose a model in which uncertainly shocks magnify the response of trade, as importers adopt a "wait-and-see" approach, in particular, in relation to their inventory demand. This mechanism is shown to explain a significant portion of the shortfall in global import demand, particularly for the durable goods sector. Our paper differs from their study in that we focus on the supply side effects of uncertainty shocks.

The rest of this paper is organized as follows. In Section 2 we introduce the model of trade and the stochastic discount factor. Section 3 derives the structural gravity equation with risk. Section 4 describes the data used in the empirical work while Section 5 presents empirical results on the impact of risk on the extensive and intensive margins of exports. Section 6 introduces time-varying risk premia, analyzes its role to help explain the 2008 trade collapse, and investigates the effects of risk premia shocks. Finally, conclusions are presented in Section 7.

2. Exporters and risk

We consider a world economy with $N+1$ countries: Home, and N foreign countries, indexed $i = 1, \ldots, N$. Consumers in each country derive utility from the consumption of differentiated varieties of goods from S different sectors, indexed $s = 1, \ldots S$. Within each sector there is a continuum of differentiated varieties, each produced by a single monopolistic firm. Firms in each country have heterogeneous productivity levels and must choose which countries to sell their products to. This choice occurs before the demand conditions are known, and thus constitutes an investment decision under uncertainty. In the sequel, our focus is on the partial equilibrium in Home, with foreign demands and factor prices taken as given.

2.1. Stand-in household

Home's stand-in household is endowed with one unit of labor which is inelastically supplied in the labor market, and has preferences at date t given by the following expected utility function

$$\begin{aligned} \mathcal{U}_t &= \mathbf{E}_t \sum_{i=0}^{\infty} \beta^i u\left(\mathcal{C}_{t+i}\right), \qquad \text{with} \\ \mathcal{C}_t &= \prod_{s=1}^{S} \left(\int_{\Omega_{st}} c_{st}\left(v\right)^{1-1/\varepsilon_s} dv \right)^{\mu_s \varepsilon_s/(\varepsilon_s - 1)}, \end{aligned} \tag{1}$$

where $\mathcal{C}_t$ is the composite consumption basket, $c_{st}(v)$ is the consumption of the differentiated variety v of good s, and Ω_{st} is the set of varieties of good s available to consumers in Home at date t, and is endogenously determined in equilibrium; $\varepsilon_s > 1$ is the elasticity of substitution across differentiated varieties in sector s, μ_s is the share of total expenditure in sector s goods, with $\sum_s \mu_s = 1$, and $\beta \in (0, 1)$ is the discount factor. We set the composite consumption basket in Home to be the numéraire good, implying that the ideal price index satisfies the condition

$$\prod_{s=1}^{S} \left(\int_{\Omega_{st}} p_{st}\left(v\right)^{1-\varepsilon_s} dv \right)^{\mu_s/(1-\varepsilon_s)} = 1, \tag{2}$$

with $p_{st}(v)$ denoting the price of variety v in sector s. The budget constraint of the stand-in household is

$$\mathcal{C}_t + (\mathcal{B}_t/\mathcal{R}_t) + \int_j \mathcal{Q}_{jt}\xi_{jt}dj = W + \mathcal{B}_{t-1} + \int_j \left(\pi_{jt} + \mathcal{Q}_{jt}\right)\xi_{jt-1}dj, \tag{3}$$

where $\mathcal{B}_t$ are one-period real bonds purchased at date t at discount price $(1/\mathcal{R}_t)$; ξ_{jt} are the shares of the domestic firm $j \in \mathcal{J}$ purchased at date t, $\mathcal{Q}_{jt}$ is the *ex*-dividend price of each share, π_{jt} are the profits distributed by firm j, and W is the real wage rate which we assume is constant over time.

There is financial autarky, so that domestic firms are entirely owned by domestic investors and each country's net foreign asset position is zero. The standard asset pricing equations solving the household saving and portfolio allocation problem are given by

$$1/\mathcal{R}_t = \mathbf{E}_t \left[\frac{\beta u'\left(\mathcal{C}_{t+1}\right)}{u'\left(\mathcal{C}_t\right)} \right], \tag{4}$$

$$\mathcal{Q}_{jt} = \mathbf{E}_t \left[\frac{\beta u'\left(\mathcal{C}_{t+1}\right)\left(\pi_{jt+1} + \mathcal{Q}_{jt+1}\right)}{u'\left(\mathcal{C}_t\right)} \right]. \tag{5}$$

Solving forward the asset pricing equation (5) and ruling out bubbles yields

$$\mathcal{Q}_{jt} = \mathbf{E}_t \left[\sum_{\iota=0}^{\infty} \beta^{\iota+1} \frac{u'\left(\mathcal{C}_{t+\iota+1}\right)\pi_{jt+\iota+1}}{u'\left(\mathcal{C}_t\right)} \right]. \tag{6}$$

Market clearing in financial markets requires $\xi_{jt} = 1$, for all domestic firms $j \in \mathcal{J}$, and $\mathcal{B}_t = 0$, at each date t.

2.2. Monopolistic firms pricing and market selection

We now turn to the problem solved by each domestic monopolistic firm $j \in \mathcal{J}$, whose objective is to maximize its share value (6). For that, we first need to define the firm's profit function. Each domestic monopolistic firm is characterized with the unit labor cost to produce output W/φ_j, with the efficiency parameter $\varphi_j \geq 1$ heterogeneous across firms.

There are N possible markets Home firms can export to, but to be able to export at date $t+1$ to country $i = 1, \ldots N$, the firm must invest in marketing at date t the amount $f_i > 0$, expressed in units of the composite consumption basket. This investment is indivisible and sunk. Moreover, firms also face a variable "iceberg" transportation cost. For a Home firm to sell one unit of the differentiated product in country i, it must ship $\tau_i \geq 1$ units.

With isoelastic preferences, the optimal quantity demanded by country i for variety v in sector s is

$$q_{jist}\left(v\right) = Z_{ist} p_{jist}\left(v\right)^{-\varepsilon_s}, \tag{7}$$

where Z_{ist} is an exogenous demand shifter for sector s goods in country i, and is assumed to follow a random walk in logs, such that

$$Z_{ist+1} = Z_{ist} \exp\left(\varepsilon_{ist+1}\right), \tag{8}$$

with ε_{ist} denoting an exogenous random variable with mean 0 and standard deviation σ_ε.[3] Optimal price setting by a Home producer j in sector s exporting to country i is

$$p_{jist} = \frac{\tau_i W}{\varphi_j} \left(\frac{\varepsilon_s}{\varepsilon_s - 1} \right), \tag{9}$$

3. We abstract from general equilibrium considerations to focus on the role of demand risk for the exporting decisions made by the firms. However, in general equilibrium $Z_{ist} = \mu_s \mathcal{C}_{it} \mathcal{P}_{it}^{\varepsilon_s - 1}$, where $\mathcal{P}_{it}$ is the ideal price index in country i, and $\mathcal{C}_{it}$ aggregate consumption in country i at date t (Chaney, 2008). Thus, assuming $\ln Z_{ist}$ follows a random walk is a good approximations to the data, since there exists a long tradition of modeling consumption and the exchange rate (and terms of trade) as random walks (see, for example, Hall, 1978; Meese and Rogoff, 1983).

resulting in the following variable profit function by firm j in sector s exporting to country i

$$\tilde{\pi}_{jit} = \lambda_s Z_{ist} \left(\frac{\tau_i W}{\varphi_j} \right)^{1-\varepsilon_s}, \tag{10}$$

with $\lambda_s = \varepsilon_s^{-\varepsilon_s} (\varepsilon_s - 1)^{\varepsilon_s - 1}$. As in Chaney (2008), the firm's idiosyncratic efficiency parameter φ_j is randomly drawn from the Pareto distribution with support $[1, +\infty]$ and shape parameter $\alpha_s > \varepsilon_s - 1$, and thus has cumulative density function

$$\mathbf{F}(\varphi) = 1 - \varphi^{-\alpha_s}. \tag{11}$$

The firm must decide at date t if it will export to each country i at date $t+1$. In units of the domestic composite consumption basket, the total profits earned by the firm j at date $t+1$ from exporting to country i are given by

$$\pi_{jit+1} = (\tilde{\pi}_{jit+1} - \mathcal{R}_t f_i)\, d_{jit}, \tag{12}$$

with d_{jit} taking value 1 if at date t the firm j selects country i as an export destination, and 0 if not. Thus, the recursive form problem solved by a firm with technology level α_j choosing at date t which export destinations to serve at date $t+1$ is

$$\mathcal{Q}_{jt} = \max_{\{d_{jit}\}_{i=1}^{n}} \mathbf{E}_t \left[\mathcal{M}_{t+1} \left(\sum_{i=1}^{n} d_{jit} \pi_{jit+1} + \mathcal{Q}_{jt+1} \right) \right], \tag{13}$$

where $\mathcal{M}_{t+1} = \beta u'(\mathcal{C}_{t+1}) / u'(\mathcal{C}_t)$ is the stochastic discount factor (SDF). The solution to this problem is simple: firms choose to serve each market for which the expected discounted value of variable profits exceeds the fixed entry cost. This results in a destination specific threshold productivity level $\bar{\varphi}_{ist}$, such that firms with productivity above it choose to export to destination i. The upshot is the following Bellman equation for the share price

$$\begin{aligned} \mathcal{Q}_{jt} = \sum_{i=1}^{n} \mathtt{I}_{\varphi_j \geq \bar{\varphi}_{ist}} \Big[\mathbf{E}_t (\tilde{\pi}_{jit+1}) \mathbf{E}_t (\mathcal{M}_{t+1}) + \operatorname{cov}_t (\tilde{\pi}_{jit+1}, \mathcal{M}_{t+1}) - f_i \Big] \\ + \mathbf{E}_t (\mathcal{M}_{t+1} \mathcal{Q}_{jt+1}), \end{aligned} \tag{14}$$

where $\mathtt{I}_{\varphi_j \geq \bar{\varphi}_{ist}}$ is an indicator function.[4]

3. Structural gravity equation and risk

In the sequel, we represent the stand-in household's preferences with the power utility function, $u(\mathcal{C}) = \left(\mathcal{C}^{1-\rho} - 1\right) / (1-\rho)$, with $\rho > 0$. Thus, the SDF admits

4. To obtain (14) we use the fact that $E(yz) = E(y)E(z) + \operatorname{cov}(y, z)$, and condition (4).

the following linear Taylor expansion around the steady state equilibrium

$$\mathcal{M}_{t+1} \simeq (1 - \rho g_{t+1})\,\beta, \tag{15}$$

where g_{t+1} denotes the net growth rate of domestic aggregate consumption at date $t+1$. We assume the growth rate of consumption is well represented by a serially uncorrelated stochastic process, with mean zero and standard deviation σ_g, with the upshot that $\mathbf{E}_t\left(\mathcal{M}_{t+1}\right) = \beta$.

Given the exogenous stochastic processes assumed for the foreign aggregate demand shocks in (8), the variable profits by Home firms that export to country i also follow random walks in logs, given by

$$\begin{aligned} \tilde{\pi}_{jit+1} &= \tilde{\pi}_{jit} \exp\left(\varepsilon_{ist+1}\right), \\ &= \lambda_s Z_{ist} \left(\frac{\varphi_j}{W\tau_i}\right)^{\varepsilon_s - 1} \exp\left(\varepsilon_{ist+1}\right). \end{aligned} \tag{16}$$

Making use of (15) and (16) to substitute in (14), we are able to simplify the Bellman equation summarizing the firm's problem, as follows

$$\begin{aligned} \mathcal{Q}_{jt} = \sum_{i=1}^{n} \mathrm{I}_{\varphi_j \geq \bar{\varphi}_{ist}} \left[\beta \lambda_s Z_{ist} \left(\frac{\varphi_j}{W\tau_i}\right)^{\varepsilon_s - 1} \left(1 - \rho \sigma_{\varepsilon,g}^{is}\right) - f_i\right] \\ + \mathbf{E}_t\left(\mathcal{M}_{t+1} \mathcal{Q}_{jt+1}\right), \end{aligned} \tag{17}$$

with $\sigma_{\varepsilon,g}^{is} = \mathrm{cov}_t\left(\varepsilon_{ist+1}, g_{t+1}\right)$, the conditional covariance between ε_{ist+1} and g_{t+1}, which is assumed to vary across sector s and export destination i.[5]

It is optimal for firm j to export to country i if doing so increases its share price. Thus, it requires

$$\beta \lambda_s Z_{ist} \left(\frac{\varphi_j}{W\tau_i}\right)^{\varepsilon_s - 1} \geq \left(\frac{f_i}{1 - \rho \sigma_{\varepsilon,g}^{is}}\right). \tag{18}$$

From (18), the threshold productivity level above which a sector s firm chooses to export to country i is given by

$$\bar{\varphi}_{ist} = \left[\frac{f_i / \left(1 - \rho \sigma_{\varepsilon,g}^{is}\right)}{\beta \lambda_s Z_{ist}}\right]^{1/(\varepsilon_s - 1)} W\tau_i. \tag{19}$$

It is assumed that f_i is sufficiently large, so that $\bar{\varphi}_{ist} > 1$, for all i and t. This formula is analogous to the threshold obtained in the perfect foresight canonical trade model (Chaney, 2008), except for the presence of the risk adjustment factor, $\sigma_{\varepsilon,g}^{is}$. Exporting to destinations delivering large profits when

5. To obtain (17) we use the fact that $\mathrm{cov}\,(ax, c + by) = ab\,\mathrm{cov}\,(x, y)$, with a and b and c constants and x, y two random variables, and also the fact that $\exp\,(x) \simeq 1 + x$ for small x.

consumption is valued most by investors (negative risk factor, $\sigma^{is}_{\varepsilon,g}$) is attractive and, thus, requires a lower threshold productivity level.

From equation (7), the value of exports by a firm with productivity φ_j conditional on exporting to destination i at date $t+1$ is given by

$$x_{jist+1} = p_{jist+1} q_{jist+1} = Z_{ist+1} p^{1-\varepsilon_s}_{jist+1}, = x_{jist} \exp\left(\varepsilon_{ist+1}\right). \tag{20}$$

Thus, the value of exports conditional on selecting a destination (individual intensive margin of trade) follows a random walk in logs. Making use of (19) and the fact that φ_j has the Pareto distribution, yields sector s aggregate bilateral exports to country i at date $t+1$, given by

$$\begin{aligned} X_{ist+1} &= \Lambda_s Z^{\alpha_s/(\varepsilon_s-1)}_{ist} \left(W\tau_i\right)^{-\alpha_s} \left(\frac{1-\rho\sigma^{is}_{\varepsilon,g}}{f_i}\right)^{\alpha_s/(\varepsilon_s-1)-1} \exp\left(\varepsilon_{ist+1}\right), \\ &= X_{ist} \exp\left(\varepsilon_{ist+1}\right), \end{aligned} \tag{21}$$

with $\Lambda_s = \alpha_s \left(1-1/\varepsilon_s\right)^{\varepsilon_s-1} \left(1-\varepsilon_s+\alpha_s\right)^{-1} \left(\beta\lambda_s\right)^{\alpha_s/(\varepsilon_s-1)-1}$, a positive constant.[6] This formula is again analogous to the one for bilateral exports in Chaney (2008), only corrected for the risk factor. If the covariance between the investors discount factor and the foreign demand shock, $\sigma^{is}_{\varepsilon,g}$, is zero the model collapses to the Chaney (2008) perfect foresight gravity model.

The key novel insight from equation (21) is that aggregate exports between two countries are determined by the importer's risk factor, $\sigma^{is}_{\varepsilon,g}$. In particular, the elasticity of aggregate exports to changes in the risk factor is given by the extensive margin export elasticity, which is $\alpha_s/(\varepsilon_s-1)-1$. As pointed out by Chaney (2008), this elasticity is larger if the degree of productivity dispersion is small (large α_s). Similarly, if the substitutability across products (measured by the elasticity of substitution, ε_s) is large, the elasticity of exports to risk will be lower. Thus, sectors in which firms have greater market power (high markup sectors) are associated with a higher risk sensitivity of exports.

3.1. The extensive and intensive margins of trade under risk

It is noteworthy that the risk factor, $\sigma^{is}_{\varepsilon,g}$, does not appear in equation (20) and, thus, does not affect the intensive margin. Risk matters only because it affects the extensive margin of trade. Specifically, from (11) and (19), the probability that Home's firm j selects country i as an export destination is given by

$$\begin{aligned} \text{Prob}\left(d_{jit}=1\right) \equiv \mathbf{P}_{jit} &= 1-\mathbf{F}\left(\bar{\varphi}_{ist}\right), \\ &= \left[\frac{\beta\lambda_s Z_{ist}}{f_i/\left(1-\rho\sigma^{is}_{\varepsilon,g}\right)}\right]^{\alpha_s/(\varepsilon_s-1)} \left(W\tau_i\right)^{-\alpha_s}. \end{aligned} \tag{22}$$

6. The detailed derivation of equation (21) is shown in Appendix A.

Taking logs yields

$$\begin{aligned}\ln\mathbf{P}_{jit} &\simeq \text{constant}+ \\ &+\left(\frac{\alpha_s}{\varepsilon_s-1}\right)Z_{ist}-\left(\frac{\alpha_s}{\varepsilon_s-1}\right)f_i-\left(\frac{\alpha_s}{\varepsilon_s-1}\right)\rho\sigma^{is}_{\varepsilon,g}-\alpha_s\ln\left(W\tau_i\right),\end{aligned} \tag{23}$$

where we use the approximation $\ln\left(1-\rho\sigma^{is}_{\varepsilon,g}\right)\simeq-\rho\sigma^{is}_{\varepsilon,g}$, for small $\sigma^{is}_{\varepsilon,g}$. In what follows, equation (23) provides the underpinnings for the risk adjusted structural gravity equation in Section 5. The upshot is that risk affects exports through the extensive margin.

PROPOSITION 1. *The probability that a firm exports to a given destination (extensive margin) is decreasing in the destination's risk factor, $\sigma^{is}_{\varepsilon,g}$. The extensive margin risk elasticity is*

$$\textit{risk elasticity} = -\left(\frac{\alpha_s}{\varepsilon_s-1}\right). \tag{24}$$

In absolute value, it increases with markups (falls with ε_s), and falls with the productivity dispersion (increases in α_s). The intensive margin of trade in not affected by risk.

Proposition 1 follows immediately from equation (23). Note that the absence of a link between risk and the intensive margin of trade is a sharp but special prediction of the benchmark model. Risk may interact with other frictions, and this could result in a link between risk and the intensive margin. In Appendix B, we develop a dynamic model of exporters' growth featuring a more realistic exporter's life-cycle, in which young firms must grow its customer base.[7] We show that in this more realistic life-cycle model of the firm there is a link between the intensive margin of trade and risk for young exporters, newly established in a given export market, whilst the disconnect between risk and the intensive margin predicted by our baseline model still applies to old firms who already have a mature presence in a given export market. We present this result formally in Appendix B, where we follow the set-up proposed in Foster et al. (2016), in which customer base accumulation derives from the exporter's past sales activity. Young exporters have an incentive to lower their markup and prices, thus increasing sales and growing its customer base. This incentive is mitigated if the future demand is riskier, implying a negative relationship between risk and the intensive margin of trade for young exporters.

Proposition 1 is our central theoretical prediction. To test this proposition, we must first develop a measure of risk. The next Section addresses this step.

7. Several empirical studies of exporters' growth dynamics show that new exporters start relatively small compared to firms already well established in the market and, subsequently, conditional on survival, grow their customer base and converge in size with the older firms (Fitzgerald et al., 2016; Foster et al., 2016; Ruhl and Willis, 2017).

3.2. Measuring risk

The risk factor is measured by $\sigma_{\varepsilon,g}^{is} = \text{cov}_t(\varepsilon_{ist+1}, g_{t+1})$, and could be time-varying. In the baseline analysis we assume homoskedasticity, and take $\sigma_{\varepsilon,g}^{is}$ to be constant over time. In Section 6.1 we relax this assumption and allow for second-moment shocks. We also model the 2008 Great Recession as a shock to the volatility of the growth rate of consumption of the stand-in agent, to investigate if risk premium shocks contributed to the 2008-2009 trade collapse.

Risk varies across sectors and export destinations. In particular, we assume the innovations to export demand from country i faced by each domestic firm follows a simple factor structure with a sector specific component, ζ_s, and an importing country component, η_{it}, given by

$$\varepsilon_{ist+1} = \zeta_s \eta_{it+1}, \tag{25}$$

where η_{it+1} is an independent random variable with mean 0 and variance σ_η^2, and where the scalars $\zeta_s \geq 0$ are sector specific factor loadings of the common shocks.[8] Without loss of generality, we impose the normalization $\sum_s \zeta_s = 1$, and making use of equation (21) we obtain

$$\varepsilon_{ist+1} = \ln\left(X_{ist+1}/X_{ist}\right), \tag{26}$$

$$\eta_{it+1} \simeq \ln\left(\overline{X}_{it+1}/\overline{X}_{it}\right), \tag{27}$$

with $\overline{X}_{it} = \sum_{s=1}^{S} X_{ist}$. We use (26) and (27) to obtain estimates of, in turn, ε_{ist} and η_{it}, denoted $\hat{\varepsilon}_{ist}$ and $\hat{\eta}_{it}$.

The risk factor for sector s and export destination i, $\sigma_{\varepsilon,g}^{is}$, is estimated as

$$\sigma_{\varepsilon,g}^{is} = \text{std}\left(\hat{\varepsilon}_{ist+1}\right)\text{std}\left(g_{t+1}\right)\varrho\left(\hat{\eta}_{it+1}, g_{t+1}\right), \tag{28}$$

where $\varrho\left(\hat{\eta}_{it+1}, g_{t+1}\right)$ is taken to be the correlation between aggregate consumption growth and the growth rate of aggregate FOB exports, and $\text{std}\left(\hat{\varepsilon}_{ist+1}\right)$ is given by the standard deviation of export sales growth by sector.[9]

Finally, we normalize the standard deviation of aggregate consumption growth, $\text{std}\left(g_{t+1}\right)$, to unity. The normalization allows us to interpret the response of trade to changes in risk measured relative to the standard deviation of aggregate consumption. This point is useful in Section 6, when we consider time-varying risk premia.

8. Imposing a factor structure to the firm-destination sales growth rates follows an approach similar to Di Giovanni et al. (2014), who also use this method to identify macroeconomic and sector-specific shocks.

9. We are able to estimate $\varrho\left(\hat{\eta}_{it+1}, g_{t+1}\right)$ using annual time series for bilateral aggregate exports, without making use of the firm level data. This is important because it means that the measure of comovement is computed from relatively long time series. Using the firm level data instead, would restrict us to very short time series (the firm level data only spans the period 2002 – 2009). In Section 4 we provide more details on the data used for the construction of the risk measure.

3.2.1. First- and second-moments shocks. To investigate the relationship between risk (second-moment shocks) and trade, we must control for the impact of level effects (first-moment shocks). This is specially important because the two are likely entangled: riskier export markets will naturally feature larger negative demand shocks and, thus, negative first-moment shocks.

Empirically, one way to do this is to include destination-specific and firm-specific time-effects. However, this approach only works if the first-moment shocks are either sector-specific and common to all countries (and, thus, captured by the firm-specific time effect), or country-specific and common to all sectors (in which case, they are captured by the destination-specific time-effect). The time-effects do not capture first-moment shocks that are driven by sector-destination specific shocks (for example, a shock to the demand for Argentinean wine by English customers). More generally, sector-destination specific shocks emerge if the country specific shock η_i affects each sector s differently, implying heterogeneous factor loadings $\zeta_s \geq 0$ in equation (25).

To overcome this potential omitted variable bias, in Section 5 we control directly for the first-moments shocks in the main empirical specification. To do this, we propose a way to recover the demand shocks (first-moment shocks) directly, exploiting the factor structure of our panel data. Specifically, to recover the demand shocks we make use of equation (26), and the fact that the demand shock from country i and sector s at time t, $\varepsilon_{ist} = \Delta \ln X_{ist}$, corresponds to the growth rate of the total sector exports. It is, therefore, possible to estimate the demand shocks for each sector, given by

$$\text{demand shock} \equiv \hat{\varepsilon}_{ist} = \Delta \ln X_{ist}. \tag{29}$$

With these estimated shocks, we can control directly for level effects.

4. Data and descriptive statistics

This Section discusses the different data sets we use in the empirical analysis, and explains how we combine information from firm-level customs data and aggregate macroeconomic time-series.

4.1. Customs data

We use firm-level export data for Argentinean exporters collected by the Argentinean customs and provided to us by a private vendor named Nosis.[10] For each export flow between 2002 and 2009 we observe the name of the exporting

10. Due to confidentiality, the Argentinean National Statistics Office (INDEC) is not allowed to reveal data at the firm level (established by Law 17,622). Nosis purchases data from Argentinean customs and uses an algorithm that compares export transactions, along with their own market knowledge. When exporter names are not available, earlier

firm, and the total value (in US dollars) of its FOB exports, and the destination country. Since exports are reported FOB they exclude transport costs, tariffs, and distribution costs in the importing country.

Nosis gathers firm-level information, such as the industry classification, Tax Identification Number (CUIT), date of establishment, and number of employees, from the tax returns submitted to the Argentinean Tax Authority. This information, while not present in customs data, can be easily retrieved through web searches on the Nosis website. This enables the calculation of a firm's average number of employees and age during the period analyzed and the determination of the firm's industry classification, using the Standard Industrial Classification (SIC) system.[11]

4.2. Macroeconomic data and the estimation of risk

In order to obtain the measure of risk in equation (28) we combine the firm-level data described previously and macroeconomic time-series on aggregate consumption, using information from different sources.[12] To compute the comovement between the growth rate of consumption and the country specific demand shocks, $\varrho\left(\hat{\eta}_{it+1}, g_{t+1}\right)$, we use annual time series for bilateral trade flows between Argentina and each trading partner, obtained from the Feenstra World Trade Flows (WTF) dataset. The bilateral trade flows data are used to get the time series for bilateral exports, $\bar{X}_{it}$, and we use the formula in (27) to calculate the estimated destination-specific demand shock, $\hat{\eta}_{it}$. To obtain an estimate of the demand shock in local currency and constant prices we adjust the nominal dollar bilateral trade flows using the Consumer Price Index (CPI) and the exchange rate obtained from the IMF International Financial Statistics. The growth rate of aggregate consumption in Argentina, g_t, is computed from the final consumption expenditure in constant local currency units (Peso),

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transactions including names are used to generate a *probable exporter*. For example, if an export transaction in 2007 has similar port, Harmonized Tariff Schedule (HTS), volume, and destination information as several of firm j's export transactions from a previous year, firm j will be listed as the *probable exporter* in 2007.

11. When information from Nosis website is not available, we use the firm's Tax Identification Number and search other public sources like the Argentinean Tax Authority. Our main sample includes firms with information on employment and age, but we also consider an alternative sample that includes firms without these characteristics. Our results are robust and available in Appendix E.

12. The stochastic discount factor is given by the intertemporal marginal rate of substitution computed using the growth rate of aggregate consumption in Argentina. This approach is valid under either financial autarky or complete international capital markets. If the former is true, Argentina firms must be owned by domestic investors and, thus, the growth rate of domestic consumption delivers the appropriate stochastic discount factor. If, instead, we have complete markets, the marginal rates of substitutions are equal across countries and (with homothetic preferences) the domestic growth rate of aggregate consumption is again the correct way to recover the stochastic discount factor.

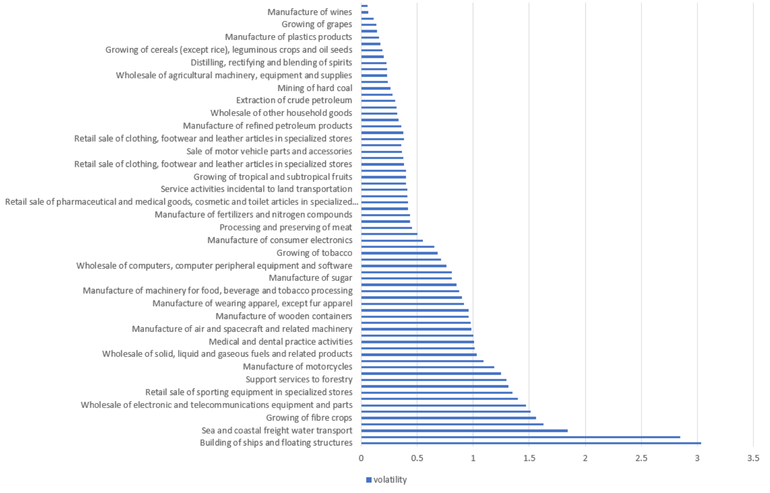

FIGURE 1. Volatility across sectors

Notes: The graph shows how volatility varies across some selected sectors. The included sectors are chosen only for illustration purposes and cover some of the most volatile sectors and some of the least volatile sectors.

obtained from the World Bank's World Development Indicators database. The time-span for the calculation of the measure of risk is 1984 – 2015.[13]

To compute the volatility of the sector specific demand shocks, $\text{std}\left(\hat{\varepsilon}_{ist+1}\right)$, we use the firm level data described above. For each sector s and destination i, we sum the FOB exports, x_{jit}, across all exporting firms j, to obtain the sector s exports to country i, $\overline{X}_{ist}$. Then, making use of (26) we obtain the estimated demand shocks, $\hat{\varepsilon}_{ist+1}$, and compute the standard deviation of this shock for each sector sector, $\text{std}\left(\hat{\varepsilon}_{ist+1}\right)$. For illustrative purposes, Figure 1 shows the computed volatility measure, $\text{std}\left(\hat{\varepsilon}_{ist+1}\right)$, for a selection of sectors chosen to include some of the most volatile and some of the least volatile sectors.

Multiplying together the sector specific volatility measure, $\text{std}\left(\hat{\varepsilon}_{ist+1}\right)$, and the destination specific correlation measure $\varrho\left(\hat{\eta}_{it+1}, g_{t+1}\right)$, yields a measure of risk that varies across sectors and destinations. In Figure 2 we show a scatter plot representing the risk measure averaged across sectors for each destination against the average (across sectors) percentage of firms exporting to the same destination (computed using the customs data described earlier). The graph suggests a negative association between risk and the probability that firms choose to export to a given market. Crucially, as the risk factor varies across sectors and import destinations, in our empirical investigation we are

13. The use of aggregate bilateral trade data allows us to extend the time dimension of our dataset for the calculation of correlations and standard deviations. The sample period spanned, 1984 – 2015, is determined by the availability of data on bilateral trade flows.

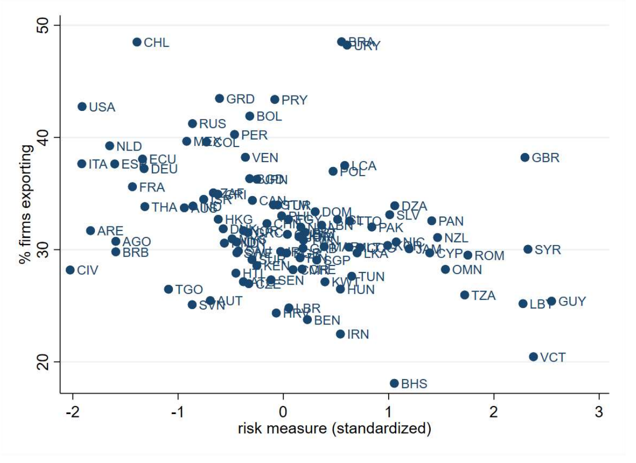

FIGURE 2. Risk and export selection

Notes: Scatter plot representing the risk measure averaged across sectors for each destination against the average (across sectors) percentage of firms exporting to the same destination.

TABLE 1. Summary statistics on exports data by year

Panel A

Year	# Exporters	Exports (Million $US)	# Destinations
2002	5,965	23,977	102
2003	6,748	26,676	102
2004	7,280	30,066	102
2005	7,664	24,912	102
2006	8,379	26,900	101
2007	9,591	36,014	100
2008	9,292	57,950	100
2009	8,546	44,730	100

Panel B

Year	mean exports	mean destinations	maximum destinations	minimum destinations	mean distance	mean age	mean employment
2002	4,019,618	11	77	1	6,300	34	140
2003	3,953,944	12	82	1	6,402	33	128
2004	4,130,444	12	82	1	6,444	32	120
2005	3,250,724	12	83	1	6,428	31	116
2006	3,210,814	11	79	1	6,356	30	110
2007	3,756,068	12	77	1	6,368	29	103
2008	6,237,628	12	77	1	6,424	29	103
2009	5,235,137	12	74	1	6,402	30	108

Notes: In panel A, for each year in the sample, we report the number exporters, the value of FOB exports (in million US dollars), and the number of destinations. In panel B, for each year in the sample, we reports the mean value of FOB exports; the mean, minimum and maximum number of destinations firms export to; the mean distance; the mean age of firms and the mean level of employment.

able to set up a baseline econometric specification containing both destination-specific and firm-specific time-effects to account for time-varying multilateral resistance (Anderson and Van Wincoop, 2003; Head and Mayer, 2014), and destination and firm specific unobserved heterogeneity.

We obtain control variables for the gravity equation from standard sources, including bilateral distances calculated using the great circle formula and population data from the Centre d'Etudes Prospectives et d'Informations

Internationales (CEPII), and nominal GDP in current US dollars from the World Bank's World Development Indicators.[14]

4.3. Descriptive statistics

Table 1 presents descriptive statistics of the firm-level database. The full sample includes 12,647 firms for which we observe their age, their business activity sectoral classification, the destination countries to which they export, the value of their exports to each destination, and the firm's total number of employees over the period analyzed.

Panel A summarizes the trade data by year. Taken together, these firms export to a total of 102 countries. The value of FOB exports nearly doubled from 2002 to 2009 and the number of exporters increased by 44%. Panel B shows that the average firm exported to 11 destinations in 2002, with an average distance of 6,300 kilometers, and 12 destinations in 2009, with an average distance of 6,402 kilometers. The average value of FOB exports per firm increased by 30%. The average firm age was 34 years in 2002 and 30 years in 2009, and the average employment decreased from 140 employees in 2002 to 108 in 2009.

5. Empirical results

In this section we test the main predictions of our model and, in particular, Proposition 1 establishing how risk affects the extensive and intensive margins of trade.

5.1. Risk and the extensive margin

Based on the theoretical model, our empirical specification is as follows

$$d_{jit} = \delta' \mathbf{F}_{jit} + \beta_1 \mathbf{Risk}_{ji}^{(is)} + \beta_2 \mathbf{demand\ shock}_t^{(is)} + \varepsilon_{jit}, \tag{30}$$

where the unit of observation is given by firm, j, exporting to destination, i, across time, t. Our main covariate is the risk measure, denoted $\mathbf{Risk}_{ji}^{(is)}$, to indicate that it varies across destinations and sectors. In our main specification, we control for the first-moment shocks directly, with $\mathbf{demand\ shock}_t^{(is)}$, obtained using equation (29). These level shocks are also destination and sector specific. The dependent variable d_{jit} is an indicator variable, based on (23), and

14. Using GDP adjusted for PPP yields similar results. Due to missing data, GDP for Iraq and Syria are from the IMF World Economic Outlook database.

defined as

$$d_{jit} = \begin{cases} 1, & \text{if firm } j \text{ exports to country } i \text{ at date } t, \\ 0, & \text{if not.} \end{cases} \tag{31}$$

The vector $\mathbf{F}_{jit}$ contains the set of control variables, including time-varying fixed effects. We consider two main specifications. The first one includes a set of control variables traditional in gravity models. These control variables are as follows. The log of the distance between Buenos Aires and the capital city of the export destination country (DIST_i), with higher distances associated with larger trade costs; the log of the gross domestic product of the destination county (GDP_{it}), predicted to raise the probability of positive selection. We also include firm-level control variables: the natural log of employment of the firm in the period analyzed (SIZE_j); and the log of the firm's age (AGE_{jt}). Both control variables are associated with higher productivity and experience, and are predicted to raise the probability of selection. In this specification we also include sector-specific time effects.

In the second and main specification we consider a more stringent regression that includes firm-year fixed and destination-year fixed effects. The former control for firm's specific characteristics such as productivity and therefore firm's age and firm's size drop out of the regression. The destination-year fixed effects control for factors such as the time-varying demand or taste of a country. Thus, destination specific characteristics such as distance and GDP drop out of the regression. The destination-specific and firm-specific time-effects, also account for time-varying multilateral resistance (Anderson and Van Wincoop, 2003; Head and Mayer, 2014). Finally, we estimate equation (30) including the lagged dependent variable, to control for export histories and persistency in market selection widely documented in the literature to play an important role (see, for example, Fitzgerald and Haller, 2018).

The model is specified as a linear probability model, following the approach made popular by Bernard and Jensen (2004). The linear specification allows us to estimate the model including destination-specific and firm-specific time-effects, without incurring the incidental parameter problem that affects non-linear models. For each set of regression coefficients, we compute robust standard errors adjusted for clustering at the firm-destination level.

Table 2 shows the main empirical results regarding the extensive margin of trade. Column (1) includes distance, firm's size, firm's age, the destination country's GDP, sector-specific time effects, and our measure of risk. Consistent with the standard gravity model, the probability of exporting to a given destination increases with firm's size and age, increases with the importing country GDP and falls with distance. More importantly for us, the measure of risk is found to lower the probability of market selection, consistent with our main prediction. The coefficient β_1, capturing the extensive margin risk-elasticity, is negative and statistically significant. In column (2) we add the

Table 2. Trade and risk (extensive margin)

	(1)	(2)	(3)	(4)	(5)	(6)
DIST	−0.077***	−0.044***				
	(0.001)	(0.001)				
GDP	0.025***	0.012***				
	(0.001)	(0.000)				
SIZE	0.029***	0.017***				
	(0.001)	(0.000)				
AGE	0.076***	0.019***				
	(0.002)	(0.002)				
Risk	−0.144***	−0.078***	−0.058***	−0.035***	−0.101***	−0.062***
	(0.010)	(0.007)	(0.014)	(0.010)	(0.022)	(0.015)
Demand shock					0.017***	0.025***
					(0.001)	(0.001)
R-squared	0.085	0.240	0.305	0.394	0.390	0.416
Observations	667,185	583,660	644,564	563,857	487,833	487,833
Destination-year FE	no	no	yes	yes	yes	yes
Firm-year FE	no	no	yes	yes	yes	yes
Sector-year FE	yes	yes	no	no	no	no
Lagged dependent	no	yes	no	yes	no	yes

Notes: Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels. The main specifications which controls for the country and sector specific demand shocks are shown in grey.

lagged dependent variable, and the main results hold. The estimated coefficient β_1 is smaller (in absolute value) and statistically significant.

The results for the more stringent specifications, including destination-year and firm-year fixed effects are shown in columns (3) and (4). The coefficient on risk remains negative and significant. Once again, including the lagged dependent variable among the control variables lowers the estimated impact of risk. This finding suggests a hierarchy of risk in market selection, with less risky markets selected first. Omitting the lagged dependent variable acts as confounding factor for risk, exacerbating the estimated negative effect of risk on market selection.

Finally, the results for our main empirical specifications are shown in columns (5) and (6), in which we also control for demand shocks (level effects). Risk is still found to have a negative impact on the extensive margin of trade. To quantify the relative effects of risk and demand shocks, consider the standard deviations of our risk measure and of the demand shocks (which are, in turn, 0.14 and 1.04). Considering the estimates in column (1), a one standard deviation shock to risk lowers the probability of market selection by roughly 1.4 percentage points ($-0.101 \times 0.14 = 1.4\%$), whilst a one standard deviation negative demand shock lowers the probability of market selection by roughly 1.8 percentage points ($-0.017 \times 1.04 = 1.8\%$). Thus, the detrimental effect of risk on market selection appears to be similar in magnitude to the effect of negative demand shocks.

At any rate, the size of the β_1 coefficient suggests a considerable role is played by risk. In particular, the interquartile range of the variable $\mathbf{Risk}_{ji}^{(is)}$ is around 10%. Overall, the value of the β_1 coefficient suggests that the probability of exporting to a riskier market (top quartile) is between 0.4 and 1.14 percentage points less compared to that of exporting to a less risky market (bottom quartile). This is an important effect, given that only a small subset of firms are actually exporters and that the probability of market entry each year (conditional on exporting at some time in our sample) is about 32%. This implies that moving a market (defined by the sector and the importing country) from the bottom quartile to the top quartile of the risk distribution lowers by around 1.3% and 4.4% the probability of market selection by the typical exporting firm.

5.2. Risk and the intensive margin

In order to test the predictions of our model for the intensive margin, we estimate the regression equation

$$\ln(x_{jit}) = \omega'\mathbf{F}_{jit} + \gamma_1 \mathbf{Risk}_{ji}^{(is)} + \gamma_2 \mathbf{demand\ shock}_t^{(is)} + \varepsilon_{jit}, \tag{32}$$

where $\ln(x_{jit})$ is the log of the FOB value of exports of firm j exporting to destination i at time t, and the main covariates, $\mathbf{demand\ shock}_t^{(is)}$ and $\mathbf{Risk}_{ji}^{(is)}$, are defined as before. Again, the vector $\mathbf{F}_{jit}$ is contains the set of control variables, including time-varying fixed effects, and we estimate the models with and without the lagged dependent variable.

From Proposition 1, risk should not affect the intensive margin of trade and, hence, we expect γ_1 not to be statistically significant. As argued above, this is a sharp but special prediction of the benchmark model. In Appendix B we show that in a more realistic exporter's life-cycle model, in which young firms must grow their customer base, there should be a negative relationship between risk and the intensive margin for young firms. Moreover, testing the baseline prediction empirically is fraught with identification challenges and, therefore, we must be careful interpreting the evidence concerning the intensive margin using individual firm-level data. For this reason, in Section 5.3 we examine the relationship between average exports conditional on participation (the average intensive margin) and risk. We show that the average intensive margin is affected by risk in a model consistent way, with the most productive firms more likely to select to the more risky destinations.

Turning first to equation (32), to test the hypothesis that $\gamma_1 = 0$, we first include any destination-firm observations for which FOB exports are positive. However, this approach is likely to be vulnerable to selection bias, whereby we oversample firms that are close to the threshold of not exporting to certain destinations. This problem is described in Fitzgerald and Haller (2018). Some markets may be unattractive for all except the most productive firms. Thus, there will be certain markets for which exporting firms only export large amounts, as only high variable profits would justify the cost to serve those market. At the same time, there will be markets for which even the least productive firms are likely to export. These least productive firms will export small quantities, conditional on exporting. This could yield a spurious negative relation between the value of exports and the risk factor, if the markets that are attractive even for the least productive firms are systematically less risky.[15] To overcome this selection bias, Fitzgerald and Haller (2018) suggest estimating the regression equation for the intensive margin of trade on a sample that includes only the firm-destination pairs for which positive exports occur in every year of the sample (thus, under-weighting those markets for which there is a high concentration of low productivity firms that are near the threshold bellow which they would not export).[16]

Another reason why it may be important to consider a restricted subsample of well established exporters follows from the exporter's life-cycle model we develop in Appendix B. The dynamic model shows that new exporters have an incentive to expand their customer base by reducing prices.. This incentive is stronger in less risky markets, yielding a negative relationship between risk and the intensive margin for young exporters. Instead, it is natural to assume that firms who have always exported to a given destination are already mature exporters. For these more mature firms, there should be no relationship between sales and risk driven by an incentive to grow the firm's presence in the market through its pricing strategy. Therefore, by only including firms who have always exported to a given destination we are able to test the hypothesis $\gamma_1 = 0$ more accurately.

The main results for the intensive margin are reported in Table 3. We focus first on the least saturated specifications, which do not include the destination-year and firm-year fixed effects and, instead, include sector-year fixed effects and the vector of control variables traditionally included in firm-level gravity equations: DIST_i, GDP_{it}, SIZE_j, and AGE_{jt}. Once again, we consider regression specifications both omitting and controlling for the lagged dependent variable, with the results reported, in turn, in columns (1) and (2) of Table 3.[17] Consistent with Proposition 1, the intensive margin "risk-elasticity" coefficient on $\mathbf{Risk}_{ji}^{(is)}$ is not statistically significant, and the point estimate is,

15. As demonstrated in Section 5.3, such a mechanism may help to explain why the average intensive margin may vary with risk differently than the firm-level intensive margin regression results. The positive correlation between the average intensive margin and risk may be due to selection, while the firm-level intensive margin may show a negative correlation with risk if variable trade costs are negatively correlated with risk. The average intensive margin and extensive margin are crucial factors in explaining aggregate exports.

16. As explained in Fitzgerald and Haller (2018), applying the Heckman selection correction (which is the conventional way to deal with sample selection bias in models with incidentally truncated dependent variables) is not feasible in our setting because there are no instruments available that would at the same time predict export participation but not export revenue conditional on participation.

17. Controlling for the lagged dependent variable in the intensive margin regressions should improve the model specification because positive serial correlation has been shown to be important in the dynamics of export market penetration (Albornoz et al., 2012). Controlling for the history of past sales is also consistent with the dynamic model of exporter growth that we propose in Appendix B.

Table 3. Trade and risk (intensive margin)

	(1)	(2)	(3)	(4)	(5)	(6)
DIST	−0.212***	−0.055***				
	(0.007)	(0.003)				
GDP	0.199***	0.056***				
	(0.005)	(0.002)				
SIZE	0.302***	0.096***				
	(0.005)	(0.003)				
AGE	0.114***	−0.055***				
	(0.019)	(0.009)				
Risk	−0.098	−0.003	−0.435***	−0.177	−0.674***	−0.153
	(0.089)	(0.049)	(0.137)	(0.146)	(0.205)	(0.133)
Demand shock					0.262***	0.499***
					(0.009)	(0.017)
R-squared	0.272	0.697	0.518	0.858	0.567	0.872
Observations	260,124	155,381	236,772	46,193	136,763	46,193
Destination-year FE	no	no	yes	yes	yes	yes
Firm-year FE	no	no	yes	yes	yes	yes
Sector-year FE	yes	yes	no	no	no	no
Lagged dependent	no	yes	no	yes	no	yes
Selection adj.	no	no	no	yes	no	yes

Notes: Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels. The main specifications which controls for the country and sector specific demand shocks are shown in grey.

in fact, very close to 0 when we control for serial correlation by including the lagged dependent variable.

Next, we examine a more stringent specification that incorporates destination-time and firm-time fixed effects. In column (3), we present results without adjusting for sample selection. We find that risk negatively impacts the intensive margin of trade for this specification. This result may be due to a selection bias where we oversample firms close to the threshold for not exporting to certain destinations, which tend to be smaller firms that export smaller volumes, as previously noted in studies by Albornoz et al. (2012) and Eaton et al. (2007). Additionally, our finding that risk affects the intensive margin for younger firms aligns with the dynamic version of our model presented in Appendix B, which more accurately captures the life-cycle of a firm. Notably, in column (4), when we include only well-established firms that have consistently exported to the considered destination, we do not find an association between the intensive margin and risk, in line with the predictions of our dynamic model.

In our main specification, we control for demand shocks and find consistent results in columns (5) and (6). Our dynamic model predicts that young firms have an incentive to increase their customer base by charging lower markups, but this channels is weaker for riskier destinations. Consistently, our results show that risk negatively impacts the intensive margin of exports for all firms, particularly for young exporters to a specific destination. However, when controlling for the exporter's history and restricting the sample to firms that have consistently exported to the destination and no longer need to expand their customer base, we do not observe a significant relationship between the value of FOB exports, conditional on market selection, and risk.

5.3. Selection, aggregation and the risk channel

In this Section we investigate the relationship between the average firm exports conditional on selection into a market. We denote this the average intensive margin (AIM). This alternative definition of the intensive margin which internalizes the endogenous selection is often used in empirical studies and, for example, is proposed in Bernard et al. (2012) and Fernandes et al. (2018). Doing aggregation to obtain the AIM enables us to use the model explicitly to tackle the selection problem and, thus, eliminates firm-specific unobservables. In particular, in Appendix C we show that, in sector s, the average value of firm's exports conditional on exporting to destination i is

$$\begin{aligned} \bar{\mathrm{x}}_{ist} &= \frac{X_{ist}}{N_{ist}} = \beta^{-1}\left[\frac{\alpha_s\varepsilon_s}{\alpha_s-(\varepsilon_s-1)}\right]\left(\frac{f_i}{1-\rho\sigma^{is}_{\varepsilon,g}}\right), \\ &\Rightarrow \ln\left(\bar{x}_{ist}\right) = \omega_s+\omega_i+\rho\sigma^{is}_{\varepsilon,g}, \end{aligned} \tag{33}$$

where $\omega_s = \ln\left(\alpha_s\varepsilon_s\right) - \ln\left(\alpha_s - \varepsilon_s + 1\right) - \ln\left(\beta\right)$ is a sector fixed effed, $\omega_i = \ln\left(f_i\right)$ is a destination fixed effect, and $\sigma^{is}_{\varepsilon,g}$ captures risk.

Thus, the average value of exports conditional on selection is increasing with the fixed cost of exporting, f_i, and in the level of priced risk, $\sigma^{is}_{\varepsilon,g}$, of the destination market. Instead, the average value of exports conditional on selection is not affected by the variable trade costs, τ_i. This result is analogous to that obtained in the canonical Melitz (2003) and Chaney (2008) trade models. Variable trade costs have two offsetting effects on the intensive margin. High variable trade costs lower the value of exports of a given exporter, which reduces average firm's exports. However, higher variable trade costs also imply that some exporters near the productivity threshold for exporting no longer generate sufficient variable profits to cover the fixed costs of exporting (selection effect). With the Pareto distribution, these two effects exactly offset one another, leaving the AIM independent of variable trade costs (see Bernard et al., 2012; Fernandes et al., 2018, for a detailed discussion of this result).

Based on the structural equation (33) we estimate the following model for the AIM relationship

$$\ln\left(\bar{\mathrm{x}}_{ist}\right) = \omega_{it} + \omega_s + \gamma\mathbf{Risk}^{(is)} + \varepsilon_{ist}, \tag{34}$$

where $\ln\left(\bar{\mathrm{x}}_{ist}\right)$ is the log of the average FOB value of exports conditional on participation, ω_{it} and ω_s denote destination-year and sector fixed effects, $\mathbf{Risk}^{(is)}$ denotes the measure of risk, and ε_{ist} is the error term. This specification follows exactly from the structural relationship (33), with the only difference being that we allow for a time-varying destination fixed effect and, thus, ω_{it} varies with time. The empirical results are reported in Table 4 and show that the coefficient on risk is positive and statistically significant. The finding that the AIM varies positively with our measure of risk confirms the

Table 4. Risk and the average intensive margin

Risk	0.415***
	(0.128)
R-squared	0.411
Observations	50,770
Destination-year FE	yes
Sector FE	yes

Notes: This table shows the estimation of equation (34). Robust standard errors reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels.

importance of the extensive margin to explain how risk affects exports: only the most productive firms select into risky export markets.[18]

5.4. Extensions and robustness

In Appendix D, we estimate the model separately for small, medium, and large firms to investigate if there is evidence of heterogeneous risk-elasticities. We find that the extensive margin risk elasticities are higher for larger firms. Appendix E provides several robustness checks, including using alternative samples and estimating the selection equation using a Probit model. Our results are robust to these changes. In addition, we also check the sensitivity of our findings to estimating the aggregation equation (34) using the Poisson Pseudo Maximum Likelihood (PPML), in Appendix E.3.

6. Time-varying risk premia

This section investigates the role of time-varying risk premia as a source of fluctuations in aggregate bilateral trade flows. We first analyze the global financial crisis and then the role of risk premium shocks.

18. Interestingly, the model's property that the AIM is independent of the variable cost, τ_i, can also help reconcile the finding in Section 5.2, that there is some evidence of a negative relationship between individual firm level exports, x_{jist}, and risk, despite the dominant role of the selection effect at the aggregate level (implied by the positive association between the AIM and risk). Specifically, if the correlation between variable trade costs, τ_i, and risk is positive, then there would be a negative relationship between individual firm level exports and risk. However, because variable trade costs do not affect the AIM, there would still be a positive relationship between risk and the average exports conditional on exporting.

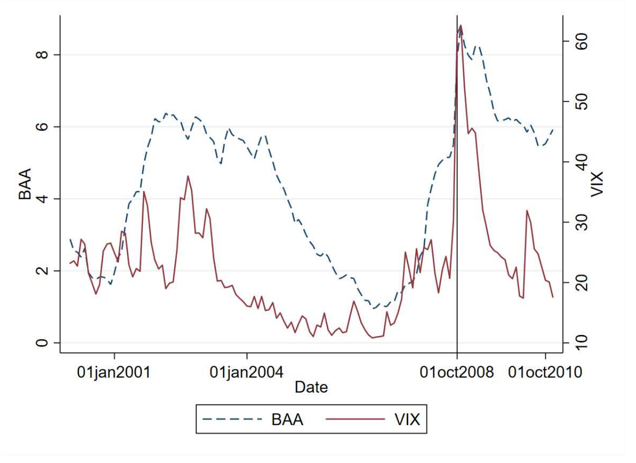

FIGURE 3. Risk in the Great Recession

Notes: The Figure compares the monthly evolution of the Chicago Board Options Exchange Volatility Index (the VIX index), and the Moody's Seasoned Baa Corporate Bond spread *vis-à-vis* the US federal funds rate. Both measures are sourced from the Federal Reserve Bank of St. Louis Fred.

6.1. Risky business cycles and the trade collapse

The global financial crisis is an example of a period of heightened volatility and risk premia. Thus, we introduce time-varying volatility and, in particular, consider variation in aggregate consumption growth risk, $\text{std}_t\left(g_{t+1}\right)$, as a factor contributing to the trade collapse during the 2008–2009 Great Recession.

The crisis is typically dated between the forth quarter of 2008 and the third quarter of 2009 (see Chor and Manova, 2012). We corroborate the dates of the crisis by inspecting both volatility and trade data. Figure 3 shows two popular measures of uncertainty: the Chicago Board Options Exchange Volatility Index (the VIX index) and the Moody's Seasoned Baa Corporate Bond spread *vis-à-vis* the US federal funds rate. It is clear that volatility peaked around the start of the crisis but remained high until the end of 2009.

The timing of the heightened uncertainty is in line with the aggregate time series trends for the overall exports by Argentinean firms, plotted in Figure 4, which shows the evolution of exports at quarterly frequency between 2007 and 2009. For comparison, the Figure displays the evolution of aggregate exports both from the IMF International Financial Statistics (IFS) and from our customs dataset. Total exports reached a peak in the third quarter of 2008 (2008Q3), fell sharply until the third quarter of 2009 (2009Q3), after which they began to slowly recover. In 2009Q3, total exports were 35% lower relative to their value in 2008Q3. The decline in exports between the last quarter of 2008 and the third quarter of 2009 (henceforth, 2008Q4–2009Q3) is stark, and coincides with the period of heightened global uncertainty. Therefore,

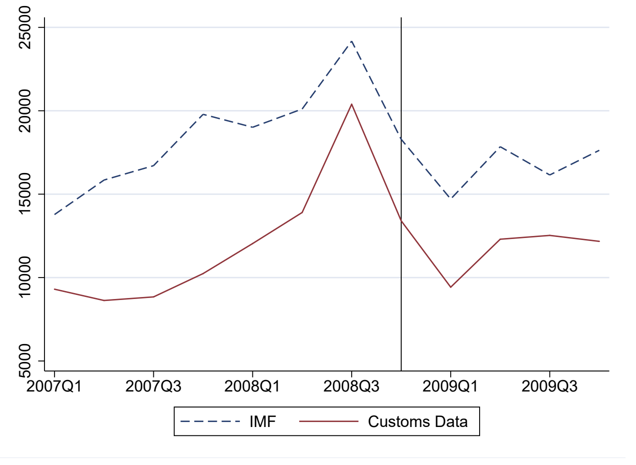

FIGURE 4. Trade in the Great Recession
Notes: The figure compares the evolution of Argentinean exports (million US dollars) between 2007Q1 and 2009Q4 using the International Financial Statistics of the IMF data (blue line) and the aggregate FOB from our customs data set (red line).

we select these dates as the high uncertainty episode. As shown in Table D3 of Appendix D, the trade collapse affected both the extensive and intensive margins. In particular, starting in 2008Q4, because risk was greatly elevated compared to normal times, firms' decision to enter export markets was likely affected.[19]

6.1.1. Risk and firm-level exports during the financial crisis. Our model predicts that the effect of heightened uncertainty is heterogeneous across export destinations and, in particular, is large for export destinations which are "risky" in the sense that they comove positively and strongly with the domestic households' growth rate of consumption. These are the countries for which our measure of comovement, $\varrho\left(\hat{\eta}_{it+1}, g_{t+1}\right)$, is large and positive. To test this prediction we obtain data at the quarterly frequency, spanning the period from 2007 until 2009 and estimate the following difference-in-difference (DID) specification

$$d_{jit} = \delta' \mathbf{F}_{jit} + \beta\, \mathbf{Crisis}_t \times \mathbf{Risk}_{ji}^{(is)} + \varepsilon_{jit}, \tag{35}$$

19. The change in total exports can be decomposed into the part explained by the fall in sales conditional on exporting (the average intensive margin) and the fall in the number of exporting firms (the extensive margin). The intensive margin accounts for a large part of the trade collapse, and has been shown to be mostly explained by the negative demand shock, with the global recession inducing a disproportionate fall in the demand for tradable goods, as argued, for example by Behrens et al. (2013), Bems et al. (2013) and Novy and Taylor (2020).

Table 5. Time-varying risk premium and the trade collapse

	Extensive Margin		Intensive Margin	
	(1)	(2)	(3)	(4)
Crisis × Risk	-0.020**	-0.021**	-0.052	-0.088
	(0.008)	(0.009)	(0.080)	(0.134)
R-Squared	0.45	0.47	0.828	0.848
Observations	477,000	417,375	146,636	80,612
Destination-time FE	yes	yes	yes	yes
Firm-destination FE	yes	yes	yes	yes
Sector-time FE	yes	yes	yes	yes
Lagged dependent variable	no	yes	no	yes

Notes: Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. The pre-crisis period corresponds to 2007Q4-2008Q3 and the crisis period corresponds to 2008Q4-2009Q3. *, **, and *** indicate significance at 10%, 5% and 1% levels.

where the dependent variable, d_{jit}, is again a dummy variable taking value 1 if the firm j exports to destination i at time t. The covariate $\mathbf{Risk}_{ji}^{(is)}$ denotes the baseline measure of risk, varying across sector and destination, while $\mathbf{Crisis}_t$ is a dummy variable capturing the aggregate risk premium shock. In our baseline specification, $\mathbf{Crisis}_t$ is defined to take value 1 starting in 2008Q4, and until 2009Q3. For the pre-crisis period, we use data from 2007Q4-2008Q3.

Our main specification includes destination-firm fixed effects, and destination-specific and sector-specific time effects, collected in the vector $\mathbf{F}_{jit}$. Note that the inclusion of the time effects absorbs the individual effects (non-interacted) of the covariates $\mathbf{Crisis}_t$ and $\mathbf{Risk}_{ji}^{(is)}$, which are, therefore, not included in the regression specification. Our main prediction is that the coefficient β should be negative, implying that the heightened uncertainty has a more detrimental impact on the choice to export to risky destinations.

In addition to the extensive margin specification, we also estimate a similar model to (35) but for the intensive margin of trade. Thus, the dependent variable is the logarithm of FOB exports. With regards to the intensive margin, the model's prediction is that fluctuations in risk premia should have no direct impact on the value of exports, regardless of the riskiness of the export destination. Results are shown in Table 5. Columns (1) and (2) report the results for the extensive margin while columns (3) and (4) include the ones for the intensive margin. For the extensive margin, the coefficient on the interaction term, $\mathbf{Crisis}_t \times \mathbf{Risk}_{ji}^{(is)}$ is found to be negative and is statistically significant. Thus, the heightened risk premia is found to affect the cross-sectional profile of selected destinations, lowering the probability that firms select into the most risky destinations, consistent with the model's predictions.

In line with Proposition 1, we find that risk premium shocks are not associated with greater declines in the intensive margin. However, as discussed before, the finding that time-varying risk has no direct impact on the intensive

Table 6. Time-varying measure of risk

	(1)	(2)	(3)	(4)	(5)	(6)
	Extensive Margin			Intensive Margin		
Risk × VIX	-0.004**	-0.003***	-0.002	-0.013	-0.012	-0.010
	(0.002)	(0.001)	(0.001)	(0.016)	(0.016)	(0.013)
Risk		-0.002	-0.004**		0.008	-0.026
		(0.002)	(0.002)		(0.019)	(0.019)
VIX			-0.012***			-0.063***
			(0.001)			(0.004)
R-squared	0.356	0.199	0.240	0.776	0.685	0.712
Observations	619,740	655,875	655,875	114,251	138,942	137,699
Destination-time FE	yes	yes	no	yes	yes	no
Firm-time FE	yes	no	no	yes	no	no
Exporter FE	no	no	yes	no	no	yes
Sector FE	no	yes	yes	no	yes	yes
Destination FE	no	no	yes	no	no	yes
Firm characteristics	no	yes	no	no	yes	no
Destination country GDP	no	no	yes	no	no	yes
Lagged dependent variable	yes	yes	yes	yes	yes	yes

Notes: Notes: Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels.

margin of trade does not imply that the heightened uncertainty during the 2008 financial crisis did not affect the intensive margin. From the results by firm size described in Section 5.4 and Appendix D.1 , we already know that the extensive margin risk channel is heterogeneous across firms and affects mostly large firms. Next we investigate if the effects of elevated risk premia are also heterogeneous across firms of different size. The results are reported in Appendix D.2, and are consistent with our previous findings. Large firms suffer a larger decline in the extensive margin concentrated on the riskier markets, while the risk channel is unimportant for the small firms. The risk channel has no direct effect on the intensive margin. However, since large firms export more, the risk channel indirectly affects the intensive margin: the extensive margin response to the increase in risk leads, indirectly, to a lowering of the average value of exports conditional on exporting (intensive margin).

6.2. Risk premium shocks

In the baseline specification we have used a measure of risk which is not time-varying. As explained in Section 3.2, this is as a result of normalizing $\text{std}\left(g_{t+1}\right)$ to unity in equation (28). In this section, we depart from this assumption and allow for transitory risk premium shocks. Empirically, this term is given by a measure of the price of risk. We use the VIX index, as it is a commonly used proxy for macroeconomic uncertainty (Bloom, 2009) and innovations in this aggregate market volatility index have been shown to carry a negative price of risk in the cross-section of asset returns (Ang et al., 2006). The empirical specifications for the extensive and intensive margins shown in equations (30) and (32) are augmented to include a time-varying risk measure and become

$$d_{jit} = \delta' \mathbf{F}_{jit} + \beta_1 \mathbf{Risk}_{ji}^{(is)} \times \mathbf{VIX}_t + \beta_2 \mathbf{Risk}_{ji}^{(is)} + \beta_3 \mathbf{VIX}_t + \varepsilon_{jit}, \quad (36)$$

$$\ln\left(x_{jit}\right) = \omega' \mathbf{F}_{jit} + \gamma_1 \mathbf{Risk}_{ji}^{(is)} \times \mathbf{VIX}_t + \gamma_2 \mathbf{Risk}_{ji}^{(is)} + \gamma_3 \mathbf{VIX}_t + \varepsilon_{jit}. \quad (37)$$

where $\mathbf{Risk}_{ji}^{(is)}$ captures the persistently high risk premium in the cross-section of sector-destination pairs, $\mathbf{Risk}_{ji}^{(is)} \times \mathbf{VIX}_t$ pins down the time-varying dimension of risk premium, and $\mathbf{VIX}_t$ captures the effect of transitory risk premia shocks common across markets. To facilitate comparison, all the measures of risk have been standardized to have mean zero and unit standard deviation. We use specifications with a different set of controls and fixed effects included in $\mathbf{F}_{jit}$ to allow for the identification of all the coefficients, and, in particular, the coefficients measuring the effect of time-varying risk premia common across all markets, and the effect of persistently high risk premium in some markets.

Table 6 presents the extensive and intensive margin results using the same quarterly data from 2007Q1 to 2009Q4 as in the previous section.[20] Starting from the extensive margin results, the first column includes destination-time fixed effects, which control for first-moment demand effects, and firm-time fixed effects. Therefore, the individual impacts of $\mathbf{VIX}_t$ and $\mathbf{Risk}_{ji}^{(is)}$ drop out from the regression while we can estimate how transitory risk premium shocks affect differently markets with different persistent exposures to risk (given by the interaction factor, $\mathbf{Risk}_{ji}^{(is)} \times \mathbf{VIX}_t$). Higher risk premium shocks lower the probability of exporting to a given destination, and this effect is larger for persistently riskier destinations. In the second column, we keep the destination-time fixed effect, exclude the firm-time fixed effect, and add sector fixed effects and firm characteristics controls (firms' age and employment). With this specification $\mathbf{VIX}_t$ drops out from the regression but we can estimate the coefficients β_1 and β_2. The time-varying measure of risk remains negative and significant.

Finally, in column (3) we include separately all three risk factors: $\mathbf{Risk}_{ji}^{(is)}$ capturing the effect of persistently higher risk premia, $\mathbf{VIX}_t$ capturing the effect of transitory risk premia shocks common across markets, and $\mathbf{Risk}_{ji}^{(is)}$ $\times$ $\mathbf{VIX}_t$ to capture how persistently riskier markets are affected differently when there are transitory risk premia shocks. Thus, we can estimate the coefficients β_1, β_2, and β_3. In this specification, it is still possible to identify exporter, sector, and destination fixed effects, while controlling for first-moment demand factors using the destination country GDP. All the coefficients have the expected sign. The effects of $\mathbf{Risk}_{ji}^{(is)}$ and $\mathbf{VIX}_t$ lower the probability of exporting to a given destination, and the effect of the interaction between these two risk factors has the expected sign but is just insignificant.

Each of the columns of the intensive margin regressions follow the same set of fixed effects previously described. All in all, the measures of risk are all

20. Since the VIX varies at a higher frequency we use quarterly instead of annual data.

insignificant (consistent with the baseline theoretical prediction), but column (6) shows that the individual effect of $\mathbf{VIX}_t$ lowers trade flows.

7. Conclusion

During large economic downturns, risk premia can play an important role in driving trade fluctuations, as it happened during the 2008–2009 trade collapse. However, the models currently used to predict the direction and magnitude of trade do not include a role for risk premia. In this paper we propose an extension of the model by Chaney (2008) to include a role for risk, and study empirically how risk affects the behavior of exporters using firm-level data on Argentinean exporters.

The model delivers testable predictions about how risk affects the extensive and intensive margins of trade. Risk should affect the extensive margin directly by discouraging exports to riskier destinations whilst there should be no direct effect of risk on the firm's exports conditional on participation (individual intensive margin). Furthermore, the extensive margin risk-elasticity should be larger in sectors with greater product differentiation resulting in firms enjoying larger markups. Importantly, although the static model predicts that risk does not affect the intensive margin directly, an extension of the static model to capture realistic features of an exporter's life-cycle, can reconnect risk and the intensive margin of trade. Specifically, we show that when young exporters have an incentive to increase their sales to grow their customer base, there may be a negative link between risk and the intensive margin of trade.

We test the predictions of our model using firm-level Argentinean export data between 2002 and 2009. Consistent with the theoretical predictions, we find that risk affects directly the extensive margin of trade. Once we restrict the sample to include only exporters who have been long-term exporters to a given market and control for history dependence, risk appears not to have a direct impact on the intensive margin of trade. However, the empirical evidence on the intensive margin also offers support for the differential impact of risk across younger and more mature exporters, as suggested by the life-cycle version of our theoretical model. As an application, we investigate the impact of risk on bilateral trade flows during the 2008–2009 Global Financial Crisis, since this is a typical example of a period of heightened risk premia. In line with the model predictions, during this period, we find that Argentinean exporters shifted away from more risky destinations.

One promising avenue for future research would be to use our framework to identify how risk shapes the composition of products exported in addition to the export destinations.

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Appendix A: Aggregate bilateral exports

In this section we provide the detailed derivation of equation (21).

Conditional on exporting to destination i, the value of exports by a firm with productivity φ_j at date $t+1$ is given by

$$\begin{aligned} x_{jist+1} &= Z_{ist+1} p_{jist+1}^{1-\varepsilon_s}, \\ &= \left(\frac{\varepsilon_s}{\varepsilon_s - 1}\right)^{1-\varepsilon_s} \left(\frac{W\tau_i}{\varphi_j}\right)^{1-\varepsilon_s} Z_{ist+1}. \end{aligned} \tag{A.1}$$

But in sector s only firms with productivity $\varphi_j \geq \bar{\varphi}_{ist}$ export to country i at date $t+1$. Since φ_j has the Pareto distribution with shape parameter $\alpha > \varepsilon_s - 1$, aggregate exports at date t from Home to country i are given by

$$\begin{aligned} X_{ist+1} &= \int_{\bar{\varphi}_{ist}}^{\infty} x_{jist+1}(\varphi)\, d\mathbf{F}(\varphi), \\ &= \left(\frac{\varepsilon_s}{\varepsilon_s - 1}\right)^{1-\varepsilon_s} \int_{\bar{\varphi}_{ist}}^{\infty} Z_{ist+1} \left(\frac{W\tau_i}{\varphi}\right)^{1-\varepsilon_s} d\mathbf{F}(\varphi), \\ &= \left(\frac{\varepsilon_s}{\varepsilon_s - 1}\right)^{1-\varepsilon_s} Z_{ist+1} W^{1-\varepsilon} \tau_i^{1-\varepsilon} \int_{\bar{\varphi}_{ist}}^{\infty} \alpha \varphi^{(\varepsilon-1)-\alpha-1} d\varphi, \\ &= \left(\frac{\alpha}{1-\varepsilon_s+\alpha}\right) \left(\frac{\varepsilon_s}{\varepsilon_s - 1}\right)^{1-\varepsilon_s} Z_{ist+1} W^{1-\varepsilon_s} \tau_i^{1-\varepsilon_s} \bar{\varphi}_{ist}^{(\varepsilon_s-1)-\alpha}. \end{aligned} \tag{A.2}$$

Making use of equation (19) to substitute for $\bar{\varphi}_{ist}$ in (A.2) yields

$$\begin{aligned} X_{ist+1} = &\left(\frac{\alpha}{1-\varepsilon_s+\alpha}\right) \left(\frac{\varepsilon_s}{\varepsilon_s - 1}\right)^{1-\varepsilon_s} \times \\ &Z_{ist+1} (W\tau_i)^{-\alpha} \left[\beta \lambda_s Z_{ist} \left(\frac{1-\rho\sigma_{\varepsilon,g}}{f_i}\right)\right]^{\alpha/(\varepsilon_s-1)-1}. \end{aligned} \tag{A.3}$$

Finally, making use of equation (8) yields expression (21) in the main text.

Appendix B: Exporter's growth and the intensive margin

Our baseline model does not feature firm growth dynamics and, consequently, may miss some of the impacts of risk on the firm's investment and pricing policies. In particular, several empirical studies of exporters' growth dynamics have shown that new exporters start relatively small compared to firms already well established in the market and, subsequently, conditional on survival, grow their customer base and converge in size with the older firms (Fitzgerald et al., 2016; Foster et al., 2016; Ruhl and Willis, 2017). Thus, one question is if enriching the model with more realistic firm growth dynamics changes the relationship between exports and risk. We show that if endogenous customer base accumulation plays an important role in explaining how new exporters grow, then the intensive margin of trade is also affected by risk.

To examine this question formally we consider a dynamic model in which there are new firms and mature firms. For simplicity, we assume firms last at most two periods: they start as young firms, with age denoted $a = 0$ and, conditional on survival, become mature firms the following period, aged $a = 1$.[21] Also, for simplicity, we assume there is a single export destination, so that firms either export or not. An exporting firm aged $a \in \{0, 1\}$ at date t is confronted with the demand function

$$q_a = Z_t c_a p_a^{-\varepsilon}, \tag{B.1}$$

where p_a is the price charged by the firm, Z_t is an exogenous stochastic demand shock common to all firms active in period t, and c_a is an endogenous demand shifter that captures the experience of a firm aged a and, in particular, the firm's customer base which depends on the firm's past sales. We follow the framework in Foster et al. (2016) and assume that the customer base evolves as follows

$$c_a = (1 - \delta)\, c_{a-1} + q_a, \tag{B.2}$$

with $\delta \in (0, 1)$ the customer base depreciation rate.[22] As in the baseline static model, the cost of exporting each unit of output for a firm with productivity level φ is given by $(\tau W/\varphi)$.

We bypass the participation choice problem by considering the problem of the firm after it has already incurred the sunk entry cost. In particular, we assume young firms having just entered the market already paid the sunk cost f, which is only paid once. Thus, we consider young firms endowed with an idiosyncratic productivity level $\varphi \geq \bar{\varphi}$, which is sufficiently high to have enticed

21. Of course, this leads to a very simple life-cycle model of the firm. However, this very simple model is enough to illustrate how endogenous firm growth leads to a connection between risk and the firm's sales. Extending the model to a larger life-cycle model is, of course, possible.

22. Here we deviate slightly from the Foster et al. (2016) original set-up, as we assume that the customer base grows with the volume of sales, q_a, instead of the value, $p_a q_a$.

market entry. However, not all young firms survive into maturity. There is an exogenous probability $\chi \in [0,1]$ that a young firm is forced to exit the export market after the first period. This exogenous exit shock is meant to capture the low survival rate of young exporters.

The key feature of the pricing problem solved by young firms is the incentive to grow its customer base. It does so by charging a lower markup whilst young to raise its current sales and, thus, increase its future customer base if it survives into old age.[23] This incentive to grow its customer base introduces an intertemporal dimension to the pricing problem of young firms. The dynamic pricing problem solved by a young firm at date t is

$$\max_{p_{t,0}} v_{0,t}\left(c_0, \varphi\right) = \left\{ \left(p_{t,0} - \frac{\tau W}{\varphi} \right) Z_t c_0 p_{t,0}^{-\varepsilon} + \chi \mathbf{E}_t \Big[\mathcal{M}_{t+1} v_{1,t+1}\left(c_1, \varphi\right) \Big] \right\},$$

$$\text{subject to: } c_1 = (1-\delta)\, c_0 + Z_t c_0 p_{t,0}^{-\varepsilon}, \tag{B.3}$$

where $p_{t,0}$ is the price chosen, $v_{0,t}\left(c_0, \varphi\right)$ is the value function of a young firm at date t with customer base c_0 and idiosyncratic productivity level φ, $\mathcal{M}_{t+1}$ is the date t stochastic discount factor for date $t+1$ payoffs, and $v_{1,t+1}\left(c_1, \varphi\right)$ is the value function of an old firm at date $t+1$ with customer base c_1 and idiosyncratic productivity level φ. Old firms simply set their price to achieve the optimal static markup, so that $p_1 = \left(\tau W / \varphi\right) \varepsilon / \left(\varepsilon - 1\right)$ is the price chosen by an old firm with productivity φ. Thus, $v_{1,t+1}\left(c_1, \varphi\right)$ is given by

$$\begin{aligned} v_{1,t+1}\left(c_1, \varphi\right) &= \max_{p_1} \left(p_1 - \frac{\tau W}{\varphi} \right) Z_{t+1} c_1 p_1^{-\varepsilon}, \\ &= \lambda Z_{t+1} c_1 \left(\frac{\tau W}{\varphi} \right)^{1-\varepsilon}, \end{aligned} \tag{B.4}$$

with $\lambda = \varepsilon^{-\varepsilon}\left(\varepsilon - 1\right)^{\varepsilon - 1}$.

The euler equation solving the problem of young firms is

$$\begin{aligned} p_{t,0} &= \left(\frac{\varepsilon}{\varepsilon - 1} \right) \left[\left(\frac{\tau W}{\varphi} \right) - \chi \lambda \left(\frac{\tau W}{\varphi} \right)^{1-\varepsilon} \mathbf{E}_t \left(\mathcal{M}_{t+1} Z_{t+1} \right) \right], \\ &= \left(\frac{\varepsilon}{\varepsilon - 1} \right) \left(\frac{\tau W}{\varphi} \right) - \chi \left(\frac{\varepsilon}{\varepsilon - 1} \right) \lambda \left(\frac{\tau W}{\varphi} \right)^{1-\varepsilon} \mathbf{E}_t \left(\mathcal{M}_{t+1} \right) \mathbf{E}_t \left(Z_{t+1} \right) \\ &\quad - \chi \left(\frac{\varepsilon}{\varepsilon - 1} \right) \lambda \left(\frac{\tau W}{\varphi} \right)^{1-\varepsilon} \operatorname{cov}_t \left(\mathcal{M}_{t+1}, Z_{t+1} \right). \end{aligned} \tag{B.5}$$

23. This mechanism follows Foster et al. (2016), in that the firm uses its pricing strategy to grow its customer base. Fitzgerald et al. (2016) consider an alternative model of customer base accumulation in which the firm must realize direct investment activities in marketing and advertising to grow its demand. We consider the dynamic pricing model of Foster et al. (2016) for analytical convenience, but the link between investment and risk would be similar in the alternative framework by Fitzgerald et al. (2016).

Recall from the main text we had

$$\begin{aligned}\mathcal{M}_{t+1} &\simeq (1-\rho g_{t+1})\,\beta,\\ Z_{t+1} &= Z_t \exp(\varepsilon_{t+1}) \simeq Z_t\,(1+\varepsilon_{t+1}),\\ &\Rightarrow \mathrm{cov}_t\,(\mathcal{M}_{t+1}, Z_{t+1}) = -\beta Z_t \rho\sigma_{\varepsilon,g} = -\mathbf{E}_t\,(\mathcal{M}_{t+1})\,\mathbf{E}_t\,(Z_{t+1})\,\rho\sigma_{\varepsilon,g}.\end{aligned} \tag{B.6}$$

Moreover, without loss of generality (simply to obtain a more elegant formula), we normalize the constant $\mathbf{E}_t\,(\mathcal{M}_{t+1})\,\mathbf{E}_t\,(Z_{t+1}) = (1/\lambda)\,(\tau W/\varphi)^{\varepsilon}$. Thus, substituting in (B.5) yields the price chosen by young firms at date t

$$p_{t,0} = (1-\chi)\left(\frac{\varepsilon}{\varepsilon-1}\right)\left(\frac{\tau W}{\varphi}\right) + \chi\left(\frac{\varepsilon}{\varepsilon-1}\right)\left(\frac{\tau W}{\varphi}\right)\rho\sigma_{\varepsilon,g}. \tag{B.7}$$

So the main upshot is that the price level chosen by young firms at date t is increasing in the level of risk $\sigma_{\varepsilon,g}$.

The intuition for this result is clear and instructive. First, the relationship between risk and the intensive margin emerges only if the firm's life-cycle is important. Thus, if the probability of exporters' survival is zero, $\chi = 0$, young exporters charge the optimal static markup $\varepsilon/(\varepsilon-1)$ and risk is irrelevant. If dynamics matter, $\chi > 0$, and there is no risk, $\sigma_{\varepsilon,g} = 0$, then young firms charge a lower markup $(1-\chi)\,\varepsilon/(\varepsilon-1)$, so as to increase sales and its customer base. Finally, this incentive to charge lower markups is dampened if the future demand confronted by the young firm is risky, $\sigma_{\varepsilon,g} > 0$, and, instead, is stronger if the export market lowers risk, $\sigma_{\varepsilon,g} < 0$, since in this case growing the customer base not only raises the level of future expected demand, it also contributes to lower the overall risk to which the stand-in investor who owns the firm is exposed.

These results are important to interpret the empirical findings in Section 5.2 about the relationship between risk and the intensive margin of trade. There, we found that when we restrict the sample of firms to include only those exporters who have always exported to a given destination, there is no relationship between risk and the firm's sales. It is natural to assume that firms who have always exported to a given destination are already mature exporters in that market. These firms are already well established and, therefore, no longer engage in price strategies aimed at increasing their customer base. Thus, for these firms there should be no relationship between the intensive margin and risk, consistent with our findings. Instead, when we include all the firms there is some evidence of a negative relationship between the intensive margin and risk. Again, this is consistent with the exporter's life cycle model. When young firms are included, we expect those firms to have to invest in growing their customer base. As we have shown, this incentive is stronger in less risky markets, yielding a negative relationship between risk and the intensive margin.

Appendix C: Average exports conditional on selection and risk

Conditional on selecting destination i, the value of exports to this destination by a firm with productivity level φ_j is

$$x_{jist} = \left(\frac{\varepsilon_s}{\varepsilon_s - 1}\right)^{1-\varepsilon_s} \left(\frac{W\tau_i}{\varphi_j}\right)^{1-\varepsilon_s} Z_{ist+1}.$$

The threshold productivity level above which firms export is

$$\bar{\varphi}_{ist} = \left[\frac{f_i / \left(1 - \rho\sigma^{is}_{\varepsilon,g}\right)}{\beta\lambda_s Z_{ist+1}}\right]^{1/(\varepsilon_s - 1)} W\tau_i. \tag{C.1}$$

Thus, the number of sector s firms exporting to destination i (the extensive margin) is

$$N_{ist} = 1 - \mathbf{F}\left(\bar{\varphi}_{ist}\right) = \left[\frac{f_i / \left(1 - \rho\sigma^{is}_{\varepsilon,g}\right)}{\beta\lambda_s Z_{ist+1}}\right]^{\alpha_s/(1-\varepsilon_s)} \left(W\tau_i\right)^{-\alpha_s}. \tag{C.2}$$

The sector s aggregate bilateral exports to destination i is

$$X_{ist} = \Lambda_s Z^{\alpha_s/(\varepsilon_s - 1)}_{ist+1} \left(W\tau_i\right)^{-\alpha_s} \left(\frac{1 - \rho\sigma^{is}_{\varepsilon,g}}{f_i}\right)^{\alpha_s/(\varepsilon_s - 1) - 1}, \tag{C.3}$$

with $\Lambda_s = \alpha_s \left(1 - 1/\varepsilon_s\right)^{\varepsilon_s - 1} \left(1 - \varepsilon_s + \alpha_s\right)^{-1} \left(\beta\lambda_s\right)^{\alpha_s/(\varepsilon_s - 1) - 1}$. It follows that, in sector s, the average export conditional on exporting to destination i is

$$\begin{aligned} \bar{\mathrm{x}}_{ist} = \frac{X_{ist}}{N_{ist}} &= \beta^{-1} \left[\frac{\alpha_s \varepsilon_s}{\alpha_s - \left(\varepsilon_s - 1\right)}\right] \left(\frac{f_i}{1 - \rho\sigma^{is}_{\varepsilon,g}}\right), \\ \Rightarrow \ln\left(\bar{x}_{ist}\right) &= \omega_s + \omega_i + \rho\sigma^{is}_{\varepsilon,g}, \end{aligned} \tag{C.4}$$

where $\omega_s = \ln\left(\alpha_s \varepsilon_s\right) - \ln\left(\alpha_s - \varepsilon_s + 1\right) - \ln\left(\beta\right)$ is a sector fixed effed, $\omega_i = \ln\left(f_i\right)$ is a destination fixed effect, and $\sigma^{is}_{\varepsilon,g}$ captures risk.

Therefore, average exports conditional on selection are increasing with the fixed cost of exporting, f_i, and in the level of priced risk, $\sigma^{is}_{\varepsilon,g}$, of the destination market. Instead, average exports conditional on selection are not affected by the variable trade costs. Variable trade costs have two offsetting effects on the intensive margin. High variable trade costs lower the value of exports of a given exporter, which reduces average firm's exports. However, higher variable trade costs also imply that some exporters near the productivity threshold for exporting no longer generate sufficient variable profits to cover the fixed costs of exporting (selection effect). With the Pareto distribution, these two effects exactly offset one another, leaving the average intensive margin (AIM) independent of variable trade costs (see Bernard et al., 2012; Fernandes et al., 2018, for a detailed discussion of this result).

Appendix D: Extensions

D.1. Risk elasticity and firm size

In this section we estimate our model separately for small, medium, and large firms, to investigate if there is evidence of heterogeneous risk-elasticities. Recall that our model predicts that the extensive margin risk-elasticity should be larger for sectors in which the elasticity of substitution across differentiated varieties is smaller and, thus, where firms enjoy higher markups. Direct evidence on the size of markups suggests that in markets in which firms enjoy higher markups (for example, markets for higher quality goods), firms are on average larger (see, for example, Atkin et al., 2015; Chen and Juvenal, 2022).

In order to understand the heterogeneity of our results across firms' size, we estimate our model by splitting firms into small, medium and large. The sample split is obtained by calculating the median and the 75^{th} percentile of employment. In order to avoid having a disproportionate number of observations for one group, we define small firms as those with an employment level lower than the median; medium firms are the ones with employment ranging between the median and the 75^{th} percentile and large firms are those with employment larger than the 75^{th} percentile.[24] This results in classifying firms as small if they have less than 18 employees, medium if the number of employees ranges from 18 to 50, and large if they have more than 50 employees. As we did for our main analysis, we consider the extensive margin and the intensive margin risk-elasticities.

Table D1 reports the extensive margin results (top panel) and the intensive margin results (bottom panel).[25] There is evidence of substantial heterogeneity across firms of different size. The extensive margin risk elasticities appear to be substantial for large firms and modest for small firms. Venturing outside the scope of our model, it is possible to argue that large firms are able to invest more in R&D and advertisement (Kugler and Verhoogen, 2011), and therefore are associated with higher quality products and higher product differentiation. Indeed, our model predicts larger elasticities in markets in which firms enjoy higher markups and higher market shares on average, and large firms are associated with larger market-shares and greater markups.

The first two columns of the intensive margin results report the estimations for non-zero FOB values while the last two columns control for selection.

24. We include all firms with employment below the median as small and firms with employment above the top quartile as large to avoid having a disproportionate number of observations for one group. This is needed, because large firms export to more destination on average, and our unit of observation is the firm-destination pair. The results, presented in Table D1 are robust to different sample splits.

25. We only report the results based on the most stringent specification to preserve space but the ones based on the other specification are robust and available upon request.

TABLE D1. Extensive and intensive margins by firm size

	Extensive Margin											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	small				medium				large			
DIST	-0.046***	-0.031***			-0.074***	-0.044***			-0.110***	-0.057***		
	(0.0014)	(0.001)			(0.002)	(0.001)			(0.002)	(0.001)		
GDP	0.022***	0.013***			0.022***	0.010***			0.030***	0.014***		
	(0.001)	(0.001)			(0.001)	(0.001)			(0.001)	(0.001)		
AGE	0.076***	0.017***			0.070***	0.017***			0.098***	0.033***		
	(0.004)	(0.003)			(0.005)	(0.004)			(0.004)	(0.002)		
Risk	-0.046***	-0.024***	0.001	0.007	-0.105***	-0.061***	-0.031	-0.022	-0.174***	-0.090***	-0.082***	-0.049***
	(0.011)	(0.008)	(0.018)	(0.014)	(0.017)	(0.011)	(0.023)	(0.017)	(0.016)	(0.010)	(0.021)	(0.014)
R-squared	0.335	0.384	0.070	0.172	0.087	0.230	0.315	0.393	0.095	0.291	0.269	0.393
Observations	205,085	179,410	219,606	192,122	147,068	128,646	142,421	124,579	288,007	251,951	285,250	249,536
Destination-year FE	no	no	yes	yes	no	no	yes	yes	no	no	yes	yes
Firm-year FE	no	no	yes	yes	no	no	yes	yes	no	no	yes	yes
Sector-year FE	yes	yes	no	no	yes	yes	no	no	yes	yes	no	no
Lagged dependent variable	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes

	Intensive Margin											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	small				medium				large			
Risk	0.359**	0.104	2.237	0.572	-0.0672	0.0780	0.790	0.115	-0.815***	-0.395***	-0.583	-0.0887
	(0.144)	(0.137)	(1.422)	(0.469)	(0.190)	(0.146)	(1.098)	(0.394)	(0.192)	(0.115)	(0.529)	(0.150)
R-squared	0.573	0.772	0.757	0.879	0.500	0.733	0.687	0.848	0.462	0.759	0.620	0.847
Observations	56,378	25,973	4,376	3,829	49,272	27,160	7,728	6,762	130,966	83,489	40,384	35,336
Destination-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sector-year FE	no	no	no	no	no	no	no	no	no	no	no	no
Lagged dependent variable	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes
Selection adjustment	no	no	yes	yes	no	no	yes	yes	no	no	yes	yes

Notes: Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels.

Overall, the results are consistent with the prediction that risk does not affect directly the intensive margin of trade, especially after controlling for selection. However, given the evidence above, that the extensive margin risk elasticity is heterogeneous across firm size, risk will affect the intensive margin of trade indirectly. Our results indicate that large firms are more affected by risk in the extensive margin. Since large firms export more on average, conditional on serving a given market, the upshot is that an increase in risk will affect disproportionately large firms and indirectly will result in lower average exports conditional on exporting. Thus, the intensive margin is indirectly affected by the risk channel. We discuss this further in Section 6.1.1, which looks at time-varying risk premium as a contributing factor to the 2008–2009 trade collapse.

D.2. Risk elasticity and firm size during the trade collapse

We explore whether the heterogeneity in risk-elasticities by firm size is present when we focus on the trade collapse. To that aim, we extend the results presented in Table 5 by estimating equation (35) separately for small, medium, and large firms. The results are presented in Table D.2.

TABLE D2. Time-varying risk premium and the trade collapse by firm size

	Extensive Margin					
	small firms		medium firms		large firms	
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis × Risk	-0.006	-0.013	-0.043***	-0.028	-0.033***	-0.029**
	(0.012)	(0.014)	(0.016)	(0.018)	(0.011)	(0.013)
R-Squared	0.348	0.374	0.417	0.437	0.501	0.515
Observations	151,504	132,566	104,584	91,511	220,128	192,612
	Intensive Margin					
	small firms		medium firms		large firms	
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis × Risk	-0.047	0.054	-0.198*	-0.165	0.133	0.092
	(0.100)	(0.198)	(0.116)	(0.180)	(0.118)	(0.140)
R-Squared	0.801	0.825	0.779	0.798	0.824	0.845
Observations	31,684	13,448	29,632	14,836	85,111	52,122
Destination-time FE	yes	yes	yes	yes	yes	yes
Firm-destination FE	yes	yes	yes	yes	yes	yes
Sector-time FE	yes	yes	yes	yes	yes	yes
Lagged dependent variable	no	yes	no	yes	no	yes

Notes: Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. The pre-crisis period corresponds to 2007Q4-2008Q3 and the crisis period corresponds to 2008Q4-2009Q3. *, **, and *** indicate significance at 10%, 5% and 1% levels.

Starting in 2008Q4, because risk was greatly elevated compared to normal times, firm's decision to enter export markets was likely affected. In Table D3 we assess the contributions of the extensive and intensive margins to the dynamics of Argentinean exports during the crisis.

Table D3. Decomposition of margins

	Total exports	Extensive margin		Intensive margin
		Firms	Destinations	Sales
2007Q4-2008Q3	56,575	9,377	4	631,621
2008Q4-2009Q3	47,656	8,791	4	580,832
Growth	-16%	-6%	0%	-8%
Contribution		49%		51%

Notes: Destinations and Sales denote average destinations and average sales, respectively. Total exports are in million US dollars while average sales per firm-destination are in US dollars. In line with Behrens et al. (2013), we decompose nominal exports X in a given time period as $X = j \times \bar{i} \times \bar{x}$, where j denotes the number of exporting firms, $\bar{i}$ the mean number of countries each firm exports to and $\bar{x} = X/(j \times \bar{i})$ is the mean sales per firm-destination. Defining exports in the following period as, $\tilde{X}$, the change in exports from 2007Q4-2008Q3 and 2008Q4-2009Q3 can be written as $\Delta X = \tilde{X}/X$. Therefore, $\Delta X = \Delta j \times \Delta\bar{i} \times \Delta\bar{x}$. Note that Δj and $\Delta\bar{i}$ capture the changes at the extensive margin and $\Delta\bar{x}$ the changes at the intensive margin.

As shown in Table D3, exports contracted by 16 percent during the crisis. This fall was driven by a 6 percent reduction in the extensive margin, while the intensive margin, given by the mean value of exports per firm-destination fell by 8 percent. Overall, the relative contributions of the intensive and extensive margins to the collapse of exports amounted to 51 and 49 percent, respectively. Rising risk premia can discourage exports in sectors with high risk-elasticity. This can also indirectly lower the average value of exports if these sectors are dominated by larger firms. Thus, it is important to keep in mind that the extensive and intensive margins of trade are closely linked when analyzing them.

Appendix E: Robustness

In this section we check the robustness of our findings. We start by using different samples. We then estimate our baseline extensive margin regression using a probit model. We also estimate our model using Poisson Pseudo Maximum Likelihood (PPML) (see, for example, Santos Silva and Tenreyro, 2006).

E.1. Alternative samples

Our main sample is composed of firms from all sectors for which we have information on the level of employment and age of the firm. We check the robustness of our findings to the use of two alternative samples of firms. First, we narrow down the set of exporters to include only manufacturing firms. Second, we also include the exporters for which we could not obtain firm-level characteristics but we have the sectoral classification of the firm.

E.1.1. Manufacturing firms subsample. In this section we check the sensitivity of our findings when we restrict our analysis to the sample of manufacturing firms. Tables E1 and E2 show the descriptive statistics. The sample of manufacturing firms is composed by 6,683 firms which export to a total of 102 destinations. We observe that in 2002 these firms exported to an average of 12 destinations with a mean distance of 6,025 kilometers while in 2009 they exported to an average of 13 destinations and a mean distance of 6,079 kilometers. Between 2002 and 2009 the average value of FOB exports by firm increased 28%. In terms of firm's characteristics, the average firm's age goes from 35 years in 2002 to 31 in 2009, and the average employment drops from 137 to 109 employees between 2002 and 2009.

Table E1. Summary statistics: manufacturing firms

Year	# Exporters	Exports (Million $US)	# Destinations
2002	3,565	15,617	102
2003	4,040	16,676	102
2004	4,348	20,018	102
2005	4,597	16,595	102
2006	4,912	17,390	101
2007	5,385	24,217	100
2008	5,314	38,847	100
2009	5,008	28,094	100

Notes: For each year in the sample, the table reports the number exporters, the value of FOB exports (in million US dollars), and the number of destinations for the sample of manufacturing firms.

The empirical results including manufacturing firms only are reported in Tables E3 and E4 for the extensive and intensive margins, respectively. Looking first at the extensive margin results reported in Table E3, the risk-elasticity coefficient, β, has the predicted negative sign, and is similar in magnitude compared to the baseline estimated coefficient in Table 2.

Table E2. Descriptive statistics: manufacturing firms

year	mean exports	mean destinations	maximum destinations	minimum destinations	mean distance	mean age	mean employment
2002	4,380,713	12	77	1	6,025	35	137
2003	4,127,660	12	82	1	6,127	34	126
2004	4,603,980	13	82	1	6,183	33	119
2005	3,609,898	12	83	1	6,166	33	113
2006	3,540,327	12	79	1	6,023	32	110
2007	4,497,093	12	77	1	6,080	31	103
2008	7,310,261	13	77	1	6,115	31	104
2009	5,609,863	13	74	1	6,079	31	109

Notes: For each year in the sample, the table reports the mean value of FOB exports; the mean, minimum and maximum number of destinations firms export to; the mean distance; the mean age of firms and the mean level of employment for manufacturing firms.

Table E3. Extensive margin: Manufacturing Firms

	(1)	(2)	(3)	(4)
DIST	-0.092***	-0.052***		
	(0.001)	(0.001)		
GDP	0.026***	0.012***		
	(0.001)	(0.000)		
SIZE	0.037***	0.021***		
	(0.001)	(0.001)		
AGE	0.077***	0.020***		
	(0.003)	(0.002)		
Risk	-0.240***	-0.120***	-0.100***	-0.049**
	(0.019)	(0.012)	(0.031)	(0.020)
R-squared	0.292	0.398	0.087	0.263
Observations	396,615	346,955	406,094	355,257
Destination-year FE	no	no	yes	yes
Firm-year FE	no	no	yes	yes
Sector-year FE	yes	yes	no	no
Lagged dependent variable	no	yes	no	yes

Notes: Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels.

Table E4 reports the results for the intensive margin regression. Again the results for the manufacturing subsample are very similar to the baseline results. In the least saturated specifications that include the traditional control variables, the intensive margin risk elasticity is estimated to be very close to 0. Considering the most complete specification including destination-specific and firm-specific time effects, and after adjusting for sample selection and controlling for serial correlation (column 6 of Table E4), the intensive margin risk elasticity is also not found to be statistically significant, and the point estimate is indeed very close to 0. We conclude that our results are robust if we include only the manufacturing firms.

Table E5 presents the results by firm size for manufacturing firms. We define small firms as those with less than 25 employees, medium firms are the ones which have between 50 and 65 employees and large firms have more than 65 employees. The top panel reports the extensive margin results while the bottom panel includes the intensive margin. The pattern of heterogeneity is the same for both the full sample and the subsample of manufacturing firms.

TABLE E4. Intensive margin: Manufacturing firms

	(1)	(2)	(3)	(4)	(5)	(6)
DIST	-0.272***	-0.070***				
	(0.009)	(0.004)				
GDP	0.217***	0.061***				
	(0.006)	(0.003)				
SIZE	0.374***	0.114***				
	(0.007)	(0.003)				
AGE	0.046*	-0.071***				
	(0.024)	(0.010)				
Risk	-0.212	0.034	-0.727***	-0.209*	-0.830	-0.139
	(0.143)	(0.066)	(0.229)	(0.122)	(0.606)	(0.175)
R-squared	0.263	0.698	0.415	0.768	0.646	0.858
Observations	171,963	108,014	160,167	97,757	41,256	36,099
Destination-year FE	no	no	yes	yes	yes	yes
Firm-year FE	no	no	yes	yes	yes	yes
Sector-year FE	yes	yes	no	no	no	no
Lagged dependent variable	no	yes	no	yes	no	yes
Selection adjustment	no	no	no	no	yes	yes

Notes: Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels.

TABLE E5. Extensive and Intensive Margins: Manufacturing Firms

Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	small				medium				large			
DIST	-0.058***	-0.036***			-0.089***	-0.049***			-0.123***	-0.0614***		
	(0.002)	(0.001)			(0.003)	(0.002)			(0.002)	(0.001)		
GDP	0.0219***	0.0123***			0.023***	0.010***			0.030***	0.0121***		
	(0.001)	(0.001)			(0.002)	(0.001)			(0.001)	(0.001)		
AGE	0.088***	0.025***			0.072***	0.014***			0.099***	0.034***		
	(0.005)	(0.004)			(0.007)	(0.004)			(0.005)	(0.003)		
Risk	-0.090***	-0.043***	-0.019	0.001	-0.156***	-0.068***	0.018	0.011	-0.231***	-0.122***	-0.099**	-0.062**
	(0.020)	(0.014)	(0.031)	(0.023)	(0.038)	(0.024)	(0.057)	(0.042)	(0.027)	(0.015)	(0.041)	(0.026)
R-squared	0.071	0.192	0.325	0.388	0.088	0.260	0.299	0.401	192,169	168,112	191,147	167,216
Observations	125,964	110,194	119,275	104,335	87,801	76,811	86,073	75,299	0.094	0.305	0.266	0.399
Destination-Year FE	no	no	yes	yes	no	no	yes	yes	no	no	yes	yes
Firm-year FE	no	no	yes	yes	no	no	yes	yes	no	no	yes	yes
Sector-year FE	yes	yes	no	no	yes	yes	no	no	yes	yes	no	no
Lagged dependent variable	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes

Intensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	small				medium				large			
Risk	0.0628	-0.153	3.551**	1.113*	-0.129	-0.0218	1.387	0.680	-1.231***	-0.388**	-0.607	-0.0689
	(0.209)	(0.169)	(1.647)	(0.591)	(0.440)	(0.314)	(2.078)	(0.834)	(0.324)	(0.167)	(0.684)	(0.193)
R-squared	0.515	0.737	0.743	0.875	0.440	0.703	0.644	0.817	0.429	0.752	0.603	0.845
Observations	36,555	18,344	3,536	3,094	33,581	19,938	6,688	5,852	89,880	59,307	30,704	26,866
Destination-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sector-year FE	no	no	no	no	no	no	no	no	no	no	no	no
Lagged dependent variable	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes
Selection adjustment	no	no	yes	yes	no	no	yes	yes	no	no	yes	yes

Notes: Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels.

E.1.2. Extended sample. In our baseline estimations presented in Tables 3 and 4 we only include the firms for which we have information on characteristics (i.e. employment and firm's age). In table E6 we show that our results continue to hold when we estimate our baseline regressions using an extended sample of firms which includes all of the exporters for which we have sectoral classification (including the firms for which we do not have additional information about firm characteristics).

TABLE E6. Extended Sample

	(1)	(2)	(3)	(4)
	All sectors			
	extensive margin		intensive margin	
Risk	-0.058***	-0.034***	-0.822*	-0.159
	(0.015)	(0.010)	(0.495)	(0.145)
R-squared	0.310	0.398	0.658	0.859
Observations	666,855	583,366	53,104	46,466
Destination-Year FE	yes	yes	yes	yes
Firm-year FE	yes	yes	yes	yes
Sector-year FE	no	no	no	no
Lagged dependent variable	no	yes	no	yes
Selection adjustment	no	no	yes	yes
	Manufacturing firms			
	extensive margin		intensive margin	
Risk	-0.096***	-0.048**	-0.847	-0.127
	(0.030)	(0.020)	(0.604)	(0.175)
R-squared	0.294	0.398	0.646	0.858
Observations	402,488	352,093	41,472	36,288
Destination-Year FE	yes	yes	yes	yes
Firm-year FE	yes	yes	yes	yes
Sector-year FE	no	no	no	no
Lagged dependent variable	no	yes	no	yes
Selection adjustment	no	no	yes	yes

Notes: Columns (1) and (2) present the extensive margin results and columns (3) and (4) the intensive margin results. Robust standard errors adjusted for clustering at the firm-destination level are reported in parenthesis. Top panel corresponds to firms from all sectors while the bottom panel includes only manufacturing firms. *, **, and *** indicate significance at 10%, 5% and 1% levels.

E.2. Probit

We estimate the probability of exporting into a given destination using the following Probit model

$$pr(d_{jit} > 0) = \Gamma(\delta' \mathbf{F}_{jit} + \beta \mathbf{Risk}_{ji}^{(is)} + \varepsilon_{jit}), \tag{E.1}$$

where d_{jit} is an indicator variable which equals 1 when firm j exports to destination i at time t. $\mathbf{F}_{jit}$ contains a set of control variables, including time-varying fixed effects.

The results from the probit estimates are presented in table E7 which confirm our baseline results.

Table E7. Probit estimates

	(1)	(2)
DIST	-0.214***	
	(0.003)	
GDP	0.071***	
	(0.002)	
SIZE	0.080***	
	(0.002)	
AGE	0.212***	
	(0.007)	
Risk	-0.457***	-0.154***
	(0.031)	(0.043)
Observations	666,725	666,540
Destination-year FE	no	yes
Sector-year FE	yes	yes

Notes: This table shows the estimation of equation (30) using a probit model Robust standard errors are reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels

Table E8. Risk and the average intensive margin (PPML)

Risk	0.035***
	(0.012)
Observations	50,770
Destination-year FE	yes
Sector FE	yes

Notes: This table shows the estimation of equation (34) using PPML. Robust standard errors reported in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels.

E.3. PPML

Using OLS to estimate (4) is in principle able to recover the micro-level elasticities. However, this happens under restrictive assumptions which may not hold in practice, for instance because errors are heteroskedastic, leading to an aggregation bias. As shown in Breinlich et al. (2021), the estimation of gravity equations using PPML is more robust to aggregation than estimation of log-linearized gravity equations using OLS. Therefore, in Table E8 we estimate (4) using PPML. Results are robust to this alternative estimation method.

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