Demand learning and exporter dynamics

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Abstract: This paper provides direct evidence that learning about local demand is an important driver of exporters' dynamics. We present a simple trade model with Bayesian learning in which rms are uncertain about their idiosyncratic demand parameter in each of the markets they serve, and update their beliefs as noisy information arrives at each period. We derive three main predictions: (i) a new demand shock leads rms to update more their beliefs about future demand, the younger they are; (ii) the absolute value of rms' idiosyncratic growth rates and (iii) their variance across rms decrease with age. We nd strong support for these predictions on detailed French rm-level data. Our data contains both the values and the quantities sold by a given rm, for the same product, in di erent destination markets, which allows us to purge rm sales from productivity variations and to identify separately both the demand shocks faced by the rms and their belief about future demand. The last part of the paper shows that market-speci c rm exit behavior is also consistent with a model of demand learning.

JEL classi cation: F12, F14, L11, L25
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1 Introduction

Why do some firms grow faster than others? While some firms rapidly expand after entry, many others do not survive the first few years. After some time however, those surviving firms account for a large share of sales on both domestic or foreign markets (Haltiwanger *et al.*, 2013; Bernard *et al.*, 2009; Eaton *et al.*, 2007). In the case of French firms, 53.5% of total foreign sales are made by firms that did not serve these markets a decade earlier.[1] Among these, 40% come from the post-entry growth of sales on each market. Understanding the sources of heterogeneity in same product in the same destination allows to control for aggregate market-specific conditions. Second, we use the fact that, in our model, quantity decisions only depend on the firms' beliefs (while prices and the value of sales also depend on the realized demand shocks) to separate out the firms' beliefs from the demand signal. Therefore, while requiring few, standard assumptions, our methodology allows to test predictions which directly relate age to the firms' beliefs, rather than age to firm size as typically done by the literature.

We find strong support for all three predictions of the model. The learning process appears to be especially strong in the first years after entry, although even the most experienced firms in our sample still exhibit significant belief updating. Quantitatively, our results suggest that the growth of beliefs explains a larger part of the variations in firm-level export growth than supply side dynamics. We show that these results survive to controlling for firm size, and more generally firm productivity.

Note that we concentrate on post-entry dynamics, i.e. exporters' growth and survival. Entry decisions in a given destination might be affected by the beliefs of the firm on other destinations (Albornoz et al., 2012), or on other products for the same destination (Timoshenko, 2012). These effects might be stronger for similar destinations and products (Morales et al., 2014; Defever et al., 2011; Lawless, 2009). The behavior of other firms serving the same market might also play a role (Fernandes and Tang, 2014). These are interesting but quite vast and different questions, which we indeed plan to study in future work, but that are beyond the scope of this paper.

From a methodological point of view, our paper is related to Foster et al. (2008, 2013) and Li (2014). Foster et al. (2008) use data on the prices and quantities of US homogenous goods producers to separate idiosyncratic demand shocks from firms' productivity, and quantify the effect of both elements on firm selection. Using the same sample, Foster et al. (2013) find that demand accumulation explains a large part of the relationship between firm age and firm size. Contrary to these papers, our methodology does not require measuring firm productivity to identify demand shocks. We explicitly control for all time-varying, firm-specific determinants of sales (these include productivity but also for instance capital constraints). This ensures that market specific demand learning/accumulation is the only source of dynamics driving our results. Another difference is that we focus on "passive" demand learning while Foster et al. (2013) consider "active" demand accumulation (through pricing). Our paper also relates to Li (2014) who adds Bayesian demand learning to a structural model of export dynamics in the line of Roberts et al. (2012), and estimate it on a set firms belonging the Chinese ceramic industry. Beyond methodological differences, our focus is different: Li (2014) studies exporters' entry decisions, while we concentrate on post-entry dynamics.

In theory, firms can learn about demand passively (by observing demand shocks and consequently updating their beliefs), or actively (by engaging in specific investments).[6] We focus on the first type of process. While we do not rule out the possibility that both types of learning co-exist, we show that our methodology makes very unlikely that our results reflect active demand learning, as it explicitly controls for all variations in firm-specific expenditures. We also provide results which directly support our interpretation using a test initially proposed by Pakes and Ericson (1998).

The empirical relevance of firm learning has implications for the modeling of firm and industry dynamics in general. The most direct one is that firm size is not only driven by supply side factors but also reflects the evolution of managers' beliefs about their profitability. Therefore, models which aim at explaining the dynamics of firm size distribution (within and across industries) based solely on productivity dynamics would gain at introducing demand learning mechanisms. Second, our results imply that firms at different stages of their learning process will respond differently to idiosyncratic demand shocks. They also suggest that firms of different ages do not face the same amount of uncertainty, which might have implications for the impact of uncertainty shocks on aggregate outcomes (Bloom et al., 2012). Finally, we find that it takes time for firms to discover their profitability in a given market (we find evidence of learning even 7 years after which bears important policy relevance { is to try to understand which factors a ect the speed

Table 1 performs two exercises. In panel A, we first decompose total export growth into the contributions of firm and products-destinations entry and exit (the net "extensive margin"[9]) and of the pure intensive margin (i.e. the growth of firm-product-destination triplets already present in 1996). We follow the decomposition proposed by Bricongne *et al.* (2012), to which we refer the reader for more details. Column (1) shows the average yearly contribution of each margin, while column (2) concentrates on the contribution to total growth of French exports over the entire time-period. On a yearly basis, the majority of export growth comes from incumbents (column 1, Panel A). Over a decade however, new firms and markets account for almost two our sample period (column (2)). These new rms and market represent only 12% of exports in their rst year, but account for 53.5% of total exports after a decad952387(/.3%(a)-283ueof)-283(d952387(new)

3.1 Economic environment

Demand . Consumers in country j maximize utility derived from the consumption of goods from K sectors. Each sector is composed of a continuum of di erentiated varieties of product k:

$$U_j = E \sum_{t=0}^{+1} {}^{t} \ln(C_{jt})$$

$$\text{with } C_{jt} = \prod_{k=0}^{K}$$

where w_{it} is the wage rate in the origin country, φ_{ikt} is the product-time specific productivity of firm i.

Learning. Firm i is uncertain about the parameter $\overline{a_{ijk}}$. Before observing any signal, the firm's prior beliefs about $\overline{a_{ijk}}$ are normally distributed with mean μ_0 and variance σ_0^2. The firm observes t independent signals about $\overline{a_{ijk}}$: $a_{ijkt} = \overline{a_{ijk}} + \varepsilon_{ijkt}$, where each ε_{ijkt} is normal with (known) mean 0 and variance σ_ε^2. According to Bayes' rule, the firm's posterior beliefs about $\overline{a_{ijk}}$ after t signals are normally distributed with mean $\tilde{\mu}_t$ and variance $\tilde{\sigma}_t^2$, where:[15]

$$\tilde{\mu}_t = \mu_0 \frac{\frac{1}{\sigma_0^2}}{\frac{1}{\sigma_0^2} + \frac{t}{\sigma_\varepsilon^2}} + \bar{a}_t \frac{\frac{t}{\sigma_\varepsilon^2}}{\frac{1}{\sigma_0^2} + \frac{t}{\sigma_\varepsilon^2}} \tag{3}$$

$$\tilde{\sigma}_t^2 = \frac{1}{\frac{1}{\sigma_0^2} + \frac{t}{\sigma_\varepsilon^2}} \tag{4}$$

and $\bar{a}$ is the average signal value, $\bar{a}_t = \frac{1}{t} \sum_t a_{ijkt}$. Note that contrary to $\tilde{\mu}_t$, the posterior variance $\tilde{\sigma}_t^2$ does not depend on the realizations of the signals and decreases only with the number of signals (i.e. learning reduces uncertainty). The posterior variance is thus always smaller than the prior variance, $\tilde{\sigma}_t^2 < \tilde{\sigma}_{t-1}^2$. In the following, it will be useful to formulate the Bayesian updating recursively. Denoting $\Delta\tilde{\mu}_t = \tilde{\mu}_t - \tilde{\mu}_{t-1}$, we have:

$$\Delta\tilde{\mu}_t = g_t \left(a_{ijkt} - \tilde{\mu}_{t-1} \right) \quad \text{with } g_t = \frac{1}{\frac{\sigma_\varepsilon^2}{\sigma_0^2} + t}$$

quantities and prices:[17]

$$q_{ijkt} = \left(\frac{k}{k-1}\frac{w_{it}}{\varphi_{ikt}}\right)^{-k} \frac{k Y_{jt}}{P^{1-k}_{jkt}} E_{t-1}\left(e^{\frac{a_{ijkt}}{k}}\right)^{k} \qquad (7)$$

$$p_{ijkt} = \frac{k}{k-1}\frac{w_{it}}{\varphi_{ikt}} \left(\right.$$

rewrite the above expressions for sales, quantities and prices as:

$$S_{ijkt} = C^{S}_{ikt}\, C^{S}_{jkt}\, Z^{S}_{ijkt} \quad (10)$$

$$q_{ijkt} = C^{q}_{ikt}\, C^{q}_{jkt}\, Z^{q}_{ijkt} \quad (11)$$

$$p_{ijkt} = C$$

At the beginning of period t, rms make quantity decisions based on their belief about local demand for their product. Then, demand is realized and rms update their belief. A higher than expected demand, induced by $a_{ijkt} > e_{t\ 1}$, leads the rm to update upwards its belief. As a consequence, the expected growth rate of the belief between period t and t + 1, will be positive. The opposite is true for a lower than expected demand. Importantly, as clear from equation (16), this upward or downward updating is larger for younger rms. It follows our rst prediction, that directly illustrates the updating process:

<u>Prediction # 1</u> (updating): [illegible] a_{ijkt} [illegible] [illegible] rms

Proof. See appendix.

In order to test this prediction, we need to identify the demand shock a_{ijkt} as well as the growth of rm's beliefs about expected demand as expressed in (16), which is only driven by rm's belief and rm age. It may be also interesting to note that one consequence of this prediction is that, in the absence of any dynamics of the ikt and jkt terms, we should observe a reversion to the mean size after any demand shock. We however want to get closer to the model testing directly for the evolution of the belief and thus allowing for any dynamics of the ikt and jkt terms.

The next two predictions are also closely related to the evolution of $\ln E_t[e^{a}$

Prediction 2 also holds for Z^S_{ijkt} provided that the negative covariance between $\ln E_t\left(e^{\frac{a_{ijkt+1}}{\sigma_k}}\right)$ and a_{ijkt+1} is not too strong.[22]

4 Identification

To test predictions 2 and 3, we only need to isolate the Z^X_{ijkt} terms, i.e. we need to purge the quantities, prices and sales from supply side and market specific factors. This is achieved by estimating the following quantities, price and sales equations in logs:[23]

$$\ln q_{ijkt} = FE_{ikt} + FE_{jkt} + \varepsilon^q_{ijkt} \quad (17)$$

$$\ln p_{ijkt} = FE_{ikt} + \varepsilon^p_{ijkt} \quad (18)$$

$$\ln S_{ijkt} = FE_{ikt} + FE_{jkt} + \varepsilon^S_{ijkt} \quad (19)$$

where q is a 6-digit product and t is a year. FE_{ikt} and FE_{jkt} represent respectively firm-product-year and destination-product year fixed effects. In our baseline estimations, we stick to the model and estimate the price equation without the jkt fixed effects, as implied by the CES assumption. We however systematically check that relaxing this assumption by including jkt fixed effects does not affect the results. Note that we do not have direct price data, so we rely on unit values, defined as S_{ijkt}/q_{jkt}, to proxy them.

Given that we control for all time-varying, market- and firm-product-specific determinants of quantities, prices and sales, the residuals $\{\varepsilon^q_{ijkt}; \varepsilon^p_{ijkt}; \varepsilon^S_{ijkt}\}$ are by construction orthogonal to the standard determinants of firm dynamics (i.e. productivity and market conditions). This is an important contribution of the paper: our methodology would survive to the inclusion of any process underlying the evolution of firm productivity – including Markov processes, imitation, R&D investments, or even learning –, provided that productivity is the same across destination markets for a given firm-product. Importantly, the ikt fixed effects also control for any other time-varying, firm-specific factors that might affect growth rates. These include in particular financial constraints which have been suggested as being an important determinant of firm dynamics (Cooley and Quadrini, 2001; Cabral and Mata, 2003).

To be more specific, the residuals $\{\varepsilon^q_{ijkt}; \varepsilon^p_{ijkt}; \varepsilon^S_{ijkt}\}$ provide estimates of the Z^X_{ijkt} terms. Using equations (7), (8), (9) and (10), we get:

$$\varepsilon^q_{ijkt} = \ln Z^q_{ijkt} = \sigma_k \ln E_{t-1}\left(e^{\frac{a_{ijkt}}{\sigma_k}}\right) \quad (20)$$

$$\varepsilon^p_{ijkt} = \ln Z^p_{ijkt} = \frac{1}{\sigma_k} a_{ijkt} - \ln E_{t-1}\left(e^{\frac{a_{ijkt}}{\sigma_k}}\right) \quad (21)$$

$$\varepsilon^S_{ijkt} = \ln Z^S_{ijkt} = (\sigma_k - 1)\ln E_{t-1}\left(e^{\frac{a_{ijkt}}{\sigma_k}}\right) + \frac{1}{\sigma_k} a_{ijkt} \quad (22)$$

With these residuals at hand, we can directly compute the growth rates of the Z^X_{ijkt} terms, allowing to test for predictions 2 and 3. Note that this identification strategy is possible to

[22] Formally, this will be the case if $\sigma_k > 1 + \frac{\sigma^2}{\sigma_0^2} + t$. See appendix for details.

[23] We use the Stata routine reg2hdfe developed by Guimaraes and Portugal (2010).

to identify separately the demand shock from the belief and therefore to test prediction 1, but bears no impact on the other predictions.[28] Precisely, in our model we only need quantities to adjust ls than prices for the predictions to hold. We believe this is a realistic assumption, especially given that we look at international trade ows. Empirically, we perform a number of robustness checks related to this assumption. In particular, in section 5.4 we concentrate on sectors and destinations for which it is more likely that production is xed ta (sectors in which adjustment costs are higher).

drop firm-product-destination triplets already served in 1994 and 1995, as these years are used to define entry.

Finally, we define a cohort of new exporters on a product-destination market as all firms starting to export in year t but that were not exporting in year $t-1$, and we are able to track all firms belonging to a cohort over time.[29]

5 Main results

disaggregation by the literature, using very different methodologies. For instance Broda and Weinstein (2006) report average elasticities in the range of 12-17 when estimated at the 7-10 digits level. In Romalis (2007), elasticities are estimated at the HS6-level and are generally comprised between 6 and 11. Imbs and Mejean (2014) provide a detailed literature review, and show that lower estimates are typically obtained when using more aggregated data.[31] Our estimates of $_k$ also follow expected patterns: considering Rauch (1999) classification, the median (resp. mean) across products is 8.6 (resp. 11.1) for differentiated goods, 9.9 (resp. 13.6) for

Table 3: Prediction 1: demand shocks and beliefs updating

	(1)	(2)	(3)	(4)
Dep. var.		ε^{q}_{ijkt}		
Age de nition		# years since last entry		

of both quantities and prices decrease with age. We estimate:

$$\varepsilon^X_{ijkt} = \alpha^X + \beta^X \text{AGE}_{ijkt} + u_{ijkt} \qquad \forall X = \{q; p\} \tag{27}$$

Alternatively, we will again relax the linearity assumption and replace AGE_{ijkt} by a set of categorical variables as we did in prediction 1. We expect β^X to be negative. The model also predicts that $|\beta^q| > |\beta^p|$: the growth rate of quantities should decrease relatively faster with age than the growth rate of prices.

Table 4: Prediction 2: age and mean growth rates

	(1)	(2)	(3)	(4)
Dep. var.	ε^q_{ijkt}		ε^p_{ijkt}	
Age definition	# years since last entry (reset after 1 year of exit)			
Age_{ijkt}	-0.040[a]		-0.024[a]	
	(0.000)		(0.000)	
$\text{Age}_{ijkt} = 3$		-0.076[a]		-0.053[a]
		(0.001)		(0.001)
$\text{Age}_{ijkt} = 4$		-0.119[a]		-0.079[a]
		(0.002)		(0.001)
$\text{Age}_{ijkt} = 5$		-0.152[a]		-0.096[a]
		(0.002)		(0.001)
$\text{Age}_{ijkt} = 6$		-0.184[a]		-0.109[a]
		(0.002)		(0.001)
$\text{Age}_{ijkt} = 7+$		-0.216[a]		-0.129[a]
		(0.002)		(0.001)
Observations	2795979	2795979	2795979	2795979

Robust standard errors in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Controlling for year dummies does not affect the results.

The results are provided in Table 4. We consider sequentially the growth rate of quantities (columns (1) and (2)) and prices (columns (3) and (4)). Both significantly decrease with firm age.[32] The effect is quantitatively more pronounced in the case of quantities than prices, as predicted by the theory.

Prediction 3 . Our last prediction relates the variance of growth rates within cohorts to the age of the cohort. We estimate:

$$\text{Var}\left(\varepsilon^X_{ijkt}\right) = \beta^X \text{AGE}_{cjkt} + \text{FE}_{cjk} + u_{ijkt} \qquad \forall X = \{q; p\} \tag{28}$$

where FE_{cjk} represent cohort fixed effects. As mentioned earlier, we define a cohort of new exporters on a product-destination market as all firms starting exporting in year t. We again expect our coefficient of interest β^X to be negative: because firms update less their beliefs when

[32] Columns (1) and (2) of Table 11 in the appendix show that this is also the case of firm sales.

they gain experience on a market, their quantities and prices become less volatile.

Table 5: Prediction 3: age and variance of growth rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.		Var(ε^{q}_{ijkt})				Var(ε^{p}_{ijkt})		
Age de nition		# years since last entry (reset after 1 year of exit)				# years since last entry (reset after 1 year of exit)		
Sample		All		Permanent exporters[1]		All		Permanent exporters[1]
Age_{cjkt}	-0.067[a]		-0.060[a]	-0.043[a]	-0.033[a]		-0.029[a]	-0.014[a]
	(0.001)		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
Age_{cjkt} = 3		-0.130[a]				-0.072[a]		
		(0.003)				(0.002)		
Age_{cjkt} = 4		-0.208[a]				-0.108[a]		
		(0.004)				(0.002)		
Age_{cjkt} = 5		-0.271[a]				-0.134[a]		
		(0.005)				(0.003)		
Age_{cjkt} = 6		-0.314[a]				-0.153[a]		
		(0.006)				(0.003)		
Age_{cjkt} = 7+		-0.375[a]				-0.184[a]		
		(0.006)				(0.003)		
# observations			0.007[a]	0.015[a]			0.003[a]	0.003[c]
			(0.001)	(0.004)			(0.000)	(0.002)
Observations	598821	598821	598821	262849	598821	598821	598821	262849
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered by cohort in parentheses. Cohort xed e ects included in all estimations. [c] signi cant at 10%; [b] signi cant at 5%; [a] signi cant at 1%. [1] rms present all years on market jk .

The results related to the variance of the growth rate of quantities and prices are provided in Table 5. Columns (1) to (4) consider quantities, columns (5) to (8) use prices as a dependent variable. Within cohort, the variance of the growth rate of both quantities and prices sharply decreases with age in all columns.[33] This is still true when controlling for the number of observations of the cohort (columns (3)-(4) and (7)-(8)). Note that our results are not due to attrition: concentrating on the rms which survive over the entire period in columns (4) and (8) leads to similar conclusions.

5.3 Age de nition and the learning process

How fast does demand learning depreciate when the rm exits the market? So far we have treated each entry of rms into a market as a new one: age was reset to zero in case of exit.

assumption that all experience is kept during exit periods, whatever the length of these periods. Tables A.5 and A.6 in the online appendix contain the equivalent sensitivity exercises applied to predictions 2 and 3.

Table 6: Prediction 1: alternative age definitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.		ε^q_{ijkt}				ε^q_{ijkt}		
Age definition		# years since last entry (reset after 2 years exit)				# years exporting since first entry		
b0	0.075[a]	0.106[a]	0.106[a]		0.075[a]	0.101[a]	0.101[a]	
	(0.002)	(0.004)	(0.004)		(0.002)	(0.004)	(0.004)	
Age_{ijkt}		-0.036[a]	-0.036[a]			-0.034[a]	-0.034[a]	
		(0.000)	(0.000)			(0.000)	(0.000)	
b0 Age_{ijkt}		-0.008[a]	-0.008[a]			-0.007[a]	-0.007[a]	
		(0.001)	(0.001)			(0.001)	(0.001)	
b0 $Age_{ijkt} = 2$				0.102[a]				0.098[a]
				(0.003)				(0.003)
b0 $Age_{ijkt} = 3$				0.069[a]				0.070[a]
				(0.004)				(0.004)
b0 $Age_{ijkt} = 4$				0.063[a]				0.072[a]
				(0.005)				(0.005)
b0 $Age_{ijkt} = 5$				0.062[a]				0.064[a]
				(0.006)				(0.006)
b0 $Age_{ijkt} = 6$				0.051[a]				0.062[a]
				(0.007)				(0.007)
b0 $Age_{ijkt} = 7+$				0.051[a]				0.051[a]
				(0.006)				(0.006)
Observations	2726474	2726474	2726474	2726474	2726474	2726474	2726474	2726474

Robust standard errors in parentheses (bootstrapped in columns (3) and (7)). [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Age dummies included alone in columns (4) and (8) but coefficients not reported.

The results are qualitatively similar to our baseline estimates, but they differ quantitatively; the effect of age on firm belief's updating following demand shocks is slightly lower in Table 6. Similar results are found in the case of predictions 2 and 3 (Tables A.5 and A.6 in the online appendix).

While these results confirm the robustness of our findings to the measurement of age, we cannot directly infer from them whether and how accumulated learning is lost during periods of exit. In order to do so, we directly test whether firms update their belief in response to a new signal similarly after their first entry and subsequent re-entries on a given market, depending on the time elapsed since last exit. We expect a lower response of beliefs during re-entries whenever the firm keeps some stock of knowledge of its demand in the market.

Table 8: Prediction 1: relaxing the CES assumption

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			ε^q_{ijkt}			
Age definition			# years since last entry (reset after 1 year of exit)			
Robustness	Controlling for FE_{jkt} in prices		Controlling for FE_{jkt} in prices and size			
			$Size_{ijk,t-1}$		$\overline{Size}_{ijk,t=t-1}$	
$\hat{b}$	0.159[a]		0.095[a]		0.075[a]	

Table 9: Passive versus active learning

6 Firm survival

Prediction # 4 (firm exit): A_{ijkt} ... t (...) ... e_{t-1}.

To test this prediction, note that from equation (5), e_{t-1} can be expressed as:

$$e_{t-1} = \frac{e^2_{t-1}}{2} a_{ijkt-1} + \left(1 - \frac{e^2_{t-1}}{2}\right) e_{t-2} \qquad (31)$$

where we used the fact that $g_{t-1} = \frac{e^2_{t-1}}{2}$. e_{t-1} thus increases with e_{t-2} and a_{ijkt-1}. We therefore want to test if, conditional on A_{ijkt} and firm age, the probability to exit decreases with e_{t-2} and a_{ijkt-1}. While prediction 4 has been traditionally associated with learning in the literature, it has usually been tested showing that exit rates decline with firm size, sometimes conditional on age. We mainly depart from these papers because our identification strategy provides us with estimates of e_{t-2} and a_{ijkt-1}, thus allowing to test directly the impact of beliefs updating on the firm exit decision.

More formally, to test prediction 4 we estimate the following probabilistic model:

$$\begin{aligned} Pr(S_{ijkt} > 0 | S_{ijk;t-1} = 1) &= 1 \text{ if } \beta_1 AGE_{ijkt-1} + \beta_2 b_{ijk;t} + \beta_3 "^{q}_{ijkt-1} + FE + u_{ijkt} > 0 \\ &= 0 \text{ otherwise.} \end{aligned}$$

We expect β_2 and β_3 to be negative. FE include the two sets of fixed effects FE_{ikt} and FE_{jkt}, which capture C^S_{ikt} and C^S_{jkt}. We estimate this equation using a linear probability model which does not suffer from incidental parameters problems, which might be important here given the two large dimensions of fixed effects we need to include.

The results are shown in Table 10, columns (1) to (3). These are largely consistent with the model's predictions: conditional on age, exit probability significantly decreases with positive demand shocks b and with the firm's belief (columns (1) to (3)).

Interestingly, the literature has also usually associated learning with exit rate declining with age, and we indeed find this to be the case in our estimations. However, as discussed in Pakes and Ericson (1998), this prediction is not robust to the learning mechanism we put forward. Indeed, the decision to exit not only depends on the extent of firm updating (which indeed declines with age) but also on how $\underline{e}_{t-1}(A_{ijkt}; t)$ evolves through time. If this threshold increases very rapidly for some t, the exit rate could actually be higher for older firms.

On the other hand, a clear prediction of our passive learning model is that negative demand shocks should trigger less exits for older firms. The reason is apparent in equation (31): firm posterior beliefs e_{t-1} depend less and less on demand shocks as firms age. Thus, the exit rate may not be decreasing with age, but demand shocks should have a lower impact on the exit decision in older cohorts because they imply less updating. Note that this prediction can also be understood as another robustness check for our formulation of a passive learning model: in an active learning model, no matter the age of the firm, demand shocks may trigger new investments. Their impact on future expected profits stream should thus not be weakened for older firms (see Ericson and Pakes, 1995). This (discriminant) prediction is not directly tested in Pakes and Ericson (1998) because they use a much less parametric model than ours that

Table 10: Firm exit

containing the prices and the quantities sold by French firms on export markets, we have shown that this model can be used to estimate firm-market specific demand shocks and prior beliefs about demand, and that its three predictions are strongly supported by the data. Importantly, our methodology and therefore our results are consistent with any possible dynamics of firm productivity.

Overall, the learning mechanism we uncover is quantitatively important: the growth of beliefs explains a larger part of the variance in the firm-market specific growth rates than supply side dynamics. Although the learning process appears to be especially strong in the first years after entry, even the most experienced firms in our sample still exhibit significant belief updating. Interestingly, we also provide evidence that the accumulated learning is quickly lost during exit periods: after exiting the market two years or more, firms essentially behave like a first-time entrant. A direct extension of our work would be to consider the – market, sector or firm-specific – determinants of learning speed.

Finally, we have considered the predictions of our model in terms of firm survival. When firm productivity follows a Markov process, the model predicts that given age, the probability to

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A Appendix

A.1 Theory

Optimal quantities, prices and sales. Firms choose quantities by maximizing expected profits subject to demand. Using (1), we get:

$$\max_q \int \pi_{ijkt}\, dG_{t-1}(a_{ijkt}) = \max_q \int q_{ijkt}\, p_{ijkt}\, dG_{t-1}(a_{ijkt}) - \frac{w_{it}}{\varphi_{ikt}} q_{ijkt} - F_{ijk}$$

$$= \max_q q_{ijkt}^{1-\frac{1}{\sigma_k}} \left(\frac{\kappa Y_{jt}}{P_{jkt}^{1-\sigma_k}}\right)^{\frac{1}{\sigma_k}} E_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right] - \frac{w_{it}}{\varphi_{ikt}} q_{ijkt} - F_{ijk}$$

The FOC writes:

$$\left(1-\frac{1}{\sigma_k}\right) q_{ijkt}^{-\frac{1}{\sigma_k}} \left(\frac{\kappa Y_{jt}}{P_{jkt}^{1-\sigma_k}}\right)^{\frac{1}{\sigma_k}} E_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right] = \frac{w_{it}}{\varphi_{ikt}}$$

$$\Leftrightarrow q_{ijkt} = \left(\frac{\sigma_k}{\sigma_k - 1}\frac{w_{it}}{\varphi_{ikt}}\right)^{-\sigma_k} \left(\frac{\kappa Y_{jt}}{P_{jkt}^{1-\sigma_k}}\right) \left(E_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]\right)^{\sigma_k}$$

And from the constraint, we get

$$p_{ijkt} = \frac{\sigma_k}{\sigma_k - 1}\frac{w_{it}}{\varphi_{ikt}} \left(\frac{e^{\frac{a_{ijkt}}{\sigma_k}}}{E_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]}\right)$$

$$S_{ijkt} = q_{ijkt}\, p_{ijkt} = \left(\frac{\sigma_k}{\sigma_k - 1}\frac{w_{it}}{\varphi_{ikt}}\right)^{1-\sigma_k} \left(\frac{\kappa Y_{jt}}{P_{jkt}^{1-\sigma_k}}\right) \left(E_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]\right)^{\sigma_k - 1} \left(e^{a_{ijkt}}\right)^{\frac{1}{\sigma_k}}$$

Growth of firm's beliefs about expected demand (prior). First note that firm i has a prior about the demand shock given by $a_{ijkt} \sim N(\theta_{t-1}; \sigma_{t-1}^2 + \sigma_\varepsilon^2)$ and thus $e^{\frac{a_{ijkt}}{\sigma_k}} \sim LN\left(\frac{\theta_{t-1}}{\sigma_k}; \frac{\sigma_{t-1}^2 + \sigma_\varepsilon^2}{\sigma_k^2}\right)$. It follows that $\int e^{\frac{a_{ijkt}}{\sigma_k}} dG_{t-1}(a_{ijkt}) = e^{\frac{1}{\sigma_k}\left(\theta_{t-1} + \frac{\sigma_{t-1}^2 + \sigma_\varepsilon^2}{2\sigma_k}\right)}$. We get the expression in the text:

$$\ln E_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right] = \frac{1}{\sigma_k}\left(\theta_t + \frac{\sigma_t^2 - \sigma_{t-1}^2}{2\sigma_k}\right)$$

Using the definition of θ_t, σ_{t-1}^2 and σ_t^2 (see (3) and (4)), we further get:

$$\ln E_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right] = \frac{1}{\sigma_k\left(\frac{\sigma_\varepsilon^2}{\sigma_0^2} + t\right)}\left(a_{ijkt} - \frac{\theta_0 + \frac{\sigma_0^2}{2\sigma_k} + \bar{a}_{t-1}\frac{\sigma_0^2}{\sigma_\varepsilon^2}(t-1)}{1 + \frac{\sigma_0^2}{\sigma_\varepsilon^2}(t-1)}\right) \tag{32}$$

Proof of proposition 1. Prediction 1 states that following a new signal, updating is larger for younger rms. Updating is measured directly by $\ln E_t \; e^{\frac{a_{ijkt+1}}{k}}$ in (32). We get:

$$\frac{@ \; \ln E_t \; e^{\frac{a_{ijkt+1}}{k}}}{@ a_{ijkt}} = \frac{1}{k \; \frac{2}{2_0} + t} \; \frac{g_t}{k} > 0$$

The larger the demand shock, the larger the updating. However, the denominator increases with t: updating is larger for younger rms. This higher updating can be directly measured by g_t. It may also be of interest to note that updating decreases with uncertainty, i.e. ^{2}, as the signal is less informative when uncertainty is higher.

Proof of proposition 2. Proposition 2 states that expected absolute value of growth rates decrease with age. Growth rates are given by:

$$\ln Z^{q}_{ijk;t+1} = {}_k \; \ln E_t \; e^{\frac{a_{ijkt+1}}{k}} \tag{33}$$

$$\ln Z^{p}_{ijk;t+1} = \frac{1}{k} \; a_{ijkt+1} \quad \ln E_t \; e^{\frac{a_{ijkt+1}}{k}} \tag{34}$$

$$\ln Z^{S}_{ijk;t+1} = ({}_k \quad 1) \; \ln E_t \; e^{\frac{a_{ijkt+1}}{k}} + \frac{1}{k} \; a_{ijkt+1} \tag{35}$$

A.2 Additional results

Table 11: Prediction 2: robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	"S							

Table 12: Prediction 3: robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	$Var(\varepsilon^{S}_{ijkt})$		$Var(\varepsilon^{p}_{ijkt})$		$Var(\varepsilon^{q}_{ijkt})$		$Var(\varepsilon^{p}_{ijkt})$	
Age definition	# years since last entry (reset after 1 year of exit)							
Robustness	Export sales		Controlling for FE_{jkt} in prices		Control for size		Controlling for FE_{jkt} in prices and size	
Age_{cjkt}	-0.064[a]		-0.032[a]		-0.065[a]		-0.031[a]	
	(0.001)		(0.001)		(0.001)		(0.001)	
$Age_{cjkt} = 3$		-0.121[a]		-0.069[a]		-0.123[a]		-0.065[a]
		(0.003)		(0.002)		(0.004)		(0.002)
$Age_{cjkt} = 4$		-0.195[a]		-0.104[a]		-0.200[a]		-0.099[a]
		(0.004)		(0.002)		(0.004)		(0.002)
$Age_{cjkt} = 5$		-0.256[a]		-0.130[a]		-0.262[a]		-0.125[a]
		(0.005)		(0.003)		(0.005)		(0.003)
$Age_{cjkt} = 6$		-0.300[a]		-0.149[a]		-0.305[a]		-0.143[a]
		(0.005)		(0.003)		(0.006)		(0.003)
$Age_{cjkt} = 7+$		-0.357[a]		-0.180[a]		-0.366[a]		-0.174[a]
		(0.005)		(0.003)		(0.006)		(0.003)
$Size_{cjk;t-1}$	-0.180							

Table 13: Prediction 1: controlling for size bins

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			$"^{q}_{ijkt}$			
Age de nition	# years since last entry (reset after 1 year of exit)					
Size variable		$\text{Size}_{ijk;t\;\;1}$			$\overline{\text{Size}}_{ijk;t=t\;\;1}$	
Size dummies	Yes	Yes	No	Yes	Yes	No
Age_{ijkt}	-0.005[a]		-0.042[a]	-0.052[a]		-0.053[a]
	(0.000)		(0.000)	(0.000)		(0.000)
b Age$_{ijkt}$	-0.005[a]		-0.004[a]	-0.011[a]		-0.006[a]
	(0.001)		(0.001)	(0.001)		(0.001)
b Age$_{ijkt}$ = 2		0.365[a]			0.296[a]	
		(0.008)			(0.008)	
b Age$_{ijkt}$ = 3		0.339[a]			0.247[a]	
		(0.008)			(0.009)	
b Age$_{ijkt}$ = 4		0.340[a]			0.237[a]	
		(0.009)			(0.009)	
b Age$_{ijkt}$ = 5		0.330[a]			0.231[a]	
		(0.010)			(0.010)	
b Age$_{ijkt}$ = 6		0.318[a]			0.218[a]	
		(0.011)			(0.012)	
b Age$_{ijkt}$ = 7+		0.335[a]			0.229[a]	
		(0.009)			(0.010)	
Observations	2327572	2327572	2327572	1951476	1951476	1951476

Robust standard errors in parentheses. [c] signi cant at 10%; [b] signi cant at 5%; [a] signi cant at 1%. Size $_{ijk;t\;\;1}$ is the log of the total quantity exported by rm i in product k, destination j in year t 1, and $\overline{\text{Size}}_{ijk;t=t\;\;1}$ is the average quantity exported by rm i in market jk between t and t 1. Estimations (1), (2), (4) and (5) include size dummies (and their interactions with b) constructed according to deciles of the variable, deciles being computed by HS4-product-destination-year. Age dummies include664 682

Table 14: Prediction 1: robustness (high production adjustment costs)