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Demand learning and firm dynamics: evidence from exporters*

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Abstract

This paper provides evidence that learning about demand is an important driver of firms' dynamics. We present a simple model with Bayesian learning in which firms are uncertain about their idiosyncratic demand parameter in each of the markets they serve, and update their beliefs as noisy information arrives in each period. The model predicts that firms update more their beliefs following a new demand shock, the younger they are. To test this learning mechanism, we make use of a specific feature of exporter-level data which contains both the values and the quantities sold by a given firm for the same product in different destination markets. This allows us to derive a methodology that identifies separately the demand shocks faced by the firms and their beliefs about future demand. We find strong support for our main prediction: the updating process appears especially strong in the first years after entry. However, the bulk of accumulated knowledge is lost during short periods of exit. Second, we consider implications of this prediction for firm growth rates and survival. Consistent with the learning model, we find that: (i) the absolute value of the mean growth rate for firms' beliefs decreases with age, as does the variance within cohorts; (ii) exit probability decreases with firms' beliefs and the demand shock the firm faces. Further, demand shocks trigger more exit in younger cohorts.

JEL classification: L11, L25, F12, F14.
Keywords: firm growth, learning, demand, uncertainty.

Résumé

Cet article montre que l'apprentissage sur la demande adressée aux entreprises est un facteur explicatif important de leur dynamique. Nous développons un modèle simple de dynamique des firmes avec apprentissage bayésien, dans lequel les entreprises sont incertaines de leur paramètre idiosyncratique de demande sur chaque marché et mettent à jour leur croyance à partir de l'information qui leur parvient à chaque période. Le modèle prédit que les *jeunes* entreprises ajustent plus leurs croyances en réponse à un choc de demande. Nous testons ce mécanisme d'apprentissage à partir de données individuelles détaillées d'exportations françaises, qui nous permettent d'observer, pour une même firme, les prix et les quantités vendues sur plusieurs marchés distincts. Notre méthodologie identifie séparément les chocs de demande subis par les entreprises et leurs croyances sur leur demande future. L'analyse empirique confirme la principale prédiction du modèle et montre que le processus d'apprentissage est particulièrement fort durant les premières années de présence sur un marché. La connaissance accumulée disparaît cependant rapidement en cas de sortie du marché. Nous considérons ensuite les implications du modèle pour la croissance et la survie des entreprises et montrons que: (i) la valeur absolue du taux de croissance des croyances des entreprises, et leur variance au sein d'une cohorte, diminuent avec l'âge; (ii) la probabilité de sortie diminue avec le niveau des croyances de l'entreprise et les chocs de demande qu'elle subit. En outre, les chocs de demande entraînent plus de sortie dans les cohortes plus jeunes.

Code JEL: L11, L25, F12, F14.
Mots clés: Croissance des entreprises, apprentissage, demande, incertitude.

Non technical summary

Firm dynamics are characterized by a number of systematic patterns: new firms start small and have larger exit rates. For those that survive, the average growth of their sales declines with their age. After some time, they account for a large share of sales on both domestic and foreign markets. These facts can however be rationalized by several theories, relying on different underlying mechanisms.

This paper provides direct evidence that learning about demand is an important driver of firms' dynamics. We present a simple model with Bayesian learning in which firms are uncertain about their idiosyncratic demand parameter in each of the markets they serve, and update their beliefs as noisy information arrives in each period. The core prediction of this model is that firms update more their beliefs following a new demand shock, the younger they are.

In testing this learning mechanism, we take advantage of a unique feature of exporter-level data which contains both the values and the quantities sold by a given firm for the same product in different destination markets. Our structural methodology identifies separately the demand shocks faced by the firms and their beliefs about their future addressed demand. Importantly, our methodology and therefore our results are consistent with any possible dynamics of firm productivity. We find strong support for the core prediction of our learning model of firm dynamics: the updating process appears especially strong in the first years after entry. Accumulated knowledge about local demand is however quickly lost during periods of exit. 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.

We then consider the implications of the model for firms' growth and survival and find that: (i) the absolute value of the mean growth rate for firms' beliefs decreases with age, as does the variance within cohorts; (ii) exit probability decreases with firms' beliefs and the demand shock the firm faces. Further, demand shocks trigger more exits in younger cohorts. The exit behavior of firms, which empirically declines with age, is thus consistent with the learning mechanism. Together with a larger volatility of beliefs for younger firms, these results show that demand learning generates a negative relationship between firm age and firm growth.

The empirical relevance of firm learning has implications for the modeling of firm (and industry) dynamics in general. It explains the correlation between firms' age and net growth found in the (employment and export) data and the fact that young firms have larger exit rates. The relevance of the learning mechanism may also justify the implementation of policies supporting young firms. In addition, it underlines that firms' age is important to understand firms reaction to idiosyncratic demand shocks. Beyond idiosyncratic shocks, it also means that firms of different ages do not face the same amount of uncertainty, leading to a heterogeneous impact of firm responses to aggregate uncertainty shocks.

1 Introduction

Why do some firms grow faster than others? While some producers 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 post-entry firm dynamics – survival and growth – is therefore crucial to explain the dynamics of aggregate sales and firm size distribution.

Firm dynamics are characterized by a number of systematic patterns, which have been documented by a large body of empirical literature. New firms start small and have larger exit rates. For those that survive, the average growth of their sales declines with their age.[2] Similar behaviors have been recently reported for sales on foreign markets.[3] These facts can be rationalized by several theories, relying on different underlying mechanisms, such as stochastic productivity growth, endogenous R&D investment or demand learning. Empirically however, disentangling the role of these specific channels has been proven difficult, as it requires identifying separately the contributions of idiosyncratic demand and productivity to the variations of firms sales. This paper focuses on demand learning and provides direct evidence that it is an important driver of post-entry firm dynamics using detailed exporter-level data.

We first present a simple model with Bayesian demand learning, in the spirit of Jovanovic (1982).[4] Firms operate under monopolistic competition and face CES demand, but at the same time are uncertain about their idiosyncratic demand in each market, and learn as noisy information arrives in each period. These signals determine the firms' posterior beliefs about demand, from which they make their quantity decision. It follows that a new signal leads younger firms to update more their beliefs. The first objective of the paper is to test this core prediction, which is specific to the learning mechanism.

To do so, we derive from the model an empirical methodology which allows to separately identify the firms' beliefs and the demand shocks (the signal) they face each period, in each of the markets they serve. We use detailed exporter-level data containing the values and the quantities sold by French firms, by product and destination, over the period 1994-2005. We proceed in two steps. First, we purge quantities and prices from market-specific conditions and from firm-specific supply side dynamics (e.g, productivity). This is made possible by a unique feature of international trade data, in which we can observe the same firm selling the same product in different markets. This is key as it enables to cleanly separate productivity

[1] These numbers are based on the 1996-2005 period – see Section 2.

[2] See Evans (1987), Dunne *et al.* (1989), Caves (1998), Cabral and Mata (2003) and Haltiwanger *et al.* (2013) among many others.

[3] Eaton *et al.* (2007), Berthou and Vicard (2014), Bernard *et al.* (2014), Albornoz *et al.* (2012) or Fernandes and Tang (2014) show that these dynamics are also observed for exporters, and quantitatively magnified.

[4] In Jovanovic (1982), firms actually learn about their cost parameter. While the learning mechanism is the same, we apply it to demand, as in Timoshenko (2012).

from demand variations. In addition, observing different firms selling the 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 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 directly test predictions which relate the evolution of firms' beliefs to firm age, in contrast to the literature which has typically looked at the correlation between age and firm size.

We find strong support for the main prediction of the model: belief updating is stronger for younger firms, with age being defined at the firm-product-market level. The learning process appears to be especially strong in the first years after entry on a product-destination market, although even the most experienced firms in our sample still exhibit significant updating. Quantitatively, our results suggest that the demand learning process 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 to the relaxation of a number of modelling hypotheses. We use a variety of definitions of age to account for the fact that exporters enter and exit markets frequently and that the accumulated knowledge about demand might be partially kept even during periods of exit. We show that the bulk of accumulated knowledge is lost during periods of exit exceeding one year.

The last part of the paper considers the implications of the updating process for firms' growth and survival. In particular, the model predicts that (i) the absolute value of the mean growth rate for firms' beliefs decreases with age, as does the variance within cohorts; (ii) exit probability decreases with firms' beliefs and the demand shock the firm faces. Further, demand shocks trigger more exits in younger cohorts. Again, our empirical results are in line with these predictions. The exit behavior of firms, that empirically declines with age, is thus consistent with the learning mechanism. Together with a larger volatility of beliefs for younger firms, these results show that demand learning generates a negative relationship between firm age and firm growth.

Our paper therefore shows that demand learning is an important characteristic of the micro-dynamics of firms in narrowly defined markets. By specifically testing the mechanism of beliefs updating which lies at the core of models of firm dynamics with learning, we also more generally contribute to the literature on industry dynamics which tries to understand the determinants of firm growth and survival. Our results lend support to a class of models featuring learning (Jovanovic, 1982) which have recently been used to study exporters' dynamics (Timoshenko, 2012; Fernandes and Tang, 2014; Albornoz *et al.*, 2012; Eaton *et al.*, 2014).

An alternative class of models explains firm and exporter dynamics through stochastic shocks to productivity (Hopenhayn, 1992; Luttmer, 2007, 2011; Arkolakis, 2013, Impullitti *et al.*, 2013) and/or endogenous productivity variations (Klette and Kortum, 2004; Rossi-Hansberg and Wright, 2007). Both the theories based on demand learning and the ones based on productivity variations can replicate qualitatively most stylized facts that we observe in the data. Arkolakis (2013), for instance, shows that a model combining stochastic productivity growth (as in Luttmer, 2007) and market penetration costs (as in Arkolakis, 2010) can reproduce facts observed on the domestic and export markets on entry-exit rates, and on the relationship between average firm sales growth (or their variance) and firm age (or size). But the literature strikingly lacks direct empirical evidence documenting the relative relevance of these alternative mechanisms. A major contribution of our paper is to properly identify the idiosyncratic demand component of firms sales, i.e. to purge those sales from their firm-specific productivity component. This allows us to make a statement about the relevance of demand learning that is robust to *any possible* dynamics of 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).[5] 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 that 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

[5] See for instance Ericson and Pakes (1995); Pakes and Ericson (1998) or Abbring and Campbell (2005).

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. This may in particular justify the implementation of policies supporting young firms, as recently discussed by Arkolakis *et al.* (2014). The fact that firms of different ages do not face the same amount of uncertainty may also 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 entry), and that this "learning capital" is quickly forgotten during exit periods. The next step – which bears important policy relevance – is to try to understand which factors affect the speed of learning.

The paper proceeds as follows. In the next section, we describe our data and provide descriptive evidence on the contributions of firm's post-entry growth and survival to overall export growth. In section 3 we present our model and its implication for firms' beliefs updating with respect to age. Section 4 describes our identification strategy and section 5 our main results as well as a number of robustness exercises. In section 6 we present our results on firm growth and survival. The last section concludes.

2 Firm dynamics on foreign markets and export growth

This section describes our data and presents statistics about the dynamics of French firms in their export markets. In particular, we emphasize the role of young firms and new destination markets to aggregate growth, and discuss the role of firm-markets effects in explaining the variance of firms' growth on the markets they serve.

2.1 Data

We use detailed firm-level data by product and destination country provided by the French Customs. The unit of observation is an export flow by a firm i of a product k to a destination j in year t. The data cover the period from 1994 to 2005, and contains information about both the value and quantity exported by firms, which will allow us to compute firm-market specific unit values that we will use as a proxy for firm price in the second part of the paper.[6]

A product is defined at the 6-digit level (HS6). We focus on HS6 product categories that do not change over the time-period in order to be able to track firms over time on a specific

[6]Two different thresholds apply to the declaration of export transactions, depending on the country of destination. The declaration of extra-EU export flows is mandatory when a flow exceeds 1,000 euros or 1,000 kg. For transactions to EU countries, firms have to report their expeditions when their total exports to all EU countries exceed 150,000 euros over the year. This absence of declaration for small intra-EU flows might introduce noise in our measures of age; we will check that all our results are unchanged when removing EU destinations from the sample.

market (destination-and-product).[7] Moreover, we concentrate on the years 1996-2005, as this will be the period considered later in our estimations. The underlying reason is that we use the two first years, 1994 and 1995, to identify entry, as explained in more details in section 4.2. Our final dataset covers exports of 4,183 HS6 product categories to 180 destination markets by 100,690 firms over the period 1996-2005.

2.2 Stylized facts

Contribution to aggregate sales growth. Recent literature has emphasized the essential contribution of young firms to industry dynamics, either in terms of aggregate output, employment or trade. Haltiwanger *et al.* (2013) show for instance that US start-ups display substantially higher rates of job creation and destruction in their first ten years, and that these firms represent a large share of total employment after a decade of existence. These patterns are also found for other countries (see Criscuolo *et al.*, 2014 for evidence on 18 OECD countries; Lawless, 2014 on Irish firms, Ayyagari *et al.*, 2011 for developing countries). Similar facts characterize trade dynamics: Eaton *et al.* (2007) and Bernard *et al.* (2009) show that exporters start small but that, conditional on survival, they account for large shares of total export growth after a few years.

Our exporter-level data exhibit comparable features. Over the 1996-2005 period, we find that, on average, new firm-destination-product triplets represent only 12.3% of total export value after a year, but their share reaches 53.5% after a decade (27.3% due to new markets served by incumbents and 26.2% by new firms exporting, see Table 1). The contribution of the extensive margin to aggregate exports is determined by three components of firm dynamics: entry, survival and post entry growth on new markets. Since new exporters typically do not survive more than a few years on export markets,[8] firm selection and growth are important drivers of aggregate trade growth over longer horizons, besides the size at entry. Column (2) of Table 1 shows that pure growth after entry accounts for around 40% of the end-of-period share of newly created firm-destination-product triplets.

The objective of this paper is precisely to understand the sources of these post-entry dynamics, including firm growth and survival. We will show empirically that young firms grow more than older ones on average due to the combination of two elements: more volatile growth rates for younger firms and firm selection. Note that various alternative models, based on different mechanisms, also generate these two elements. Thus, before turning to the implications of our learning model for firm growth and survival in section 6, we first provide direct evidence of supporting the learning mechanism.

Contribution to firm sales variations. We can already provide some preliminary evidence suggesting that firm-market specific demand-side factors are key drivers of growth by

[7]The frequent changes in the combined nomenclature (CN8) prevents us to use this further degree of disaggregation of the customs' product classification.

[8]For French exporters, the average survival rate at the firm-product-destination level is 32% between the first and second year, and 9% over a five-year horizon.

Table 1: Shares in end-of-period French aggregate exports

	Average yoy 1996/2005	Overall 1996/2005
New firms	2.4%	26.2%
Initial size	-	*16.5%*
Growth since entry	-	*9.7%*
New product-destination	9.9%	27.3%
Initial size	-	*16.1%*
Growth since entry	-	*11.3%*
Incumbent firm-product-destination	87.7%	46.5%
Total	100%	100%

Note: sample of HS6 fixed over time. Source: French Customs.

decomposing the variance of post-entry sales growth. We perform an exercise which is similar in spirit to Eaton *et al.* (2011). These authors show, using firm-destination data, that firm-specific effects explain well the probability of serving a market (57%), but less so sales variations conditional on selling on a market (39%).[9] Here we first regress firm-market specific sales growth on a set of destination-product-time dummies.[10] The R^2 of such a regression is 0.12: market-specific dynamics play a limited role. Adding firm-product-time fixed effects increases the R^2 to 0.44, suggesting that supply side factors such as productivity do a good job at explaining variations of firms' sales over time. However, it appears clearly that sales growth remains largely driven by firm-market specific factors. Our paper concentrates precisely on this part of firm dynamics, with the objective to understand to which extent it can be explained by learning about demand. Anticipating a bit on our results, we will indeed find that this R^2 jumps to 0.87 when we include our estimates of the growth of firms' beliefs about future demand, which we will interpret as suggestive that learning about demand is at least as important as supply side dynamics in explaining the growth of firm sales.

3 A simple model of firm age and firm growth

In this section we present a standard model of international trade with Dixit-Stiglitz monopolistic competition and demand learning in the spirit of Jovanovic (1982) (see also Timoshenko, 2012 and Arkolakis *et al.*, 2014). It will be at the basis of our identification of the effect of demand learning on firm growth and survival. We index firms by i, destination markets by j, products by k and time by t.

[9] Munch and Nguyen (2014) find that the mean contribution of the firm component to unconditional sales variations is 49%. They also show that the firm-specific effects are more important for firms already established on a product-destination market. Lawless and Whelan (2008) find an adjusted pseudo-R2 of 45% on a sample of Irish exporters.

[10] Table A.2 in the online appendix contains the results.

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 differentiated varieties of product k:

$$\begin{aligned} U_j &= E \sum_{t=0}^{+\infty} \beta^t \ln (C_{jt}) \\ \text{with } C_{jt} &= \prod_{k=0}^{K} \left(\int_{\Omega_{kt}} (e^{a_{ijkt}})^{\frac{1}{\sigma_k}} c_{kt}(\omega)^{\frac{\sigma_k - 1}{\sigma_k}} d\omega \right)^{\frac{\mu_k \sigma_k}{(\sigma_k - 1)}} \end{aligned}$$

with β the discount factor, Ω_{kt} the set of varieties of product k available at time t, and $\sum_k \mu_k = 1$.

Demand in market j at time t for a variety of product k supplied by firm i is given by:

$$q_{ijkt} = e^{a_{ijkt}} p_{ijkt}^{-\sigma_k} \frac{\mu_k Y_{jt}}{P_{jkt}^{1-\sigma_k}} \tag{1}$$

where σ_k is the (sector-specific) elasticity of substitution, Y_{jt} is total expenditure and P_{jkt} is the ideal price index of destination j in sector k, during year t. The demand parameter a_{ijkt} is given by $a_{ijkt} = \overline{a_{ijk}} + \varepsilon_{ijkt}$, with ε_{ijkt} a white noise. $\overline{a_{ijk}}$ is an idiosyncratic constant parameter and is unknown to the firm.

Production. Each period, firms make quantity decisions for their product(s), before observing demand in each market served, i.e. before observing a_{ijkt}. The unit cost function is linear in the marginal cost and there is a per-period fixed cost F_{ijk} to be paid for each product-destination pair. Labor L is the only factor of production. Current input prices are taken as given (firms are small) and there is no wedge between the buying and selling price of the input (i.e. perfect reversibility in the hiring decision). Therefore, the quantity decision is a static decision.

We do not make any assumption on the evolution of firm productivity at the product level over time. Our results will be consistent with virtually any possible dynamics of firms unit costs at the product level. Productivity might be driven by various mechanisms, as proposed by the literature: it could simply be fixed over time, or evolve according to a Markov process (Hopenhayn, 1992), or be affected by firm's investments decisions (Klette and Kortum, 2004; Rossi-Hansberg and Wright, 2007). Additionally, as originally proposed by Jovanovic (1982), it may also be subject to learning. In that case, the firm would take a quantity decision based on its belief about its costs. As we will not back out learning from firms' productivity,[11] we do not add expectation terms here to save on notations. The only key assumption here is that firms unit costs at the firm-product level are *not* destination specific.

[11]We come back to this point in section 4. We concentrate on demand learning because identifying firm idiosyncratic demand requires few assumptions, while identifying learning on firm productivity – and more generally computing firms unit costs – comes at the expense of making more heroic hypotheses.

Per period profits in market j from product k are thus given by:

$$\pi_{ijkt} = q_{ijkt}p_{ijkt} - \frac{w_{it}}{\varphi_{ikt}}q_{ijkt} - F_{ijk} \tag{2}$$

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 belief about $\overline{a_{ijk}}$ are normally distributed with mean θ_0 and variance σ_0^2. The distribution of the initial belief (θ_0, σ_0^2) can be ijk-specific but we omit the subscripts as we do not formally model firm entry. 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 belief about $\overline{a_{ijk}}$ after t signals are normally distributed with mean $\widetilde{\theta}_{ijkt}$ and variance $\widetilde{\sigma}^2_{ijkt}$, where:

$$\widetilde{\theta}_{ijkt} = \theta_0 \frac{\frac{1}{\sigma_0^2}}{\frac{1}{\sigma_0^2} + \frac{t}{\sigma_\epsilon^2}} + \overline{a}_{ijkt} \frac{\frac{t}{\sigma_\epsilon^2}}{\frac{1}{\sigma_0^2} + \frac{t}{\sigma_\epsilon^2}} \tag{3}$$

$$\widetilde{\sigma}^2_{ijkt} = \frac{1}{\frac{1}{\sigma_0^2} + \frac{t}{\sigma_\epsilon^2}} \tag{4}$$

and $\overline{a}_{ijkt}$ is the average signal value, $\overline{a}_{ijkt} = \left(\frac{1}{t}\sum_t a_{ijkt}\right)$. Note that contrary to $\widetilde{\theta}_{ijkt}$, the posterior variance $\widetilde{\sigma}^2_{ijkt}$ 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, $\widetilde{\sigma}^2_{ijkt} < \widetilde{\sigma}^2_{ijkt-1}$. In the following, it will be useful to formulate the Bayesian updating recursively. Denoting $\Delta\widetilde{\theta}_{ijkt} = \widetilde{\theta}_t - \widetilde{\theta}_{t-1}$, we have:

$$\Delta\widetilde{\theta}_{ijkt} = g_t\left(a_{ijkt} - \widetilde{\theta}_{ijkt-1}\right) \text{ with } g_t = \frac{1}{\frac{\sigma_\epsilon^2}{\sigma_0^2} + t} \tag{5}$$

Intuitively, observing a higher-than-expected signal, $a_{ijkt} > \widetilde{\theta}_{ijkt-1}$ leads the agent to revise the expectation upward, $\widetilde{\theta}_{ijkt} > \widetilde{\theta}_{ijkt-1}$, and vice versa. This revision is large when g_t is large, which happens when t is small, i.e. when the firm is "young".

3.2 Firm size and belief updating

Firms maximize expected profits, subject to demand. Labelling $G_{t-1}(a_{ijkt})$ the prior distribution of a_{ijkt} at the beginning of period t (i.e. the posterior distribution after having observed $t-1$ signals), firm i maximizes:

$$\max_q \int \pi_{ijkt} dG_{t-1}(a_{ijkt}) \qquad \text{s.t.} \qquad p_{ijkt} = \left(\frac{\mu_k Y_{jt} e^{a_{ijkt}}}{q_{ijkt} P_{jkt}^{1-\sigma_k}}\right)^{\frac{1}{\sigma_k}} \tag{6}$$

Here, we assume for simplicity that aggregate market conditions at time t, i.e. $\mu_k Y_{jt}/P_{jkt}^{1-\sigma_k}$, are observed by firms before making their quantity decision. This leads to the following optimal quantities and prices (see appendix A.1):[12]

$$q^*_{ijkt} = \left(\frac{\sigma_k}{\sigma_k - 1}\frac{w_{it}}{\varphi_{ikt}}\right)^{-\sigma_k}\left(\frac{\mu_k Y_{jt}}{P_{jkt}^{1-\sigma_k}}\right)\left(\mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]\right)^{\sigma_k} \tag{7}$$

$$p^*_{ijkt} = \left(\frac{\sigma_k}{\sigma_k - 1}\frac{w_{it}}{\varphi_{ikt}}\right)\left(\frac{e^{\frac{a_{ijkt}}{\sigma_k}}}{\mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]}\right) \tag{8}$$

with $\mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right] = \int e^{\frac{a_{ijkt}}{\sigma_k}} dG_{t-1}(a_{ijkt})$.

As firm i makes a quantity decision before observing demand for its product, q^*_{ijkt} depends on expected demand, not on demand realization, contrary to the price.

The literature has typically computed correlations between firm age and firm growth rates, and attributed negative ones as potential evidence of demand learning. Indeed, as we formally show in section 6, the fact that younger firms adjust more their beliefs leads growth rate to decrease with age in absolute value. But of course, as is clear from equations (7) and (8), firm size, and therefore firm growth, (would it be measured in terms of employment or sales) also depend on the evolution of market-specific conditions and firm productivity, which could be correlated with firm age. Directly testing for the presence of demand learning thus requires either making assumptions about the dynamics of aggregate market conditions and firm productivity or finding a way to account for them. Our methodology follows the second path.

Let us decompose optimal quantities and prices into three components. They first depend on unit costs, which are a function of wages in country i and firm-product specific productivity φ_{ikt}. This first component is ikt-specific, i.e. is independent of the destination served; we label it C_{ikt}. Second, they depend on aggregate market conditions[13], which are common to all firms selling product k to destination j. We label this component C_{jkt}. Finally, they depend on the firm i belief about expected demand in j for its product k and on the demand shock at time t. This last composite term – labelled Z_{ijkt} – is the only one to be impacted by firm learning about its demand in a specific destination market: it is $ijkt$-specific. We can now rewrite the above expressions for quantities and prices as:

$$q^*_{ijkt} = C^q_{ikt} C^q_{jkt} Z^q_{ijkt} \tag{9}$$

$$p^*_{ijkt} = C^p_{ikt} Z^p_{ijkt} \tag{10}$$

[12]Firm size could alternatively be measured by firm sales: $S^*_{ijkt} = q^*_{ijkt} p^*_{ijkt}$. Assessing the impact of firm demand learning on quantities and prices implicitly also provides its impact on sales.

[13]Prices do not actually depend on aggregate market conditions. This a consequence of the additive separability of the CES. Since other utility functions could make prices depend on market specific conditions (and in particular on market size), we will systematically checks the robustness of our results to the inclusion of market-specific conditions in the price equation as well.

As just underlined, the impact of demand learning is fully included in the Z^q_{ijkt} and Z^p_{ijkt} terms. These terms can be understood as the quantity and price of firm i for product k on market j at time t, purged from firm unit costs and aggregate market conditions, and may be very different from the actual firm size and firm price. From a methodological point of view, we stress that any prediction about firm demand learning should be based on these Z_{ijkt} terms rather than the actual q^*_{ijkt} and p^*_{ijkt}. This means that we will not look at the dynamics of firm size (at least per se), but directly at the dynamics of the firms' beliefs about expected demand $\mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]$.

The growth rate of $\mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]$ can be expressed as:

$$\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right] = \frac{1}{\sigma_k}\left(\Delta\widetilde{\theta}_{ijkt} + \frac{\widetilde{\sigma}^2_{ijkt} - \widetilde{\sigma}^2_{ijkt-1}}{2\sigma_k}\right) \tag{11}$$

At the beginning of period t, firms make quantity decisions based on their beliefs about local demand for their product. Then, demand is realized and firms update their beliefs. A higher than expected demand, i.e. $a_{ijkt} > \widetilde{\theta}_{t-1}$, leads the firm to update upwards its belief. The opposite is true for a lower than expected demand. Importantly, as is clear from equation (11), this upward or downward updating is larger for younger firms. It follows our main prediction, that directly illustrates the updating process (the proofs are relegated to the appendix):

Prediction # 1 (updating): *A new signal a_{ijkt} leads to a larger updating of the belief $\mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]$, the younger the firm is.*

In order to directly test this mechanism of firm updating, we need to identify the demand shock a_{ijkt} and the firm's belief $\mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]$ in each period. This is one contribution of this paper: we provide a simple methodology to isolate the Z^q_{ijkt} and Z^p_{ijkt} terms, which then allows to distinguish the beliefs from the demand shock components. Our approach is thus consistent with any underlying dynamic process for the ikt and jkt terms, and does not need to make use of the time dimension of the data to identify firm belief. Note however that we assume the $\overline{a_{ijk}}$ to be independent across markets, products or firms, i.e. there is no information spillovers.

4 Identification and measurement

4.1 Identifying beliefs and demand shocks

In order to separate the Z^q_{ijkt} and Z^p_{ijkt} terms, we need to purge actual quantities and prices from supply side and market specific factors. This is achieved by estimating the following quantity and price equations in logs:[14]

$$\ln q_{ijkt} = \mathbf{FE}_{ikt} + \mathbf{FE}_{jkt} + \varepsilon^q_{ijkt} \tag{12}$$

$$\ln p_{ijkt} = \mathbf{FE}_{ikt} + \varepsilon^p_{ijkt} \tag{13}$$

where k is a 6-digit product and t is a year. $\mathbf{FE}_{ikt}$ and $\mathbf{FE}_{jkt}$ 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_{ijkt}, where S_{ijkt} denote firms sales, to proxy them.

Given that we control for all time-varying, market- and firm-product-specific determinants of quantities and prices, the residuals ε^q_{ijkt} and ε^p_{ijkt} are by construction orthogonal to the standard determinants of firm dynamics (i.e. productivity and market conditions). Our methodology would thus survive to the inclusion of any process underlying the evolution of firm productivity, 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 ε^q_{ijkt} and ε^p_{ijkt} provide estimates of the Z_{ijkt} terms. Using equations (7) and (8), we get:

$$\varepsilon^q_{ijkt} = \ln Z^q_{ijkt} = \sigma_k \ln \mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right] \tag{14}$$

$$\varepsilon^p_{ijkt} = \ln Z^p_{ijkt} = \frac{1}{\sigma_k} a_{ijkt} - \ln \mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right] \tag{15}$$

Testing prediction 1, which is the essence of the learning mechanism, requires getting estimates of both the firms's beliefs about expected demand $\mathrm{E}_{t-1}[e^{\frac{a_{ijkt}}{\sigma_k}}]$ and the demand shock a_{ijkt}. As the firm takes its quantity decision before observing the demand realization, $\ln Z^q_{ijkt}$ depends on the firms' beliefs about future demand only, while $\ln Z^p_{ijkt}$ is adjusted for the demand shock. Thus, the residual ε^q_{ijkt} provides a direct estimate of the firms' beliefs. We only need to correct for σ_k. In order to back out the demand shock and get an estimate of σ_k, we regress ε^p_{ijkt} on ε^q_{ijkt}. Using (15) and (14), we get:

$$\left(\frac{1}{\sigma_k} a_{ijkt} - \ln \mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]\right) = \beta\left(\sigma_k \ln \mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]\right) + v_{ijkt} \tag{16}$$

We estimate (16) by 6-digit product to allow σ_k to differ across products[15] and obtain[16]:

[14] We use the Stata routine `reghdfe` developed by Sergio Correia, based on Guimaraes and Portugal (2010).

[15] k is defined throughout our analysis as a 6-digit product. One potential issue here is that running estimations at such level of disaggregation implies getting too few observations for some products. We therefore perform a robustness check where equation (16) is estimated at the 4-digit level.

[16] Whenever our estimates of β are statistically insignificant or imply values of σ_k which are lower than 1,

$$\widehat{\beta} = -\frac{1}{\sigma_k} \quad \text{and} \quad \widehat{v}_{ijkt} = \frac{1}{\sigma_k} a_{ijkt} \tag{17}$$

Note that this identification strategy is possible to implement because we are able to observe the sales of the same product by the same firm in different destination markets. The use of firm-level export data is therefore key as it allows to purge market-specific firm dynamics from the evolution of firm productivity through the inclusion of $\mathbf{FE}_{ikt}$.[17]

Following the model, we interpret the residuals from equations (12) and (13) as reflecting the demand-side components of prices and quantities. Our identification assumption is that, within a given firm, costs can differ across products but not across products *and* markets. Differences in costs across markets for a given product (e.g. trade costs) are captured by $\mathbf{FE}_{jkt}$. We cannot totally exclude the possibility that costs are different across markets for the same firm and product; this would be the case, for instance, if firms sell different qualities of the same product in different countries. However, we consider as unlikely the possibility that firms *learn* about these market-specific costs, which would translate into larger revisions of ε^q_{ijkt} for younger firms. This is what we find in the data, and this comforts us in our demand-side interpretation.

4.2 Measuring firm-product-destination specific age

The last variable we need to compute to be able to test our prediction is (firm-product-market specific) age. A major advantage of exporter-level data is that it features a substantial amount of entries and exits, and allows measuring precisely and following over time firms' sales on each specific destination market. We use the time variation in the product-destination markets served by the firm to measure its market-specific experience. Given that firms enter and exit markets frequently, measuring age requires making assumptions about the learning process and about how information over local demand depreciates over time during periods of exits. Given that our model is silent on this issue, we compute three different variables.

Our baseline measure of age is the number of years since last entry of a firm in a product-destination. We assume complete depreciation of firm specific knowledge during exit periods and reset the age to zero whenever the firm exits at least one calendar year from a specific product-destination. Age is either defined as a single discrete variable or as a set of dummies, to allow the learning processes to be non-linear.

To check robustness, we also define two alternative measures of age. We first assume that information on local demand is not forgotten by the firm when it does not serve a product-destination only one year and accordingly reset age to zero only after two consecutive years of exit. Second, we assume that firms keep entirely the knowledge about local demand when

we replace $\widehat{v}$ by a missing value and do not consider the observation in the estimations. We trim the top and bottom 1% of $\widehat{v}$.

[17] The reason why we do not model learning about productivity appears more clearly in equations (14) and (15). Identifying demand variations is possible because we are able to control for productivity through the inclusion of ijk fixed effects. On the other hand, we cannot distinguish productivity variations from global demand shocks faced by firms in all the markets, as these will be mixed with unit costs in the $\mathbf{FE}_{ikt}$.

they exit, regardless of the number of exit years; this third age variable is simply the number of exporting years since the first entry of the firm. Note that in all the empirical analysis, to ensure the consistency of our measures of age, we 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.

5 Main results

We start by showing some descriptive statistics of our final sample, before discussing our methodology to test prediction 1. We then turn to a number of robustness checks on the age definition and to additional insights related to the characteristics of the learning process. We finally discuss the sensitivity of our result to our main modeling assumptions and to several measurement issues.

5.1 Sample statistics

Table 2 contains some descriptive statistics about our final sample. Over the period, the firm-market specific beliefs have been characterized by a slightly positive growth.[18]

Table 2: Sample statistics

	Obs.	Mean	S.D.	Q1	Median	Q3
$\ln q_{ijkt}$	6472999	5.28	3.05	3.04	5.06	7.27
$\ln p_{ijkt}$	6472999	3.03	1.87	1.82	3.00	4.19
$\Delta\varepsilon_{ijkt}$	2726474	0.03	1.37	-0.74	0.02	0.80
$\widehat{v}_{ijkt}$	2726474	0.00	0.52	-0.23	0.00	0.24
σ_k	2675182	11.15	8.07	5.81	8.10	13.94
Age^1_{ijkt}	2726474	3.48	1.78	2	3	4
Age^2_{ijkt}	2726474	3.65	1.84	2	3	5
Age^3_{ijkt}	2726474	3.73	1.84	2	3	5

Source: Authors computations from French Customs data. Age^1_{ijkt}: reset after 1 year of exit; Age^2_{ijkt}: reset after 2 years of exit; Age^3_{ijkt}: years of exporting.

Firms in our sample are typically young in the markets they serve: the average age is comprised between 3.5 and 3.7 years depending on the definition (note that since we focus on $\Delta\varepsilon_{ijkt}$ in the following, firms that exit during the first year are dropped). This is evidence

[18] Note that the 'calendar year effect' pointed out by Berthou and Vicard (2014) and Bernard *et al.* (2014) is likely to bias upwards the growth rate between the first and second years, because of the potential incompleteness of the first year of export measured over the calendar year. When measuring age by bins as in our estimations, the dummy for year two gets rid of the average bias. Table A.2 of the online appendix shows that our results on prediction 1 are robust to the use of reconstructed years beginning the month of first entry at the firm-product-destination level.

of the low survival rates observed during the first years a firm serves a particular market, a topic we shall specifically study in the last section of the paper.

Interestingly, our methodology generates reasonable estimates of σ_k: after cleaning the top and bottom percentile of these estimates, we get a median value of 9.1 and an average of 12.0 in our final sample. These numbers are high yet comparable to ones found at similar levels of 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.[19] Our estimates of σ_k also follow expected patterns: considering Rauch (1999) classification, the median (resp. mean) across products is 8.5 (resp. 11.1) for differentiated goods, 10.9 (resp. 14.3) for referenced priced goods and 14.7 (resp. 16.8) for goods classified as homogenous. These means and medians of σ_k are statistically different across the three groups.

Further, and consistently with our theoretical framework, the correlation between the demand shocks a_{ijkt} and the firms' beliefs at the beginning of period t ($\mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]$) is low (0.086). Beliefs are also positively correlated with age, consistently with endogenous exit of firms.

5.2 Baseline results

Prediction 1 states that following a new signal, updating is larger for younger firms. Put differently, we want to know how the demand shock a_{ijkt} affects the firms' beliefs. We estimate:

$$\Delta\varepsilon^q_{ijkt} = \alpha_0 + \alpha_1(\frac{1}{\sigma_k}a_{ijk,t-1}) + u_{ijkt} = \alpha_0 + \alpha_1\widehat{v}_{ijkt} + u_{ijkt} \tag{18}$$

and we expect α_1 to be positive. It should also be lower for older firms, a prediction that we capture by adding interaction terms between firm age and the shock:

$$\Delta\varepsilon^q_{ijkt} = \sum_{g=2}^{G}\alpha_g(\widehat{v}_{ijk,t-1} \times \mathrm{AGE}^g_{ijkt}) + \sum_{g=1}^{G}\beta_g\mathrm{AGE}^g_{ijkt} + u_{ijkt} \tag{19}$$

where AGE^g_{ijkt} are dummies taking the value 1 for each age category $g = 2, ...7+$. In both cases standard errors are robust to heteroscedasticity and clustered by firm. We expect the α_g to be decreasing with age g. Note that, as formally shown in the appendix, our model predicts that $\alpha_g = g_t = \frac{1}{\sigma^2_\varepsilon/\sigma^2_0+t}$. g_t is the speed of learning; its specific shape is due to our parametric assumption of Normally distributed priors. Looking at the way in which the α_g coefficients evolve with firm age is useful to understand how firms learn about their demand parameter, and also because it allows to discuss the relevance of the normality assumption used to infer the firms' beliefs using Bayes' rule.

[19] See Broda and Weinstein (2006), Table IV; Romalis (2007), Tables 3a and 3b; Imbs and Mejean (2014), section 3.2.

Table 3: Prediction 1: demand shocks and beliefs updating

	(1)	(2)	(3)	(4)
Dep. var.	$\Delta\varepsilon^q_{ijkt}$			
Age definition	# years since last entry (reset after 1 year of exit)			
$\widehat{v}_{ijkt}$	0.075^a	0.109^a	0.109^a	
	(0.009)	(0.009)	(0.005)	
Age$_{ijkt}$		-0.040^a	-0.040^a	
		(0.001)	(0.000)	
$\widehat{v}_{ijkt}\times$Age$_{ijkt}$		-0.009^a	-0.009^a	
		(0.001)	(0.001)	
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 2$				0.103^a
				(0.009)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 3$				0.066^a
				(0.009)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 4$				0.057^a
				(0.010)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 5$				0.056^a
				(0.014)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 6$				0.047^a
				(0.013)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 7+$				0.050^a
				(0.012)
Observations	2726474	2726474	2726474	2726474

Robust standard errors clustered by firm in parentheses (bootstrapped in columns (3)). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Age dummies included alone in column (4) but coefficients not reported.

The results are provided in Table 3 and Figure 1 (see appendix, section A.2). The first column of Table 3 considers the effect of demand shocks on the adjustment of the firms' beliefs (equation (18)). Columns (2) to (4) study how this effect varies with age (equation (19)). Column (3) is the same as column (2) except that standard errors are bootstrapped to account for the fact that the right hand side variables have been estimated.

As predicted, firms update their beliefs positively when they face a positive demand shock (column (1)). This adjustment is indeed significantly larger when firms are young (columns (2)-(4)). Including age linearly (column (2)) or through bins (column (4)) leads to the same conclusion. Similarly, bootstrapping the standard errors leaves the results unaffected. Note that the shape of the learning process seems consistent with our assumption of normal priors: age has a stronger effect in the early years (this appears more clearly in Figure 1 in the appendix). After 7 consecutive years of presence on a market, the extent of belief updating is 50 percent smaller than after entry. Interestingly, our results suggest that even for the most experience exporters, firms still learn about the market, as beliefs still significantly adjusts to demand shocks.

Quantitatively, the evolution of firms' beliefs is crucial in explaining firms' dynamics. Including the growth of beliefs as an explanatory variable of the growth of export performed in section 2 increases the R^2 to 0.87, compared to 0.44 when firm-product-time and product-destination-time fixed effects are included alone (and 0.12 when only product-destination-time are included). Interpreting our beliefs' estimates as reflecting mostly demand-side variations, this implies that demand learning contributes at least as much as supply side factors to the explanation of the variance of firms' sales on specific markets.

5.3 Age definition and the learning process

How fast does demand learning depreciate when the firm exits the market? So far we have treated each entry of firms into a market as a new one: age was reset to zero in case of exit. Table 4 tests the robustness of our results to alternative definitions of firms' age. Columns (1) to (4) assumes that experience is kept if the firm exits only during one year (but is lost if it does not sell for two years or more). In columns (5) to (8) we make the more extreme assumption that all experience is kept during exit periods, whatever the length of these periods.

The results are qualitatively similar to our baseline estimates, but they differ quantitatively; the effect of age on firms' beliefs updating following demand shocks is slightly lower in Table 4.

While these results confirm the robustness of our findings to the measurement of age, we cannot directly infer from them whether and how accumulated knowledge is lost during periods of exit. In order to do so, we directly test whether firms update their beliefs 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.

We estimate:

$$\Delta\varepsilon^q_{ijkt} = \theta_1 \widehat{v}_{ijk,t-1} + \sum_{g=2}^{6} \alpha_h(\widehat{v}_{ijk,t-1} \times \text{GAP}^h_{ijkt}) + \sum_{g=1}^{G} \beta_h \text{GAP}^h_{ijkt} + \mathbf{FE}_{ijk} + u_{ijkt} \text{ if } S_{ijk,t-2} = 0 \tag{20}$$

where GAP^h_{ijkt} are dummies for re-entries on a market by number of years since last exit. We only focus on entrants, i.e. on firms which did not serve a particular market two years before (as we need to observe the demand shock in $t-1$). Put differently, we compare the responsiveness to demand signals of firms which re-enter after a period of x years to the responsiveness of first time entrants.

Table 5 shows that when re-entering a market after two or more years of exit, firms essentially behave like first time entrants. However, when their exit lasted only one year, the level of updating of re-entrants is lower (around 40% lower given that the unreported coefficient on the non-interacted $\widehat{v}$ is 0.21), suggesting that learning capital has not been completely lost. In other words, the knowledge accumulated by the firm is not necessarily lost

Table 4: Prediction 1: alternative age definitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	$\Delta\varepsilon^q_{ijkt}$				$\Delta\varepsilon^q_{ijkt}$			
Age definition	# years since last entry (reset after 2 years exit)				# years exporting since first entry			
$\widehat{v}_{ijkt}$	0.075^a	0.106^a	0.106^a		0.075^a	0.101^a	0.101^a	
	(0.009)	(0.008)	(0.003)		(0.009)	(0.007)	(0.004)	
Age_{ijkt}		-0.036^a	-0.036^a			-0.034^a	-0.034^a	
		(0.001)	(0.000)			(0.001)	(0.000)	
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}$		-0.008^a	-0.008^a			-0.007^a	-0.007^a	
		(0.002)	(0.001)			(0.002)	(0.001)	
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=2$				0.102^a				0.098^a
				(0.008)				(0.007)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=3$				0.069^a				0.070^a
				(0.009)				(0.009)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=4$				0.063^a				0.072^a
				(0.011)				(0.012)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=5$				0.062^a				0.064^a
				(0.014)				(0.013)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=6$				0.051^a				0.062^a
				(0.012)				(0.013)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=7+$				0.051^a				0.051^a
				(0.013)				(0.014)
Observations	2726474	2726474	2726474	2726474	2726474	2726474	2726474	2726474

Robust standard errors cluster by firm 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.

when exiting, but it depreciates extremely quickly during periods of exit. After only two years out of the market, firms react as if they had entirely forgotten the accumulated knowledge.

5.4 Discussion and robustness

We discuss here the sensitivity of our results to our main modeling hypotheses and performs some robustness exercises. We start with two important assumptions that we borrow from Jovanovic (1982): i) firms learn about a parameter that is *constant* over time and ii) firms make quantity decisions before observing the demand realization. We next show that our assumption of CES preferences has no important quantitative impact on our estimates. We finish by discussing some measurement issues.

Constant demand parameter. We have assumed that consumer preferences are stable

Table 5: Temporary exit and the learning process

Dep. var.:	$\Delta\varepsilon^q_{ijkt}$					
Gap (years of exit)	1	2	3	4	5	6
$\widehat{v}_{ijkt}$×Gap	-0.079^a	-0.023	0.000	-0.011	0.177	0.452
	(0.022)	(0.036)	(0.053)	(0.093)	(0.153)	(0.280)

Robust standard errors clustered by firm-product-destination in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Dummies by number of years since last exit and $\widehat{v}$ included alone but coefficient not reported. Observations: 133,776.

over time, and that learning is passive. Firms do not engage expenses in their early years to build a consumer base, or to increase consumer demand. How can we ensure that our results are indeed consistent with a passive learning of demand? First, as mentioned earlier, our methodology controls for all the firm-product specific supply side factors – such as firm investment or marketing expenses – which could impact product demand across markets. It also controls for all the destination characteristics, which capture trends in product demand that are market specific, as well as the expenses of all French firms exporting a given product to a given market. [20]

Second, we can directly test for the presence of passive learning using a methodology initially proposed by Pakes and Ericson (1998) (see Abbring and Campbell, 2005 for an application). The general idea of the test is to discriminate between models with passive learning (as ours) and models with active learning in which firms can invest to increase demand (as in Ericson and Pakes, 1995) by regressing current firm size on its immediate past size and its initial size. The passive learning model imply that the firm initial size (more precisely in our case, the firm's initial belief) will be useful to forecast the firms' beliefs and sales throughout their life, while the active learning model does not. The idea of this test is to determine whether $\overline{a_{ijk}}$ can be considered as constant over time, i.e. whether consumers preferences are stable or not, would it be due to firms actions or for other reasons.

In Table 6, we regress the firm's belief after x years, $x = 3, ..., 8$, on the belief at the time of entry controlling for the immediate lag of the belief. We restrict our sample to firms present at least 8 years to avoid composition effects.[21] Two results are worth mentioning. First, the initial belief has a positive and significant effect on future beliefs, and this effect remains highly significant even 8 years after entry. Second, the immediate lag of the belief becomes a better predictor of the current belief as the firm gets older. Both results are consistent with

[20] Another argument in favor of our interpretation is related to the way in which prices vary with age. A way to accumulate demand is to price low in the first years in order to increase demand in the long-run (Foster *et al.*, 2013). This would imply that, purged from productivity and local demand conditions, prices of young firms are lower than prices of experienced exporters. We do not find evidence of this relationship when regressing ε_{ijkt} on firm age (the results are available upon request).

[21] Similar results are obtained when restricting the sample to firms present j years, $j = 5, ..., 9$.

Table 6: Passive versus active learning

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	Belief (ε_{ijkt})					
Age definition	# years since last entry (reset after 1 year of exit)					
Age	3	4	5	6	7	8
$\varepsilon_{ijk,t-1}$	0.511[a]	0.559[a]	0.601[a]	0.618[a]	0.633[a]	0.648[a]
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
$\varepsilon_{ijk,0}$	0.150[a]	0.131[a]	0.105[a]	0.091[a]	0.083[a]	0.072[a]
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	59425	59425	59425	59425	59425	59425

Robust standard errors clustered by firm in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%.

our assumption on $\overline{a_{ijk}}$.

At this point, it is important to note that our results do not preclude the possibility that active learning is an important determinant of firm dynamics in general. They only suggest that, if active learning is important, it is largely accounted for by the various dimensions of fixed effects included in our estimations.

Fixed quantities. A second assumption we made is that quantities are fixed ex-ante, before the firm observes its idiosyncratic demand on each market. Prices, on the other hand, take into account the realization of demand shocks. For our theoretical predictions to hold we only need quantities to adjust *less* than prices. The results of the next section will indeed support this: the growth rates of quantities (and their variance) indeed decrease more with age than the growth rate of prices.

To gauge the importance of this assumption, we have re-run our estimations on sectors and destinations for which it is more likely that production is fixed *ex-ante*. We expect adjustment costs to be higher for complex goods (in which many different relationship-specific inputs are used in the production process) and in destinations characterized by longer time-to-ship. Data on sector-specific complexity comes from Nunn (2007), and data on time-to-ship between France's main port (Le Havre) and each of the destinations' main port from Berman *et al.* (2013). We restrict our sample to sectors or destinations with high adjustment costs, i.e. sectors/destinations belonging to the top 25% of the sample in terms of input complexity or time-top-ship. The results are provided in Table 10 in the appendix. The adjustment of the firms' beliefs following a demand shock is quantitatively stronger than in our baseline estimates (columns (1) and (5)), as is the coefficient on the interaction term between demand shocks and age (columns (2)-(4) and (6)-(8)).

CES demand. With alternative consumer preferences, markups could depend on firm size, which has two implications for our empirical strategy and results. First, prices could now depend on local market conditions, i.e. the price equation (13) should include a set of jkt fixed-effects. These can be easily included, and indeed this modification leaves our results largely unchanged (see appendix, Table 11, columns (1) and (2)). Second, our estimates of demand shocks might be partially reflect the firms' mark-ups. Depending on the sign of the link between mark-ups and size, this might bias the results in either direction. In this section we provide evidence that (i) this problem has a very limited impact on our results; (ii) if anything, the bias goes against our findings.

To foster intuition, let us assume that larger firms charge higher markups. In this case, ε^p_{ijkt} will be upward biased while ε^q_{ijkt} will be downward biased for large firms, leading $\widehat{v}$ to be overestimated for large firms. The coefficient on $\widehat{v}$ in Table 3, column (1) would thus be underestimated for large firms, overestimated for small ones. When we further include the interaction term between age and $\widehat{v}$, and given that age and size are positively correlated, we partly correct for this bias and expect accordingly the coefficient on the interaction term to be positive, absent any effect of age on belief updating. Put differently, if $\widehat{v}$ is overestimated for large firms, this should bias the coefficients against our results, i.e. the effect of learning should be underestimated.

In Table 11 in the appendix, we directly control in our estimations for firm size (the log of total quantity sold in market jk by firm i in $t-1$) and its interaction with the demand shock.[22] The results are very similar compared to those found in Table 3. In addition, we find that the interaction term between size and the demand shock displays a positive coefficient (columns (3) to (6)), and that the coefficient on the interaction term between the demand shock and firm age increases slightly in absolute value when we control for size (columns (3) and (5)). These results are consistent with $\widehat{v}$ being overestimated for large firms. Quantitatively the difference between the coefficients on the interaction term in columns (1) and (3) is however extremely limited, suggesting that CES assumption has overall very little impact on our results.

Measurement issues. In Tables A.4 and A.5 of the online appendix we perform two additional robustness checks. First, in Table A.4, columns (1) and (2), we replicate the results with equation (16) being estimated at the 4-digit (HS4) instead of 6-digit level. This in particular accounts for the fact that, due to the large number of 6-digits products, many categories contain very few observations, which might lead to imprecise estimates.

Second, in Table A.4, columns (3) and (4) we check that our results are robust to the inclusion of an additional interaction term between firm age and our estimates of σ_k. This is to ensure that our results are not driven by heterogenous learning processes across sectors with different elasticities (as $\widehat{v}$ contains σ_k). In all cases, the results are extremely close to our baseline estimates shown in Table 3.

Finally, in Table A.5 of the online appendix we repeat our baseline estimations on the

[22]The online appendix (Table A.3) provides results with non-linear controls for size, replacing size variables by size bins constructed based on deciles of size computed by HS4-destination-year.

sample of extra EU-15 destinations. We do so because small intra-EU transactions are potentially not recorded in the customs data, which might introduce noise in our measures of age and therefore lead to attenuation bias. Indeed, the estimated coefficients we obtain are quantitatively larger when we restrict our sample to extra-EU countries.

6 Implications for firm growth and survival

To further illustrate the relevance of our model and beliefs estimates, we revisit in this section some tests that have been used in the literature to support the learning mechanism (see for example Evans, 1987 and Dunne *et al.*, 1989). At least since Jovanovic (1982), firm learning has been put forward as a mechanism able to explain important stylized facts about the dynamics of firms, and more specifically about the distribution of their growth rates and their exit decisions. As discussed in section 2, there is large empirical evidence that, conditional on survival, young firms exhibit larger growth rates and are thus key contributors to aggregate growth. This may be due to the fact that younger firms i) display larger *unconditional* growth rates and/or ii) have more volatile growth rates together with exit rates that are non increasing with age. Although our model generates larger unconditional growth rates for younger firms,[23] we concentrate in this section on the main implications of firms updating on the volatility of their growth rates and their exit decisions. Our empirical findings show that firm learning explains well this important contribution of young firms to aggregate growth.

6.1 Firm growth

We start with the relationship between firm age and firm growth. We show here that the average absolute value of the growth rate as well as their variance within cohorts decline with firm (resp. cohort) age. Compared to previous empirical evidence, we compute the growth rate of firms' beliefs rather than the growth rate of actual firm size which might reflect in particular supply side dynamics.

The growth rates of Z^q_{ijkt} and Z^p_{ijkt} can be expressed as:

$$\Delta \ln Z^q_{ijk,t+1} = \sigma_k \Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}} \right] \quad (21)$$

$$\Delta \ln Z^p_{ijk,t+1} = \frac{1}{\sigma_k} \Delta a_{ijkt+1} - \Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}} \right]. \quad (22)$$

Younger firms update more and thus have higher growth rates in absolute value. As firms get older, their beliefs become more accurate, lowering their growth rate in absolute value. It follows immediately that as younger firms update more than older firms, the variance of firm growth decreases with the cohort tenure on a specific market.

[23] Younger firms have larger unconditional growth rates in the model because we made the specific assumption that firms' beliefs about expected demand, $\mathrm{E}_{t-1} \left[e^{\frac{a_{ijkt}}{\sigma_k}} \right]$, are log-normally distributed (see Arkolakis *et al.*, 2014). This assumption seems however difficult to test empirically.

As formally shown in the appendix, we get the following prediction which is a direct consequence of firm updating:

Prediction # 2

(a) - (expected growth rate) - *The expected absolute value of growth rates of* Z^q_{ijkt} *and* Z^p_{ijkt} *decrease with firm age.*

(b) - (variance of growth rate) - *The within cohort variance of growth rates of* Z^q_{ijkt} *and* Z^p_{ijkt} *decrease with cohort age.*

To test prediction 2.a, we estimate:

$$\left|\Delta\varepsilon^X_{ijkt}\right| = \alpha^X + \beta^X \times \text{AGE}_{ijkt} + u_{ijkt} \qquad \forall X = \{q, p\}. \tag{23}$$

Alternatively, we again relax the linearity assumption and replace AGE_{ijkt} by a set of dummy variables as we did for 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 7: Prediction 2.a: age and mean growth rates

	(1)	(2)	(3)	(4)
Dep. var.	$\Delta\varepsilon^q_{ijkt}$		$\Delta\varepsilon^p_{ijkt}$	
Age definition	# years since last entry (reset after 1 year of exit)			
Age_{ijkt}	-0.040[a]		-0.024[a]	
	(0.001)		(0.001)	
$\text{Age}_{ijkt} = 3$		-0.076[a]		-0.053[a]
		(0.002)		(0.001)
$\text{Age}_{ijkt} = 4$		-0.119[a]		-0.079[a]
		(0.003)		(0.002)
$\text{Age}_{ijkt} = 5$		-0.152[a]		-0.096[a]
		(0.004)		(0.003)
$\text{Age}_{ijkt} = 6$		-0.184[a]		-0.109[a]
		(0.005)		(0.003)
$\text{Age}_{ijkt} = 7+$		-0.216[a]		-0.129[a]
		(0.005)		(0.004)
Observations	2795979	2795979	2795979	2795979

Robust standard errors clustered by firm 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 7. We consider sequentially the growth rate of quantities (columns (1) and (2)) and prices (columns (3) and (4)). Both significantly decrease with firm age. The effect is quantitatively more pronounced in the case of quantities than prices, as predicted by the theory.

To test prediction 2.b, we estimate:

$$\text{Var}\left(\Delta\varepsilon^X_{ijkt}\right) = \delta^X \times \text{AGE}_{cjkt} + \mathbf{FE}_{cjk} + u_{ijkt} \qquad \forall X = \{q, p\} \tag{24}$$

where $\mathbf{FE}_{cjk}$ 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 δ^X to be negative: because firms update less their beliefs when they gain experience on a market, their quantities and prices become less volatile.

Table 8: Prediction 2.b: age and variance of growth rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.		$\text{Var}(\Delta\varepsilon^q_{ijkt})$				$\text{Var}(\Delta\varepsilon^p_{ijkt})$		
Age definition		# 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)
$\text{Age}_{cjkt} = 3$		-0.130[a]				-0.072[a]		
		(0.003)				(0.002)		
$\text{Age}_{cjkt} = 4$		-0.208[a]				-0.108[a]		
		(0.004)				(0.002)		
$\text{Age}_{cjkt} = 5$		-0.271[a]				-0.134[a]		
		(0.005)				(0.003)		
$\text{Age}_{cjkt} = 6$		-0.314[a]				-0.153[a]		
		(0.006)				(0.003)		
$\text{Age}_{cjkt} = 7+$		-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 fixed effects included in all estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. [1] firms present all years on market jk.

The results related to the variance of the growth rate of quantities and prices are provided in Table 8. 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. This is still true when controlling for the number of observations in the cohort (columns (3)-(4) and (7)-(8)). Note that our results are not due to attrition: concentrating on the firms which survive over the entire period in columns (4) and (8) leads to similar conclusions.

Robustness. The online appendix, sections 2 and 3, contains additional robustness checks. We show in particular that the growth and variance of firm sales also significantly decrease with age (see columns (1) and (2) of Tables A.6 and A.9). Our tests of predictions 2.a and 2.b are also robust to: (i) controlling for firm size (Tables A.6 and A.9); (ii) focusing on sectors or destinations with higher adjustment costs (Tables A.7 and A.10); (iii) using alternative definitions of firm age (Tables A.8 and A.11).

6.2 Firm survival

A firm decides to stop exporting a particular product to a given destination whenever the expected value of the profits stream associated with this activity becomes negative. At the beginning of period t (after having received $t-1$ signals), expected profits for period t are given by:

$$\mathrm{E}_{t-1}\left[\pi_{ijkt}\right] = \frac{C^S_{ikt}C^S_{jkt}}{\sigma_k} e^{\left(\widetilde{\theta}_{t-1} + \frac{\widetilde{\sigma}^2_{t-1}+\sigma^2_{\varepsilon}}{2\sigma_k}\right)} - F_{ijk}.$$

Obviously, the exit decision also depends on the expected future stream of profits, which depends on the evolution of C^S_{ikt}, C^S_{jkt}, $\widetilde{\theta}_{t-1}$ and $\widetilde{\sigma}^2_{t-1}$ over time. Our assumption of normal prior beliefs provides the conditional distribution of $\widetilde{\theta}_t$ given $\widetilde{\theta}_{t-1}$ while the distribution of $\widetilde{\sigma}^2_{t-1}$ is deterministic. The evolution of firms' beliefs can thus be summarized by $\widetilde{\theta}_{t-1}$ and t. Up to now, we have made no assumption regarding the dynamics of the C^S_{ikt} and C^S_{jkt} terms. Here, to proceed further, we follow Hopenhayn (1992) and introduce some (mild) assumptions on their dynamics. We label $A_{ijkt} \equiv C^S_{ikt}C^S_{jkt}$ and we assume that: i) A_{ijkt} follows a Markov process, ii) A_{ijkt} is bounded and iii) the conditional distribution $F\left(A_{ijkt+1} \mid A_{ijkt}\right)$ is continuous in A_{ijkt} and A_{ijkt+1}, and $F(.)$ is strictly decreasing in A_{ijkt}.[24]

The set of firm state variables at time t can thus be summarized by $\Omega_{ijkt} = \left\{A_{ijkt}, \widetilde{\theta}_{t-1}, t\right\}$. The value function of the firm $V_{ijk}\left(\Omega_{ijkt}\right)$ satisfies the following Bellman equation:

$$V_{ijk}\left(\Omega_{ijkt}\right) = \max\left\{\mathrm{E}\left[\pi_{ijkt}\left(\Omega_{ijkt}\right)\right] + \beta \mathrm{E}\left[V_{ijk}\left(\Omega_{ijkt+1} \mid \Omega_{ijkt}\right)\right], 0\right\} \quad (25)$$

where β is the rate at which firms discount profits and where we have normalized the value of exiting to zero.[25] The value function V_{ijk} is monotonically increasing in A_{ijkt} and $\widetilde{\theta}_{t-1}$.[26] Intuitively, the flow of future expected profits inherits the properties of expected profits at time t. It follows that there exists a threshold value $\underline{\widetilde{\theta}_{t-1}}(A_{ijkt}, t)$ such that a firm exits market jk at time t if $\widetilde{\theta}_{t-1} < \underline{\widetilde{\theta}_{t-1}}(A_{ijkt}, t)$. This implies:

Prediction # 3 (firm exit): *Given A_{ijkt} and t (firm age), (a) the probability to exit decreases*

[24] While not very demanding, these assumptions restrict the set of possible dynamics for firm productivity. In particular, the Markov assumption implies that we have to assume away a learning process behind the C^S_{ikt} and C^S_{jkt} terms. In that sense, our results on firm exit decision are somewhat weaker than those about firm growth, which are consistent with any dynamics of firm productivity.

[25] Here, we assume that an exiting firm loses all the information (learning) accumulated in the past. If the firm enters again market jk in the future, new initial beliefs will be drawn. We thus treat the exit decision as irreversible. Note that this assumption is supported by our results in Table 5.

[26] See Hopenhayn (1992) and Jovanovic (1982).

with $\widetilde{\theta}_{t-1}$ and (b) negative demand shocks trigger less exit for older firms.

The literature has usually associated learning with exit rates 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 may not necessarily hold. The decision to exit not only depends on the extent of firm updating (which indeed declines with age) but also on how $\underline{\widetilde{\theta}_{t-1}}(A_{ijkt}, t)$ evolves over time. If this threshold increases very rapidly for some t, the exit rate could actually increase temporarily. For old firms however, i.e. when beliefs become accurate, and conditional on A_{ijkt} *and* t, the exit rate should tend to 0. Our results are thus only able to explain on average larger exit rates – therefore growth rates – for young firms.

Nevertheless, an important and general implication of our passive learning model is that negative demand shocks should trigger less exits for older firms (prediction 3.b). The reason is simply that firms' posterior beliefs $\widetilde{\theta}_{t-1}$ depend less and less on demand shocks as firms age. Thus, the exit rate may not always be decreasing with age, but demand shocks should always 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 prediction is not directly tested in Pakes and Ericson (1998) because they use a much less parametric model than ours that prevent them to back out demand shocks and firms' beliefs. Their test is solely based on actual firm size.

To test prediction 3, note that from equation (5), $\widetilde{\theta}_{t-1}$ depends positively on $\widetilde{\theta}_{t-2}$ and a_{ijkt-1}. We therefore want to test if, conditional on A_{ijkt} and firm age, the probability to exit at the end of period $t-1$ (i.e. beginning of period t) decreases with $\widetilde{\theta}_{t-2}$ and a_{ijkt-1}. We estimate the following probabilistic model:

$$\begin{aligned}\Pr(S_{ijkt} = 0|_{S_{ijk,t-1}>0}) &= 1 \text{ if } \alpha\text{AGE}_{ijkt-1} + \beta\widehat{v}_{ijk,t} + \gamma\varepsilon^q_{ijkt-1} + \delta\widehat{v}_{ijk,t}\text{AGE} + \mathbf{FE} + u_{ijkt} > 0 \\ &= 0 \text{ otherwise.}\end{aligned}$$

We expect β and γ to be negative, and δ to be positive. **FE** include the two sets of fixed effects $\mathbf{FE}_{ikt}$ and $\mathbf{FE}_{jkt}$, 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, an issue that might be important here given the two large dimensions of fixed effects we need to include.

The results for prediction 3.a are shown in Table 9, columns (1) to (3), and are largely consistent with the model: conditional on age, exit probability significantly decreases with the value of demand shocks $\widehat{v}$ and firm's belief (columns (1) to (3)).

Columns (4) and (5) of Table 9 test for prediction 3.b. We simply add to our baseline specification of column (3) an interaction term between age and demand shock in $t-1$.[27] We

[27]Given our need to control for all jkt-determinants here, we use the version of $\widehat{v}_{ijk,t-1}$ computed using jkt-specific fixed effects, as in Table 11. This has no importance in columns (1) to (3) as the vector of fixed

Table 9: Firm exit

	(1)	(2)	(3)	(4)	(5)
Dep. var.			$\Pr(S_{ijkt} > 0 \mid S_{ijk,t-1} = 1)$		
Age definition			# years since last entry (reset after 1 year of exit)		
Belief_{ijkt-1}	-0.041[a]		-0.041[a]		-0.041[a]
	(0.000)		(0.000)		(0.000)
Age_{ijkt-1}	-0.034[a]	-0.045[a]	-0.033[a]	-0.045[a]	-0.033[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\widehat{v}_{ijkt-1}$		-0.028[a]	-0.031[a]	-0.030[a]	-0.042[a]
		(0.000)	(0.000)	(0.000)	(0.000)
$\widehat{v}_{ijkt-1} \times \text{Age}_{ijkt-1}$				0.001[a]	0.004[a]
				(0.000)	(0.000)
Observations	8786242	8786242	8786242	8786242	8786242

Robust standard errors clustered by firm-product-destination in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%.

indeed find that the coefficient on this interaction term is positive: Young firms react more to a given demand shock than mature exporters on the market. In column (5), a 10% negative demand shock increases exit probability by 3.3 percentage points for a young firm (2 years after entry), but by only 1.3 percentage points after 7 years.

These results strongly support the view that firm learning is an important driver of faster growth rates for younger firms, and so a crucial determinant of aggregate growth overall. More specifically, in all columns of Table 9, exit rates decline with age. We already found in the previous subsection that firm-market growth rates of young firms are larger in absolute value (Table 7) and more volatile (Table 8) due to greater belief updating. The combination of these results implies that conditional upon survival, younger firms have higher growth rates, and therefore should contribute more to aggregate growth. This is precisely what we showed at the beginning of the paper, in section 2.

7 Conclusion

This paper has structurally assessed the empirical relevance of a model of export dynamics incorporating local demand learning, in the spirit of Jovanovic (1982). The model conclusions are all driven by one core prediction: a new signal leads a firm to update more its belief, the younger the firm is. This result leads to some additional predictions for firm growth and survival: (i) the absolute value of the mean growth rate of firms' beliefs decreases with age,

effects includes $\mathbf{FE}_{jkt}$, but it does in columns (4) and (5) as the the coefficient on the interaction between $\widehat{v}_{ijk,t-1}$ and age might reflect differences in $\widehat{v}_{ijk,t-1}$ along the jkt dimension (as we focus on an interaction term in this case).

as does the variance within cohorts; (ii) exit probability decreases with firms' beliefs and the demand shock the firm faces. Further, a demand shock leads to more exit in younger cohorts than in older ones.

Using detailed exporter-level data 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 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 knowledge 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.

The empirical relevance of firm learning has implications for the modeling of firm (and industry) dynamics in general. In particular, it underlines that firms' age is important to understand firms reaction to idiosyncratic demand shocks. Beyond idiosyncratic shocks, it also means that firms of different ages do not face the same amount of uncertainty, leading to a heterogeneous impact of firm responses to aggregate uncertainty shocks. This could refine the analysis of uncertainty shocks on aggregate outcomes, as for example developed in Bloom *et al.* (2012).

We concentrated on post-entry dynamics, leaving for future research the study of the impact of learning on entry decisions. The next step is to use our methodology to investigate how the differences in firms' initial size when entering a market can be explained by the firms' beliefs on other products they sell in the same market, on the same product they sell in other destinations or by other firms' beliefs serving the same market. This would allow to see how information spread over products, markets and firms.

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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:

$$\max_q \int \pi_{ijkt} dG_{t-1}(a_{ijkt}) = \max_q q_{ijkt}^{1-\frac{1}{\sigma_k}} \left(\frac{\mu_k Y_{jt}}{P_{jkt}^{1-\sigma_k}}\right)^{\frac{1}{\sigma_k}} \mathrm{E}_{t-1}\left[e^{\frac{a_{ijkt}}{\sigma_k}}\right] - \frac{w_{it}}{\varphi_{ikt}} q_{ijkt} - F_{ijk}$$

The FOC writes:

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

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

And from the constraint, we get:

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

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

$$\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right] = \frac{1}{\sigma_k}\left(\Delta\widetilde{\theta}_t + \frac{\widetilde{\sigma}_t^2 - \widetilde{\sigma}_{t-1}^2}{2\sigma_k}\right)$$

Using the definition of $\Delta\widetilde{\theta}_t$, $\widetilde{\sigma}_{t-1}^2$ and $\widetilde{\sigma}_t^2$ (see (3) and (4)), we further get:

$$\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right] = \frac{1}{\sigma_k\left(\frac{\sigma_\epsilon^2}{\sigma_0^2} + t\right)} \left(a_{ijkt} - \frac{\left(\theta_0 + \frac{\sigma_0^2}{2\sigma_k} + \overline{a}_{t-1}\frac{\sigma_0^2}{\sigma_\epsilon^2}(t-1)\right)}{\left(1 + \frac{\sigma_0^2}{\sigma_\epsilon^2}(t-1)\right)}\right) \tag{26}$$

Prediction 1. Prediction 1 states that following a new signal, updating is larger for younger firms. Updating is measured directly by $\Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]$ in (26). We get:

$$\frac{\partial \left(\Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]\right)}{\partial a_{ijkt}} = \frac{1}{\sigma_k \left(\frac{\sigma_\epsilon^2}{\sigma_0^2} + t\right)} \equiv \frac{g_t}{\sigma_k} > 0$$

The larger the demand shock, the larger the updating. However, the denominator increases with t: updating is larger for younger firms. 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. σ_ϵ^2, as the signal is less informative when uncertainty is higher.

Prediction 2a. Prediction 2a states that expected absolute value of growth rates decrease with age. Growth rates are given by:

$$\Delta \ln Z^q_{ijk,t+1} = \sigma_k \Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right] \tag{27}$$

$$\Delta \ln Z^p_{ijk,t+1} = \frac{1}{\sigma_k} \Delta a_{ijkt+1} - \Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right] \tag{28}$$

First, note that a_{ijkt+1} and a_{ijkt} being drawn from the same distribution, $\mathrm{E}\left[\Delta a_{ijkt+1}\right] = 0$. The growth rates thus only depend on $\Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]$.

Second, using (26) and the fact that $\mathrm{E}\left[a_{ijkt}\right] = \overline{a}_{t-1}$, the absolute value of the expected growth rate of $\mathrm{E}_{t-1} \left[e^{\frac{a_{ijkt}}{\sigma_k}}\right]$ is given by:

$$\mathrm{E}\left[\left|\Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]\right|\right] = \frac{\left|\left(\overline{a}_{t-1} - \theta_0 - \frac{\sigma_0^2}{2\sigma_k}\right)\right|}{\sigma_k \left(\frac{\sigma_\epsilon^2}{\sigma_0^2} + t\right)\left(1 + \frac{\sigma_0^2}{\sigma_\epsilon^2}(t-1)\right)}$$

The numerator, in absolute value, is necessarily positive and independent of age. The denominator is positive and strictly decreasing in age. And we have:

$$\begin{aligned} \mathrm{E}\left[\left|\Delta \ln Z^q_{ijk,t+1}\right|\right] &= \sigma_k \mathrm{E}\left[\left|\Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]\right|\right] \\ \mathrm{E}\left[\left|\Delta \ln Z^p_{ijk,t+1}\right|\right] &= \mathrm{E}\left[\left|\Delta \ln \mathrm{E}_t \left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]\right|\right] \end{aligned}$$

Which completes the proof. Note that the growth rates of quantities should decrease relatively faster than the one of prices.

Prediction 2b. Prediction 2b states that the variance of growth rates within cohort decrease with cohort age. The variance of these growth rates can be expressed as:

$$
\begin{aligned}
\mathrm{V}\left[\Delta \ln Z^{q}_{ijk,t+1}\right] &= \sigma_k^2 \mathrm{V}\left(\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]\right) && (29)\\
\mathrm{V}\left[\Delta \ln Z^{p}_{ijk,t+1}\right] &= \left(\frac{1}{\sigma_k}\right)^2 \mathrm{V}\left(\Delta a_{ijkt+1}\right) + \mathrm{V}\left(\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]\right)\\
&\quad -\frac{2}{\sigma_k} cov\left(\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right], \Delta a_{ijkt+1}\right) && (30)
\end{aligned}
$$

First, a_{ijkt+1} and a_{ijkt} being drawn from the same distribution, $\mathrm{V}\left[\Delta a_{ijkt+1}\right] = 2\sigma_\epsilon^2$. Second, using (26), it is straightforward to show that:

$$
\mathrm{V}\left(\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]\right) = \left(\frac{\sigma_\epsilon}{\sigma_k\left(\frac{\sigma_\epsilon^2}{\sigma_0^2}+t\right)}\right)^2
$$

Finally, using the fact that $\mathrm{E}\left[\Delta a_{ijkt+1}\right] = 0$, we have:

$$
cov\left(\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right], \Delta a_{ijkt+1}\right) = E\left[\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right]\Delta a_{ijkt+1}\right]
$$

After expanding this expression, using the fact that a_{ijkt} and a_{ijkt+1} are independent and that $E\left[a_{ijkt}\right] = E\left[a_{ijkt+1}\right] = \overline{a}_{t-1}$, we get:

$$
cov\left(\Delta \ln \mathrm{E}_t\left[e^{\frac{a_{ijkt+1}}{\sigma_k}}\right], \Delta a_{ijkt+1}\right) = -\frac{\sigma_\epsilon^2}{\sigma_k\left(\frac{\sigma_\epsilon^2}{\sigma_0^2}+t\right)}
$$

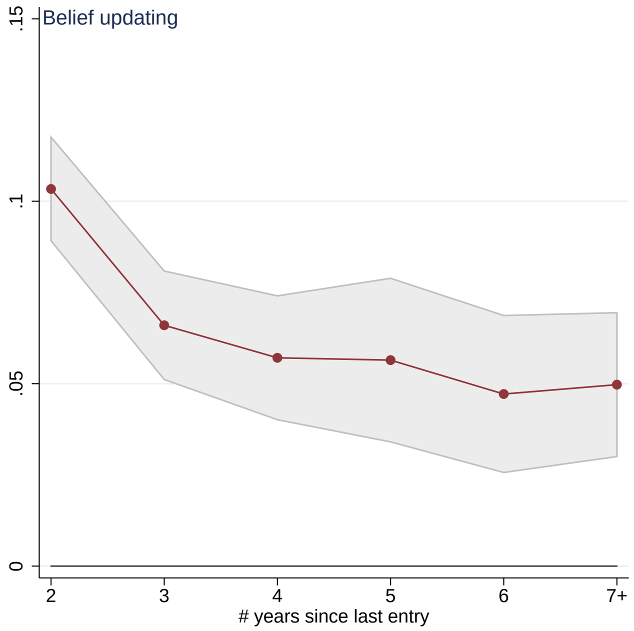
Plugging terms into (29) and (30), and after simplification, we get:

$$
\mathrm{V}\left[\Delta \ln Z^{q}_{ijk,t+1}\right] = \left(\frac{\sigma_\epsilon}{\left(\frac{\sigma_\epsilon^2}{\sigma_0^2}+t\right)}\right)^2 \tag{31}
$$

$$
\mathrm{V}\left[\Delta \ln Z^{p}_{ijk,t+1}\right] = \left(\frac{\sigma_\epsilon}{\sigma_k}\right)^2\left(\left(\frac{1}{\left(\frac{\sigma_\epsilon^2}{\sigma_0^2}+t\right)}+1\right)^2+1\right) \tag{32}
$$

A.2 Additional Figures

Figure 1: Firms' belief updating following a demand shock



This figure depicts the estimated coefficients of Table 3, column (4), together with 90% confidence intervals. Grey areas represent 90% confidence intervals.

A.3 Additional Tables

Table 10: Prediction 1: robustness (high production adjustment costs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.		$\Delta\varepsilon^q_{ijkt}$				$\Delta\varepsilon^q_{ijkt}$		
Age definition	# years since last entry (reset after 1 year of exit)							
Sample		Complex goods				Large time-to-ship		
$\widehat{v}_{ijkt}$	0.091^a	0.138^a	0.138^a		0.162^a	0.231^a	0.231^a	
	(0.011)	(0.011)	(0.008)		(0.015)	(0.012)	(0.008)	
Age$_{ijkt}$		-0.038^a	-0.038^a			-0.035^a	-0.035^a	
		(0.001)	(0.001)			(0.001)	(0.001)	
$\widehat{v}_{ijkt}\times$Age$_{ijkt}$		-0.013^a	-0.013^a			-0.022^a	-0.022^a	
		(0.003)	(0.002)			(0.003)	(0.002)	
$\widehat{v}_{ijkt}\times$Age$_{ijkt}=2$				0.126^a				0.198^a
				(0.011)				(0.013)
$\widehat{v}_{ijkt}\times$Age$_{ijkt}=3$				0.079^a				0.145^a
				(0.013)				(0.015)
$\widehat{v}_{ijkt}\times$Age$_{ijkt}=4$				0.066^a				0.134^a
				(0.017)				(0.019)
$\widehat{v}_{ijkt}\times$Age$_{ijkt}=5$				0.072^a				0.096^a
				(0.020)				(0.021)
$\widehat{v}_{ijkt}\times$Age$_{ijkt}=6$				0.044^b				0.097^a
				(0.019)				(0.025)
$\widehat{v}_{ijkt}\times$Age$_{ijkt}=7+$				0.050^b				0.093^a
				(0.023)				(0.030)
Observations	582450	582450	582450	582450	546586	546586	546586	546586

Robust standard errors clustered by firm in parentheses (bootstrapped in columns (3)). [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. Complex goods and large time-to-ship means in the last quartile of the variable.

Table 11: Prediction 1: robustness of the CES assumption

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	$\Delta\varepsilon^{q}_{ijkt}$					
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			
			$\text{Size}_{ijk,t-1}$		$\overline{\text{Size}}_{ijk,t/t-1}$	
$\widehat{v}_{ijkt}$	0.159^{a}		0.095^{a}		0.075^{a}	
	(0.011)		(0.013)		(0.011)	
Age_{ijkt}	-0.041^{a}		-0.013^{a}		-0.044^{a}	
	(0.001)		(0.001)		(0.001)	
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}$	-0.008^{a}		-0.009^{a}		-0.013^{a}	
	(0.002)		(0.002)		(0.002)	
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=2$		0.160^{a}		0.088^{a}		0.065^{a}
		(0.010)		(0.013)		(0.011)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=3$		0.118^{a}		0.048^{a}		0.013
		(0.010)		(0.014)		(0.011)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=4$		0.118^{a}		0.046^{a}		0.007
		(0.011)		(0.015)		(0.011)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=5$		0.111^{a}		0.038^{b}		-0.004
		(0.014)		(0.017)		(0.014)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=6$		0.098^{a}		0.024		-0.020
		(0.014)		(0.018)		(0.016)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=7+$		0.108^{a}		0.033^{b}		-0.014
		(0.012)		(0.017)		(0.014)
Size_{ijkt-1}			-0.082^{a}	-0.081^{a}	0.010^{a}	0.011^{a}
			(0.001)	(0.001)	(0.000)	(0.000)
$\widehat{v}_{ijkt}\times\text{Size}_{ijkt-1}$			0.014^{a}	0.015^{a}	0.018^{a}	0.019^{a}
			(0.001)	(0.001)	(0.002)	(0.002)
Observations	2739927	2739927	2739927	2739927	2739927	2739927

Robust standard errors clustered by firm in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Size_{t-1} is the log of the total quantity exported by firm i in product k, destination j in year $t-1$, and $\overline{\text{Size}}_{ijk,t/t-1}$ is the average quantity exported by firm i in market jk between t and $t-1$. Age dummies included alone in columns (2), (4) and (6) but coefficients not reported.

Demand learning and firm dynamics: evidence from exporters

Online Appendix

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Contents

1 Additional descriptive evidence on firm growth

Table A.1: Decomposition of the variance of sales

Est.	(1)	(2)	(3)	(4)
Variable	Growth of exports		Value of exports	
Product-country-time FE	Yes	Yes	-	-
Firm-product-time FE	-	Yes	-	-
Product-destination FE	-	-	Yes	-
Firm-product FE	-	-	Yes	-
Firm-product-destination FE	-	-	-	Yes
R^2	0.12	0.44	0.62	0.85

Note: OLS estimations based on French customs data.

2 Prediction 1: additional robustness

Table A.2: Prediction 1: reconstructed year beginning the month of first entry by firm-product-destination

	(1)	(2)	(3)	(4)
Dep. var.	$\Delta\varepsilon^{q}_{ijkt}$			
Age definition	# years since last entry (reset after 1 year of exit)			
$\widehat{v}_{ijkt}$	0.068^{a}	0.104^{a}	0.104^{a}	
	(0.008)	(0.009)	(0.005)	
Age_{ijkt}		-0.004^{a}	-0.004^{a}	
		(0.001)	(0.000)	
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}$		-0.010^{a}	-0.010^{a}	
		(0.002)	(0.001)	
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=2$				0.096^{a}
				(0.008)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=3$				0.049^{a}
				(0.010)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=4$				0.060^{a}
				(0.012)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=5$				0.033^{a}
				(0.011)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=6$				0.046^{a}
				(0.014)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=7+$				0.040^{a}
				(0.014)
Observations	2243176	2243176	2243176	2243176

Robust standard errors clustered by firm in parentheses (bootstrapped in columns (3)). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Age dummies included alone in columns (4) but coefficients not reported.

Table A.3: Prediction 1: controlling for size bins

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			$\Delta\varepsilon^q_{ijkt}$			
Age definition	# 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
$\widehat{\upsilon}_{ijkt}$	0.362^a		0.126^a	0.292^a		0.126^a
	(0.013)		(0.010)	(0.018)		(0.010)
Age_{ijkt}	-0.005^a		-0.042^a	-0.047^a		-0.042^a
	(0.001)		(0.001)	(0.001)		(0.001)
$\widehat{\upsilon}_{ijkt} \times \text{Age}_{ijkt}$	-0.005^a		-0.004^a	-0.010^a		-0.004^b
	(0.001)		(0.002)	(0.002)		(0.002)
$\widehat{\upsilon}_{ijkt} \times \text{Age}_{ijkt} = 2$		0.365^a			0.294^a	
		(0.012)			(0.016)	
$\widehat{\upsilon}_{ijkt} \times \text{Age}_{ijkt} = 3$		0.339^a			0.247^a	
		(0.013)			(0.017)	
$\widehat{\upsilon}_{ijkt} \times \text{Age}_{ijkt} = 4$		0.340^a			0.240^a	
		(0.014)			(0.018)	
$\widehat{\upsilon}_{ijkt} \times \text{Age}_{ijkt} = 5$		0.330^a			0.229^a	
		(0.016)			(0.021)	
$\widehat{\upsilon}_{ijkt} \times \text{Age}_{ijkt} = 6$		0.318^a			0.215^a	
		(0.015)			(0.019)	
$\widehat{\upsilon}_{ijkt} \times \text{Age}_{ijkt} = 7+$		0.335^a			0.226^a	
		(0.014)			(0.017)	
Observations	2327572	2327572	2327572	2327572	2327572	2327572

Robust standard errors clustered by firm in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $\text{Size}_{ijk,t-1}$ is the log of the total quantity exported by firm i in product k, destination j in year $t-1$, and $\overline{\text{Size}}_{ijk,t/t-1}$ is the average quantity exported by firm i in market jk between t and $t-1$. Estimations (1), (2), (4) and (5) include size dummies (and their interactions with $\widehat{\upsilon}$) constructed according to deciles of the variable, deciles being computed by HS4-product-destination-year. Age dummies included alone in columns (2), (4) and (6) but coefficients not reported.

Table A.4: Prediction 1: additional robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.		$\Delta\varepsilon^q_{ijkt}$				$\Delta\varepsilon^q_{ijkt}$		
Robustness		σ_k at HS4 level				Control for σ_k		
$\widehat{v}_{ijkt}$	0.074^a	0.108^a	0.108^a		0.075^a	0.109^a	0.109^a	
	(0.009)	(0.009)	(0.005)		(0.009)	(0.009)	(0.003)	
Age_{ijkt}		-0.040^a	-0.040^a			-0.039^a	-0.039^a	
		(0.001)	(0.000)			(0.001)	(0.001)	
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}$		-0.009^a	-0.009^a			-0.009^a	-0.009^a	
		(0.001)	(0.001)			(0.001)	(0.001)	
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=2$				0.103^a				0.104^a
				(0.009)				(0.009)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=3$				0.065^a				0.067^a
				(0.009)				(0.009)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=4$				0.056^a				0.058^a
				(0.010)				(0.010)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=5$				0.055^a				0.056^a
				(0.013)				(0.014)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=6$				0.045^a				0.048^a
				(0.013)				(0.013)
$\widehat{v}_{ijkt}\times\text{Age}_{ijkt}=7+$				0.049^a				0.050^a
				(0.012)				(0.012)
σ_k					-0.000^b	0.000	0.000	-0.000
					(0.000)	(0.000)	(0.000)	(0.000)
$\sigma_k\times\text{Age}_{ijkt}$						-0.000	-0.000^a	-0.000
						(0.000)	(0.000)	(0.000)
Observations	2786853	2786853	2786853	2786853	2675182	2675182	2675182	2675182

Robust standard errors clustered by firm 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..

Table A.5: Prediction 1: extra EU-15

	(1)	(2)	(3)	(4)
Dep. var.	$\Delta\varepsilon^q_{ijkt}$			
Age definition	# years since last entry (reset after 1 year of exit)			
$\widehat{v}_{ijkt}$	0.154^a	0.215^a	0.215^a	
	(0.013)	(0.010)	(0.007)	
Age$_{ijkt}$		-0.039^a	-0.039^a	
		(0.001)	(0.001)	
$\widehat{v}_{ijkt}\times$Age$_{ijkt}$		-0.019^a	-0.019^a	
		(0.003)	(0.002)	
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 2$				0.185^a
				(0.012)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 3$				0.144^a
				(0.014)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 4$				0.132^a
				(0.017)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 5$				0.106^a
				(0.021)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 6$				0.096^a
				(0.021)
$\widehat{v}_{ijkt}\times$Age$_{ijkt} = 7+$				0.083^a
				(0.027)
Observations	935006	935006	935006	935006

Robust standard errors clustered by firm in parentheses (bootstrapped in columns (3)). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Age dummies included alone in columns (4) but coefficients not reported.

3 Prediction 2a: additional robustness

Table A.6: Prediction 2a: robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	$\Delta\varepsilon^S_{ijkt}$		$\Delta\varepsilon^p_{ijkt}$		$\Delta\varepsilon^q_{ijkt}$		$\Delta\varepsilon^p_{ijkt}$	
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_{ijkt}	-0.037[a]		-0.024[a]		-0.032[a]		-0.014[a]	
	(0.001)		(0.001)		(0.001)		(0.001)	
$Age_{ijkt} = 3$		-0.068[a]		-0.053[a]		-0.058[a]		-0.030[a]
		(0.002)		(0.001)		(0.002)		(0.001)
$Age_{ijkt} = 4$		-0.111[a]		-0.079[a]		-0.094[a]		-0.047[a]
		(0.003)		(0.002)		(0.003)		(0.002)
$Age_{ijkt} = 5$		-0.141[a]		-0.096[a]		-0.121[a]		-0.057[a]
		(0.003)		(0.003)		(0.004)		(0.003)
$Age_{ijkt} = 6$		-0.167[a]		-0.109[a]		-0.149[a]		-0.065[a]
		(0.004)		(0.003)		(0.005)		(0.003)
$Age_{ijkt} = 7+$		-0.201[a]		-0.129[a]		-0.175[a]		-0.078[a]
		(0.004)		(0.004)		(0.005)		(0.004)
$Size_{ijkt-1}$					-0.023[a]	-0.023[a]	-0.029[a]	-0.028[a]
					(0.000)	(0.000)	(0.000)	(0.000)
Observations	2795979	2795979	2795979	2795979	2795979	2795979	2795979	2795979

Robust standard errors clustered by firm in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Controlling for year dummies does not affect the results. $Size_{ijk,t-1}$ is the log of the total quantity exported by firm i in product k, destination j in year $t-1$.

Table A.7: Prediction 2a: robustness (high production adjustment costs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	$\Delta\varepsilon^q_{ijkt}$		$\Delta\varepsilon^p_{ijkt}$		$\Delta\varepsilon^q_{ijkt}$		$\Delta\varepsilon^p_{ijkt}$	
Age definition	# years since last entry (reset after 1 year of exit)							
Sample	Complex goods				Large time-to-ship			
Age_{ijkt}	-0.038[a]		-0.031[a]		-0.027[a]		-0.032[a]	
	(0.001)		(0.000)		(0.001)		(0.001)	
$\text{Age}_{ijkt} = 3$		-0.067[a]		-0.061[a]		-0.041[a]		-0.059[a]
		(0.003)		(0.002)		(0.003)		(0.002)
$\text{Age}_{ijkt} = 4$		-0.105[a]		-0.093[a]		-0.071[a]		-0.098[a]
		(0.004)		(0.003)		(0.005)		(0.003)
$\text{Age}_{ijkt} = 5$		-0.133[a]		-0.115[a]		-0.091[a]		-0.118[a]
		(0.005)		(0.003)		(0.006)		(0.004)
$\text{Age}_{ijkt} = 6$		-0.166[a]		-0.141[a]		-0.111[a]		-0.137[a]
		(0.005)		(0.003)		(0.008)		(0.005)
$\text{Age}_{ijkt} = 7+$		-0.213[a]		-0.170[a]		-0.145[a]		-0.166[a]
		(0.005)		(0.003)		(0.008)		(0.007)
Observations	593950	593950	593950	593950	552439	552439	552439	552439

Robust standard errors clustered by firm in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Complex goods and large time-to-ship means in the last quartile of the variable.

Table A.8: Prediction 2a: alternative age definitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	$\Delta\varepsilon^{q}_{ijkt}$		$\Delta\varepsilon^{p}_{ijkt}$		$\Delta\varepsilon^{q}_{ijkt}$		$\Delta\varepsilon^{p}_{ijkt}$	
Age definition	# years since last entry (reset after 2 years exit)				# years exporting since first entry			
Age_{ijkt}	-0.034^{a}		-0.020^{a}		-0.032^{a}		-0.018^{a}	
	(0.001)		(0.001)		(0.001)		(0.001)	
$\text{Age}_{ijkt} = 3$		-0.065^{a}		-0.042^{a}		-0.054^{a}		-0.032^{a}
		(0.002)		(0.001)		(0.002)		(0.001)
$\text{Age}_{ijkt} = 4$		-0.101^{a}		-0.063^{a}		-0.083^{a}		-0.049^{a}
		(0.003)		(0.002)		(0.003)		(0.002)
$\text{Age}_{ijkt} = 5$		-0.127^{a}		-0.077^{a}		-0.110^{a}		-0.064^{a}
		(0.004)		(0.002)		(0.004)		(0.003)
$\text{Age}_{ijkt} = 6$		-0.155^{a}		-0.089^{a}		-0.139^{a}		-0.076^{a}
		(0.004)		(0.003)		(0.005)		(0.003)
$\text{Age}_{ijkt} = 7+$		-0.191^{a}		-0.110^{a}		-0.181^{a}		-0.102^{a}
		(0.005)		(0.004)		(0.005)		(0.004)
Observations	2795979	2795979	2795979	2795979	2795979	2795979	2795979	2795979

Robust standard errors clustered by firm in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

4 Prediction 2b: additional robustness

Table A.9: Prediction 2b: robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	Var($\Delta\varepsilon^S_{ijkt}$)		Var($\Delta\varepsilon^p_{ijkt}$)		Var($\Delta\varepsilon^q_{ijkt}$)		Var($\Delta\varepsilon^p_{ijkt}$)	
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$_{cjk,t-1}$					-0.020^a	-0.014^a	-0.012^a	-0.008^a
					(0.002)	(0.002)	(0.001)	(0.001)
Observations	598821	598821	598821	598821	598821	598821	598821	598821
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered by cohort in parentheses. Cohort fixed effects included in all estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. [1] firms present all years. Size$_{cjk,t-1}$ is the log of the average total quantity exported by the firms in cohort cjk in year $t-1$.

Table A.10: Prediction 2b: robustness (high production adjustment costs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	Var($\Delta\varepsilon^q_{ijkt}$)		Var($\Delta\varepsilon^p_{ijkt}$)		Var($\Delta\varepsilon^q_{ijkt}$)		Var($\Delta\varepsilon^p_{ijkt}$)	
Age definition	# years since last entry (reset after 1 year of exit)							
Sample	Complex goods				Large time-to-ship			
Age_{cjkt}	-0.071^a		-0.041^a		-0.064^a		-0.041^a	
	(0.002)		(0.001)		(0.003)		(0.002)	
$\text{Age}_{cjkt} = 3$		-0.139^a		-0.083^a		-0.126^a		-0.078^a
		(0.008)		(0.005)		(0.009)		(0.006)
$\text{Age}_{cjkt} = 4$		-0.224^a		-0.131^a		-0.193^a		-0.125^a
		(0.010)		(0.006)		(0.013)		(0.008)
$\text{Age}_{cjkt} = 5$		-0.285^a		-0.169^a		-0.246^a		-0.161^a
		(0.012)		(0.007)		(0.016)		(0.009)
$\text{Age}_{cjkt} = 6$		-0.325^a		-0.194^a		-0.270^a		-0.177^a
		(0.014)		(0.008)		(0.020)		(0.012)
$\text{Age}_{cjkt} = 7+$		-0.395^a		-0.228^a		-0.331^a		-0.207^a
		(0.014)		(0.008)		(0.022)		(0.013)
Observations	138834	138834	138834	138834	119514	119514	119514	119514
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered by cohort in parentheses. Cohort fixed effects included in all estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. [1] firms present all years. Complex goods and large time-to-ship means in the last quartile of the variable.

Table A.11: Prediction 2b: alternative age definitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	$\text{Var}(\Delta\varepsilon^q_{ijkt})$		$\text{Var}(\Delta\varepsilon^p_{ijkt})$		$\text{Var}(\Delta\varepsilon^q_{ijkt})$		$\text{Var}(\Delta\varepsilon^p_{ijkt})$	
Age definition	# years since last entry (reset after 2 years exit)				# years exporting since first entry			
Age_{cjkt}	-0.064^a		-0.038^a		-0.062^a		-0.036^a	
	(0.001)		(0.000)		(0.001)		(0.000)	
$\text{Age}_{cjkt} = 3$		-0.096^a		-0.074^a		-0.075^a		-0.058^a
		(0.003)		(0.002)		(0.003)		(0.002)
$\text{Age}_{cjkt} = 4$		-0.0161^a		-0.115^a		-0.133^a		-0.094^a
		(0.004)		(0.003)		(0.004)		(0.003)
$\text{Age}_{cjkt} = 5$		-0.221^a		-0.149^a		-0.191^a		-0.128^a
		(0.005)		(0.003)		(0.005)		(0.003)
$\text{Age}_{cjkt} = 6$		-0.278^a		-0.175^a		-0.252^a		-0.157^a
		(0.005)		(0.003)		(0.005)		(0.003)
$\text{Age}_{cjkt} = 7$		-0.375^a		-0.227^a		-0.357^a		-0.213^a
		(0.005)		(0.003)		(0.005)		(0.003)
Observations	304858	304858	304858	304858	310247	310247	310247	310247
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered by cohort in parentheses. Cohort fixed effects included in all estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] firms present all years.

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