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Uncertainty, Imperfect Information, and Learning in the International Market[*]

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Abstract

This paper uses a unique dataset of Japanese multinational affiliates, which contains information on sales forecasts, to detect information imperfection and learning in the international market. We document three stylized facts concerning affiliates' forecasts. First, forecast errors (FEs) of sales decline with the affiliate's age. Second, if the parent firm has previous export experience to the region where its affiliate is set up, the entering affiliate starts with a smaller absolute value of FEs. Third, FEs of sales are positively correlated over time and this positive correlation becomes stronger when the affiliates are located further away from Japan. In total, we view these facts as direct evidence for the existence of imperfect information and learning in the international market. We then build up and quantify a dynamic industry equilibrium model of trade and foreign direct investment (FDI), which features information rigidity and learning, in order to explain the documented facts. Counterfactual analysis shows that the variance of time-invariant demand draws and that of transitory shocks have qualitatively different and quantitatively important implications for dynamic patterns of trade/multinational production, dynamic selection, and aggregate productivity.

Keywords: Imperfect information and learning, Uncertainty and firm expectations, Time-invariant and transitory shocks, Multinational firms, Firm dynamics
JEL classification: F1; F2; D83; D84; E23

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1 Introduction

When firms enter new markets, they face considerable uncertainty and information imperfection. Other than macroeconomic fluctuations induced by business cycles or government policies, firms also face uncertainty and information imperfection at the microeconomic level. This is especially true for firms that enter foreign markets. For instance, exporters or multinational affiliates may not know how popular their products would be in the foreign market before entry. Naturally, such an information problem can be resolved by gradually discovering and learning the popularity of their products after entry. Moreover, for firms that plan to do foreign direct investment (FDI) and multinational production (MP), they may use the strategy of sequential entry (i.e., using exporting as an intermediate stage before FDI) to acquire information about their demand. In this paper, we utilize a unique dataset of Japanese multinational enterprises (MNEs) which contains information on sales forecasts at the affiliate level to detect information imperfection and learning in the international market.

Two strands of literature have started to investigate how uncertainty and information imperfection affect firm dynamics and trade patterns. The empirical macroeconomic literature has shown that uncertainty and firm expectations matter for investment substantially (Guiso and Parigi (1999), Bachmann et al. (2013), Bachmann et al. (2017), Chen et al. (2017)). The international economics literature has shown that the specification of the firm's information set has important implications for trade/FDI patterns (Conconi et al. (2016)) and the estimation of trade frictions (Dickstein and Morales (2016)). Although research in the macroeconomic literature has substantiated the existence of imperfect information for aggregate variables such as the inflation rete (see Coibion and Gorodnichenko (2012), Coibion et al. (2015), Coibion and Gorodnichenko (2015)), there is a lack of evidence for the existence of imperfect information for firm-level variables. Moreover, how firm heterogeneity (e.g., age and market experience) and different types of shocks affect the degree of information imperfection and learning remains unexplored. In the international economics literature, some researchers emphasize the importance of imperfect information and learning for trade/multinational production (MP) patterns[1], although *direct* evidence for the existence of these phenomena is not presented.[2] Given that in-

[1]See, for example Akhmetova and Mitaritonna (2013), Timoshenko (2015), Cebreros (2016) and Conconi et al. (2016).

[2]This causes some other researchers to question the premise of this line of research. For instance, Gumpert et al. (2016) claims that even without the existence of imperfect information and learning, selection and persistent productivity shocks *alone* can account for the dynamics of exporters and MNEs (e.g., a negative relationship between previous export experience and exit rates of MNEs). In particular, Arkolakis et al. (2017) which emphasizes the importance of learning admits that firm dynamics models with financial constraints can generate age-dependent growth rates of sales (e.g., Cooley and Quadrini (2001)), although it uses the age-dependent growth rates as the key evidence for learning.

formation imperfection and learning matter for various economic outcomes and are more likely to exist in the international market, it is crucial to provide direct evidence for the existence of these phenomena and show how the international aspect affects these phenomena. Moreover, it is important to develop a model that can match salient empirical regularities of imperfect information and learning observed in the data and derive implications on how various shocks and learning affect dynamic trade/MP patterns, dynamic selection. These objectives are the goal of this paper.

In this paper, we utilize a dataset on Japanese MNEs which contains a direct measure of firm's expectation (i.e., forecasts for future sales). Specifically, affiliates of Japanese MNEs are required to report their forecasted sales for the next year in an annual survey conducted by the Japanese government. Then, we provide evidence that Japanese MNEs face imperfect information concerning their firm-specific demand (or supply) conditions in the destination market and can resolve this problem via learning. In order to achieve this goal, we construct a measure of "forecast error" (FE) of sales, which is defined as the percentage deviation of the forecasted sales from the realized sales. We then treat the absolute value of FEs as a measure of firm-level uncertainty and relate it to other variables such as affiliate age and parent firms' previous export experience in the same region. Three facts concerning learning emerge from the empirical analysis. First, as multinational affiliates become older, the value of their absolute FEs decline, which suggests that firms learn about their demand (or supply) conditions over the life cycle.[3] Second, multinational affiliates whose parent firms have previous export experience (in the region where the affiliates are located) have smaller absolute value of FEs initially, which indicates that export experience helps reduce uncertainty faced by firms that conduct MP.

Thirdly, we use a statistical test on the serial correlation of FEs to detect the existence of imperfect information. In the study of forecasting models (Andrade and Le Bihan (2013), Coibion and Gorodnichenko (2015)), whether FEs made in different periods are correlated is used to detect the existence of information imperfection.[4] Intuitively, as full information rational expectation (FIRE) models imply that agents have perfect information, errors made by the forecasts in the current period are all attributed to unexpected contemporaneous shocks in future periods. Thus, FEs made in two different periods are serially uncorrelated, as the unexpected contemporaneous shocks in different periods are uncorrelated by definition.[5] In our data, we

[3]Since we cannot distinguish between firms' prices and quantities in our data, such evidence can also be interpreted as learning about production costs (i.e., productivity), as in Jovanovic (1982). To be comparable with the recent literature on demand uncertainty and exporter dynamics, our quantitative model assumes that the only information imperfection that firms face is on the demand side.

[4]The correlation of FEs over time refers to the serial correlation between $FE^{\log}_{t-1,t}$ and $FE^{\log}_{t,t+1}$, where $FE^{\log}_{t-1,t}$ refers to the error in period t made by the forecast in period $t-1$.

[5]The validity of this test is robust to different functional forms and distributional assumptions of the model

find that FEs made in two consecutive years are positively correlated and this finding is robust to various specifications and to different subsamples of observations. Therefore, we confidently accept the assumption of imperfect information assumption in our model.[6]

Next, we build up a model featuring imperfect information and learning in order to explain the above three empirical findings above. We follow Jovanovic (1982) to set up the model. Specifically, we assume that firms face a downward sloping demand curve and differ in their fundamental firm-specific demand draws which are time-invariant. Each period, the firm also receives a transitory demand shock, which is independent and identically distributed (i.i.d.). These two shocks together determine the overall demand of the firm every period. The firm does not observe a time-invariant demand draw and needs to learn it over time, although it knows the prior distribution of the draw before entry. After entering the market, the firm updates its belief about this demand draw using information on past sales in the Bayesian fashion, as the firm cannot differentiate the time-invariant component of its demand from the transitory component.[7] Thanks to the accumulation of market experience, the firm's posterior belief about its fundamental demand becomes more precise when it operates in the market for a longer period of time and accumulate more experience (either through exporting or MP). This explains why forecasts for future sales become more precise, when the affiliates become older *and* when their parent firms have previous export experience in the region where the affiliates are set up. However, the Jovanovic model implies zero serial correlation of FEs (i.e., the same as in the FIRE model), as there are offsetting forces that perfectly cancel out each other when we calculate the correlation coefficient.[8] Therefore, we extend the Jovanovic model in order to match the finding of positively correlated FEs.

We modify the Jovanovic model *at the minimum level* in order to match all the three stylized empirical facts documented above. Specifically, we incorporate the sticky information component of the model presented in Mankiw and Reis (2002) into the Jovanovic model and assume that all entering firms do not know how to use information (on past sales) to update their beliefs initially (i.e., the uninformed firms). Every period after entry, a randomly selected fraction uninformed firms become informed and figure out how to update their beliefs using past sales. When they become informed, they begin to utilize information on sales to update their beliefs and will never become uninformed again. For the uninformed firms, they still use the prior belief when forecasting future sales. Under this setup, FEs are positively correlated over time, as uninformed

(e.g., whether the variance of the contemporaneous shock is log normal or time-varying).

[6] Even if we consider endogenous exits by firms after entry, the implied serial correlation of FEs from FIRE models is negative. Therefore, we can still reject the perfect information assumption made by FIRE models.

[7] Note that the existence of the transitory component of the demand shock prevents the firm from learning its fundamental demand draw perfectly in finite time.

[8] In other words, models with imperfect information do not necessarily yield serially correlated FEs.

firms always use the (same) prior belief to forecast future sales and create positively correlated FEs over time. In short, the extended Jovanovic model with sticky information rationalizes all the three stylized empirical patterns.

In order to understand the importance of uncertainty and imperfect information for aggregate economic outcomes, we incorporate the extended Jovanovic model into a dynamic industry equilibrium model in which firms endogenously choose to serve the foreign market via exporting or MP. We use this model to study how the variance of the time-invariant demand draws and that of the transitory shocks affect dynamic trade/MP patterns, dynamic selection into different production modes and aggregate productivity. Similar to Arkolakis et al. (2017), the firm learns about its time-invariant demand by selling products in the destination market. Different from Arkolakis et al. (2017), we allow the firm to make *dynamic* choices on its mode of service (i.e., exporting v.s. MP). Although MP helps firms save on the (variable) iceberg trade cost, it requires higher entry costs compared to exporting. This trade-off is the same as in the standard horizontal FDI model such as Helpman et al. (2004). The crucial departure of our model from the static horizontal FDI model is that there is a *dynamic interaction* between exporting and MP. Specifically, MP becomes attractive to firms, only when they are *certain* that their fundamental demand draws are good enough. Thus, firms do not want to start MP immediately when they are uncertain about its fundamental demand. Instead, the firm can export to the destination market before setting up an affiliate there, as exporting helps the firm solve the information problem and entails lower sunk entry costs (Conconi et al. (2016)).

The key channel we emphasize in the model is a *dynamic selection channel* between different production modes which include exiting, and this channel is shaped by the two key components of the model discussed above. Essentially, FDI is a more productive technology than exporting, as it helps firms save on the variable cost. Furthermore, firms with good time-invariant demand draws should stay in the market if information were perfect. Due to imperfect information, firms that do MP are not necessarily those with the best time-invariant demand draws (i.e., the most efficient firms), and firms that exit are not necessarily those with the worst time-invariant demand draws (i.e., the least efficient firms). An increase in the variance of the transitory demand shocks reduces the signal-to-noise ratio and the effectiveness of learning. As a result, such an increase prevents the economy from selecting the most efficient firms to do MP and the least efficient firms to exit. In other words, the dynamic selection channel is negatively affected by the increasing uncertainty caused by an increase in the variance of the transitory shocks, which eventually reduces aggregate productivity and welfare. To the contrary, an increase in the variance of the time-invariant demand draws improves the effectiveness of learning and therefore helps the economy select the most efficient firms to do FDI and the least efficient firms to exit. Therefore, the dynamic selection channel is positively affected by the increasing uncertainty caused by larger variance of the time-invariant demand draws, which explains why the variance of these draws positively affects aggregate productivity and welfare.[9]

In order to investigate how our model fits the data, we calibrate our model to match moments regarding exporter and multinational dynamics and moments related to affiliates' FEs. The calibrated model can qualitatively replicate the dynamics of FEs, average exporter sales growth and endogenous exits, which are *not* directly targeted in the calibration. We then implement two counterfactual experiments. First, we increase the variance of the transitory shocks and find that such a change reduces aggregate productivity and welfare. In the simulation, we find a lower (positive) correlation between the fundamental demand draw and being a multinational firm among active firms when the variance of the transitory shocks is increased. The other change in the dynamic selection channel comes from the exit margin. This is reflected by a lower (positive) correlation between the fundamental demand draw and staying in the market among all firms, when the variance of the transitory shocks increases. Eventually, these changes translate into lower aggregate productivity and welfare.[10] When we increase the variance of the transitory shocks from the low level (for the U.S.) to the high level (for China), aggregate productivity and welfare are reduce by 1.9% and 1.5% respectively. To the contrary, aggregate productivity and welfare increase, when we increase the variance of the time-invariant demand draws. This result comes from the dynamic selection channel as well (although in the opposite direction). In summary, our analysis shows that when we analyze how uncertainty affects economic outcomes, it is crucial to distinguish between these two sources of uncertainty.

The remainder of the paper is organized as follows. In Section 2, we review related literature. In Section 3, we document three new facts regarding firms' FEs in the international market. In Section 4, we first build up an industry equilibrium model of trade and MP to rationalize the three new empirical findings. Then, we calibrate the model and implement counterfactual analysis concerning the variance of the two types of demand shocks. We conclude in Section 5.

2 Literature Review

In macroeconomics, researchers have long been interested in the information structure of agents and its implications for economic outcomes. Similar to our work, some empirical studies use

[9] Other than the channel of dynamic selection channel, an increase in the variance of any type of shock improves welfare in the CES framework, as the ideal price index is negatively related to the variance of the shock (i.e., heterogeneity), thanks to the variety effect.

[10] Aggregate productivity is defined as the aggregated composite CES good divided by the total amount of labor used for variable, fixed and entry costs.

firm/consumer survey data or analyst forecasts to measure expectations directly (Guiso and Parigi (1999); Bachmann et al. (2013); Bachmann and Bayer (2014); Bachmann et al. (2017); Coibion and Gorodnichenko (2012); Coibion et al. (2015); Coibion and Gorodnichenko (2015); Senga (2016)). However, none of these studies focus on the extensive margin of firm-level activities (i.e., market entry) and on how firm heterogeneity (e.g., age, market experience etc.) affects the firm-level expectations and uncertainty. In addition, few papers in this literature investigates aggregate implications of firm-level uncertainty for resource allocation and welfare.[11] Our paper fill the gap in this literature by studying how firm-level uncertainty affects market entry, resource allocation and welfare.

A related literature studies the impact of expectation and uncertainty on firm-level and aggregate outcomes. Early works by Abel (1983) and Bernanke (1983) reveal how firm expectations affect its investment behavior.[12] Recent research in international trade also incorporates uncertainty and examines how it impacts exports (Handley (2014); Novy and Taylor (2014); Handley and Limão (2015); Handley and Limao (2017)) and MP (Ramondo et al. (2013); Fillat and Garetto (2015)). Conceptually, this literature treats uncertainty as a technology parameter that firms cannot influence. We provide evidence that uncertainty faced by the firm is endogenous to firm activities. Importantly, we use different data moments to differentiate information imperfection from volatility/uncertainty, and the two dimensions of information have different policy implications. We also illustrate that different sources of uncertainty (i.e., the time-invariant shock and the transitory shock) have qualitatively different implications for dynamic selection and welfare.

Imperfect information and learning are more likely to exist in the international market. This probably explains why international economists have already begun to explore implications of learning models for the exporter dynamics (Akhmetova and Mitaritonna (2013); Timoshenko (2015); Cebreros (2016); Conconi et al. (2016)). Despite of the extensive studies in the literature, there is a lack of direct evidence for the existence of imperfect information and learning in the international market. Our study fills this gap by utilizing a measure of firm's expectation to show the existence of imperfect information and learning in the international market.

Finally, our work relates to a large literature on trade and multinational firm dynamics. A series of studies on exporter dynamics describe typical patterns such as rapid growth in export value and the declining exit rates over exporters' life cycles.[13] Gumpert et al. (2016) studies

[11]Bachmann et al. (2013) and Senga (2016) are important exceptions.

[12]Other studies include Bertola and Caballero (1994), Dixit and Pindyck (1994), Abel and Eberly (1996), Bloom et al. (2007) and Bloom (2009). Bloom (2014) is a synthetic survey of this literature.

[13]See, for example, Eslava et al. (2015); Albornoz et al. (2012); Aeberhardt et al. (2014) and Ruhl and Willis (2016).

the joint dynamics of exporting and MP under an exogenous AR(1) productivity process. We complement their work by focusing on learning as a mechanism of reducing uncertainty faced by firms and by highlighting the information value generated by exporting for market entry (i.e., FDI).

3 New Facts: Uncertainty Dynamics and Imperfect Information in the International Market

In this section, we first present new facts regarding multinational firms' subjective uncertainty over their life cycles, which suggests the existence of imperfect information and learning (i.e., gradual revelation of information). Specifically, we introduce our data and show descriptive statistics on our measure of firm-level subjective uncertainty. We then show how this subjective uncertainty measure changes with affiliate age and how it is correlated with parent firms' previous export experience. Next, we present key evidence that substantiates the existence of information rigidity (or imperfect information) in the international market. Finally, we show that the degree of information rigidity is positively related to gravity variables such as the distance between the parent firm (i.e., Japan) and the affiliate (i.e., the destination country), which is likely to act as a barrier to information flows across border.

3.1 Data

We combine two Japanese firm-level datasets prepared by the Ministry of Economy, Trade and Industry (METI): the Basic Survey of Japanese Business Structure and Activities ("firm survey" hereafter) and the Basic Survey on Overseas Business Activities ("FDI survey" hereafter). The firm survey provides information about business activities of Japanese firms and covers firms from a large set of industries that employ more than 50 workers and have more than 30 million Japanese yen in total assets.[14] Firms also report their exports to seven regions: North America, Latin America, Asia, Europe, Middle East, Oceania and Africa. Combined with the FDI survey, we are able to measure previous export experience in a region before an affiliate is established.

The FDI survey contains information about overseas subsidiaries of Japanese multinational enterprises (MNEs). This survey covers two types of overseas subsidiaries of Japanese MNEs: (1) direct subsidiaries with ratios of investment by Japanese enterprises' being 10% or higher as of the end of the year, (2) second-generation subsidiaries with the ratio of investment by Japanese subsidiaries of 50% or higher as of the end of the year. Tracing the identification codes

[14]The industries included are mining, manufacturing, wholesale and retail trade, and eating and drinking places (excluding "Other eating and drinking places").

over time, we are able to construct a panel of affiliates and parent firms from 1995 to 2013. The matched dataset contains on average 2300 parent firms and 14000 affiliates each year.[15] Similar to other surveys of multinational firms, this dataset contains information on affiliates' location, industry affiliation, sales, employment, investment etc.

More important for our study, the FDI survey asks each affiliate to report their *projected sales* for the next fiscal year. We define the deviation of the realized sales from the projected sales as the forecast error (FE) of the firm. We construct three measures of forecast errors (FEs). The first measure is the log point deviation of the projected sales from the realized sales, calculated as

$$FE_t^{\log} \equiv \log\left(R_{t+1}/E_t^S\left(R_{t+1}\right)\right),$$

where $E_t^S\left(R_{t+1}\right)$ denotes the subjective belief of next period sales R_{t+1} in the current period t. The second measure is the percentage deviation of the projected sales from the realized sales

$$FE_t^{pct} = \frac{R_{t+1}}{E^S\left(R_{t+1}\right)} - 1.$$

Since we focus on firms' subjective uncertainty about idiosyncratic demand, we want to exclude systemic FEs that are caused by unexpected aggregate shocks (e.g., recessions). We therefore project our first measure $FE_t^{\log}$ onto country-year and industry-year fixed effects and use the residuals as our last measure of FEs. The fixed effects only account for about 11% of the variation, which suggests that micro-level subjective uncertainty plays a large role in generating firms' forecast errors. Finally, as FEs calculated using above methods contain extreme values, we trim top and bottom one percent observations of FEs.

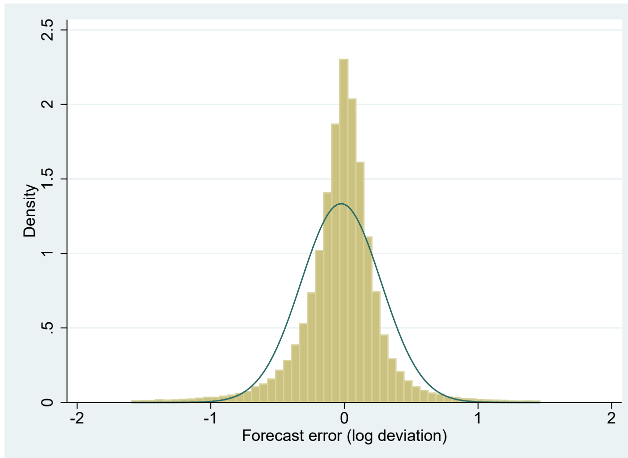
In Figure 1, we plot the distribution of our first measure of FEs, $FE^{\log}$, across all affiliates in all years. The FEs are centered around zero, and the distribution appears to be symmetric. The shape of the density is similar to a normal distribution, though the center and the tails seem to have more mass than the fitted normal distribution (solid line in the graph). This motivates us to assume firm-level shocks to be log-normal in our quantitative model.[16]

In Table 1, we report summary statistics regarding FEs. In the first two rows, we report the level of FEs, calculated as log and percentage deviation of the realized sales from the projected sales reported in the previous year, $FE^{\log}$ and FE^{pct}, respectively. The mean and median of

[15] Affiliates with relatively small parent firms are lost in this process. We have approximated 3200 parent firms (per year) in the FDI survey, while 2300 parent firms (per year) in the merged data. We use all the data in the FDI survey whenever possible (e.g., when examining the dynamics of forecast errors over affiliates' life cycle). We use the merged sample when estimating the effect of previous export experience on affiliates initial subjective uncertainty.

[16] By this assumption, the first measure of FEs has a log-normal distribution in our model. We focus on moments calculated using this measure, which simplifies our numerical implementation (see section 4.2.2).

Figure 1: Distribution of forecast errors



Note: Histogram of FE^{log} with fitted normal density (solid line).

these measures are very close to zero, suggesting that firms do not make systemic mistakes when making the forecasts. In the third and fourth rows, we report the summary statistics of the absolute value of FEs, which we view as measures of firms' subjective uncertainty. On average, firms under- or over-estimate 20% of the sales. In the last row, we compute the residual FEs and examine their absolute values. Since the country-year and industry-year fixed effects do not account for a large fraction of the variation, the mean (and median) and standard deviation of the absolute value of residual FEs are similar to those of $\left|FE^{\log}\right|$ and $\left|FE^{pct}\right|$.

Table 1: Summary statistics for forecast errors

	Obs.	mean	std. dev.	median
FE^{log}	131268	-0.025	0.299	-0.005
FE^{pct}	131771	0.016	0.332	-0.006
$\lvert FE^{log}\rvert$	131268	0.200	0.224	0.130
$\lvert FE^{pct}\rvert$	131771	0.203	0.263	0.130
$\lvert\hat{\epsilon}_{FE^{log}}\rvert$	130968	0.184	0.213	0.116

FE^{log} is the log deviation of the realized sales from the projected sales, while FE^{pct} is the percentage deviation of the realized sales from the projected sales. The last variable, $|\hat{\epsilon}_{FE^{log}}|$, is the absolute value of the residual forecast error, which we obtain by regressing FE^{log} on a set of industry-year and country-year fixed effects. Top and bottom one percent observations of forecast errors are trimmed.

3.2 Validation of Firm-level Forecasts

In this subsection, we show that the projected sales reported by Japanese MNEs' affiliates' and FEs constructed by us are reliable and make intuitive sense for three reasons. First, the FDI survey is mandated by METI and not imposed by the parent firms of these affiliates. As a result, the affiliate reports the projected sales to the government and not to the parent firm. Therefore, the strategic communication is not likely to be a concern here.[17] Second, we show that the projected sales have statistically significant and economically strong impact on realized sales, employment and investment in the future. Specifically, we regress the realized sales (or employment or investment) in year t on projected sales in year $t-1$ (for sales in year t), lagged sales in year $t-1$ and $t-2$ and a set of fixed effects. Robustly, we find that sales forecast not only positively and statistically significantly affects on realized sales (and employment and investment), but also has much stronger predictive power than the realized sales in previous years. This empirical result verifies the reliability and usefulness of the information on firm-level sales forecast.[18]

Finally, we show that the constructed FEs are positively correlated with aggregate-level risk or volatility such as the Country Risk Index (from the BMI research database) and the standard deviation of real GDP growth rates, which makes intuitive sense. In total, the empirical regularities described in Appendix reassure us that the projected forecast for sales provided by the Japanese affiliates abroad and the constructed FEs contain reliable and useful information concerning micro-level uncertainty. In the next three subsections, we examine how firm-level uncertainty gets resolved over the firm's life cycle and how it is related to the parent firms' previous export experience. Moreover, we present key evidence that substantiates the existence of imperfect information in the international market, which cannot be rationalized by FIRE models.[19]

3.3 Fact 1: Uncertainty Declines over Affiliates' Life Cycle

In this subsection, we discuss how affiliates' subjective uncertainty regarding future sales evolves over their life cycles. We measure subjective uncertainty using the absolute value of FEs. Table 2 shows the simple average of affiliates' $\left|FE^{\log}\right|$. As affiliates grow from age one to age seven, their FEs decline from 36% to 18%, which means they are better at predicting future sales as they become older. Similar patterns emerge when we consider alternative measures of FE.

We further confirm these patterns formally by estimating an OLS regression of affiliate i's FE in year t

$$|FE^{\log}|_{it} = \delta_t + \beta X_{it} + \delta_{ct} + \delta_s + \varepsilon_{it},$$

[17]Specifically, the affiliate should not have the incentive to over-report the projected sales in order to impress the parent firm.

[18]If the affiliates randomly or non-rationally reported their projected sales, the projected sales should have no or weak predictable power for future sales, employment and investment.

[19]For details, see Appendix 7.1.

Table 2: Average (s.e.) of absolute forecast errors by age

	1	2	3	4	5	6	7	8	9	10
$\lvert FE^{log} \rvert$	0.369	0.311	0.263	0.234	0.219	0.213	0.208	0.200	0.197	0.177
	(0.007)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
$\lvert FE^{pct} \rvert$	0.366	0.314	0.263	0.234	0.222	0.214	0.210	0.202	0.203	0.181
	(0.008)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
$\lvert \hat{\epsilon}_{FE^{log}} \rvert$	0.352	0.294	0.249	0.219	0.208	0.201	0.194	0.186	0.181	0.160
	(0.007)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)

FE^{log} is the log deviation of the realized sales from the projected sales, while FE^{pct} is the percentage deviation of the realized sales from the projected sales. $\hat{\epsilon}_{FE^{log}}$ is the residual forecast error, which we obtain by regressing FE^{log} on a set of industry-year and country-year fixed effects.

where δ_t is a vector of age dummies, δ_{ct} represents the country-year fixed effects and δ_s represents the industry fixed effects. We also control for affiliate or parent sales X_{it} in some regressions. We use age one as the base category, therefore the age fixed effects represent the difference in the absolute value of FEs between age t and age one. To further control for heterogeneity in subjective uncertainty across affiliates, we also run a regression with affiliate fixed effects δ_i instead of the industry fixed effects δ_s.

We report the regression results in Table 3. Column 1 shows the baseline specification with industry and country-year fixed effects. It is clear that as affiliates become older, absolute value of their FEs declines. On average, affiliates that are at least ten years old have absolute FEs that are 18 log points lower. Most of the decline happens before age five.

In column 2, we control for affiliates' sales and their parent firms' sales in Japan to address the concern that larger firms may have smaller uncertainty. Indeed, larger affiliates tend to have lower uncertainty. This may be because larger affiliates tend to diversify their products or these affiliates have better planning and thus more precise forecasts. Controlling for firm size does not alter the uncertainty-age profile. Interestingly, affiliates with larger parent firms (measured by domestic sales) tend to have larger forecast errors. We conjecture that this is because larger parent firms may choose to enter riskier markets. This is confirmed by our regression in column 3, where we controlled for the subsidiaries' fixed effects and the parent firm size effect disappears.

The uncertainty-age profile is also robust when we restrict our sample to affiliates that have survived for at least seven years. Endogenous exit may affect our estimates of the age effects for two reasons. First, affiliates with higher uncertainty may exit early because they are more likely to be hit by bad shocks. They may also delay their exit because they have already paid the sunk cost (of FDI) and there is an option value of remaining in the foreign market (Bloom (2009)). Second, FEs are censored because we do not observe the realized sales for affiliates that exit before the end of the year. To partially address these concerns, we focus on a subsample of affiliates that had survived for at least 7 years. The decline in subjective uncertainty over the

Table 3: Age effects on the absolute forecast errors

	(1) All	(2) All	(3) All	(4) Survived 7 years
Age=2	-0.060	-0.059	-0.061	-0.067
	(0.008)	(0.008)	(0.009)	(0.013)
Age=3	-0.108	-0.096	-0.087	-0.092
	(0.008)	(0.008)	(0.009)	(0.013)
Age=4	-0.136	-0.120	-0.104	-0.105
	(0.008)	(0.008)	(0.009)	(0.012)
Age=5	-0.147	-0.128	-0.106	-0.116
	(0.008)	(0.008)	(0.009)	(0.014)
Age=6	-0.152	-0.130	-0.104	-0.120
	(0.008)	(0.008)	(0.009)	(0.013)
Age=7	-0.157	-0.135	-0.105	-0.140
	(0.008)	(0.008)	(0.009)	(0.013)
Age=8	-0.165	-0.140	-0.108	-0.133
	(0.008)	(0.008)	(0.010)	(0.014)
Age=9	-0.166	-0.142	-0.106	-0.124
	(0.008)	(0.008)	(0.010)	(0.015)
Age=10	-0.181	-0.145	-0.103	-0.124
	(0.008)	(0.008)	(0.010)	(0.014)
log(Parent Domestic Sales)		0.008	0.002	0.011
		(0.001)	(0.002)	(0.002)
log(Affiliate Sales)		-0.025	-0.059	-0.034
		(0.001)	(0.003)	(0.002)
N	130963	117048	111679	14948
R^2	0.098	0.129	0.383	0.154
Affiliate Fixed Effect	No	No	Yes	No
Industry Fixed Effect	Yes	Yes	No	Yes
Country-year Fixed Effect	Yes	Yes	Yes	Yes

Standard errors are clustered at parent firm level. All coefficients are significant at 1% level, except for the log of parent firm's domestic sales in column 3. The dependent variable is the absolute value of forecast errors (log deviation), $|FE^{log}|$, in all regressions. Regressions in columns 1, 2 and 3 include all affiliates, while the regression in column 4 only includes affiliate that survived at least 7 years.

firm's life cycle is only slightly smaller than column 2, indicating that the forces discussed above might be small in the data.

3.4 Fact 2: Learning about Market Demand through Exporting

In this subsection, we show that for affiliates that enter the destination country for the first time, they face lower subjective uncertainty if their parent firms have previous export experience to the region. The reduction in subjective uncertainty is economically significant compared to the average subjective uncertainty faced by entering affiliates and to the overall decline of affiliates' subjective uncertainty over time.

We restrict our sample to first-time entrants into countries or regions that we identify using the founding year of the affiliates. We focus on affiliates in either the manufacturing sector or the wholesale and retail sector whose parent firms are in manufacturing. Following Conconi et al. (2016), we include distribution-oriented FDI such as wholesale and retail in our analysis since affiliates in these industries may sell the same products as what the parent firms had previously exported. As a result, previous export experience helps reduce demand uncertainty for these distribution-oriented affiliates as well. We obtain information on parent firms' previous export experience using the firm survey data, which is at the region level.[20] Using export information at the regional level introduces additional measurement errors into our proxy for the export experience and can lead to attenuation bias in our regressions. One can see the estimates as a lower bound for the reduction in firm-level subjective uncertainty due to previous exporting.

We define previous export experience following a similar approach as in Conconi et al. (2016) and Deseatnicov and Kucheryavyy (2017). Due to the lumpiness in international trade, we define export entry if the firm does not export to the region for two consecutive years and starts exporting afterwards (the variable of *Exp Expe*. used in Table 5). Similarly, we define export exit if the firm stops exporting to the region for two consecutive years. For firms that have begun to export but have not exited yet, their previous export experience is positive and defined as the number of years since export entry. We assign zero year of export experience to firms that have exited. In our main regression analysis, we show that our results are robust to alternative measures of previous export experience.

Comparing to existing studies of first-time entrants of Japanese MNEs (Deseatnicov and Kucheryavyy (2017)), our sample has fewer observations (see Table 4). The main reason is that we only include first-time entrants that report sales at age two and *projected sales* at age one. However, we obtain very similar patterns regarding exporting and affiliate entry. The majority

[20]Ideally, we would like to have export information at the country level, and explore how previous exports to particular countries affect affiliates' subjective uncertainty in those countries.

(73%) of the affiliates' parents in our sample have previous export experience to the region before their affiliates enter a new country in the same region.[21]

Table 4: Summary statistics

	Frequency	Percent
0	191	27.4
1	50	7.2
2	47	6.7
3	50	7.2
4	38	5.4
5	47	6.7
6	39	5.6
7	32	4.6
8	32	4.6
9	22	3.2
10	38	5.4
11	33	4.7
12	19	2.7
13	23	3.3
14	16	2.3
15	21	3.0
Total	698	100.0

Only first-time entrant affiliates (into a country) that report their sales at age = 2, project sales at age = 1 and have nonmissing exporting experience are included in the sample.

In Table 5, we provide evidence that previous export experience reduces the initial subjective uncertainty faced by the foreign affiliates that enter a country for the first time. We calculate the affiliates' absolute FEs at age one (log deviation of the realized sales at age two from the projected sales at age one) and regress this measure on various measures of previous export experience, controlling for industry fixed effects and country-year fixed effects. In columns 1 and 2, we use dummy variables that equal one if and only if the parent firm of the affiliate exported to the same region in the year (or in one of the two years) before the affiliate enters. In column 3, we use the more sophisticated definition of export experience, and the dummy variable equals one if and only if export experience is positive. These regressions show that having previous export experience reduces absolute forecast errors by 13 log points. In column 4, we use a continuous measure of export experience instead of indicator variables. On average, one additional year of export experience reduces FE by 1.3 log points.

In Appendix 7.2, we provide a battery of robustness checks for Table 5. In one specification, we include parent firm size and affiliate size into the regression in order to control for firm-level heterogeneity between experienced and non-experienced affiliates. In another regression, we focus on horizontal FDI only (i.e., foreign affiliates that sell at least 1/3 of their sales in

[21]The share of Japanese affiliates with previous export experience is higher than that of Norwegian MNE affiliates (39%) and French MNE affiliates (42%), as reported in Gumpert et al. (2016), but lower than that of Belgium MNE affiliates (86%), as reported in Conconi et al. (2016).

Table 5: Learning from exporting: basic regression

	Dependent Variable: $\|FE^{log}\|$			
	(1)	(2)	(3)	(4)
$Exp_{-1} > 0$	-0.159**			
	(0.065)			
$Exp_{-1} > 0$ or $Exp_{-2} > 0$		-0.151**		
		(0.064)		
$Exp \quad Expe. > 0$			-0.132*	
			(0.070)	
$Exp \quad Expe.$				-0.013**
				(0.006)
Industry FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
N	553	561	658	658
R^2	0.486	0.499	0.472	0.472

Standard errors are clustered at parent firm level, * 0.10 ** 0.05 *** 0.01. Exp_{-1} or Exp_{-2} indicates whether the parent firm exported one year or two years before its FDI in the destination economy. $Exp \quad Expe.$ is the total number of years of exporting, and export entry is defined to be one if the firm does not export to the region for two consecutive years and starts exporting afterwards.

the hosting economy). In the final robustness check, we exclude intra-firm exports from total exports when measuring previous export experience of parent firms. All robustness checks yiled qualitatively the same result as in the baseline regression. Taken together, we show that previous export experience is associated with lower initial uncertainty for first-time entering affiliates in the destination markets. This suggests that testing the market and gradual learning about foreign demand can provide a motive for firms to export before doing FDI (i.e., the information value of exporting).

3.5 Fact 3: Correlated Forecast Errors over Time

In this subsection, we present evidence on the existence of imperfect information in the international market and how the level of information imperfection is correlated with the gravity variables such as the physical distance. This is important for our study for several reasons. First, as we are going to present a model that features imperfect information and learning, it is *necessary* to present evidence to motive the premise of the model. Second, the test we are going to use to detect information rigidity helps us differentiate between models even with the class of models featuring imperfect information and learning. Finally, how distance affects the flow of information across border is a central question in the study of trade and FDI. Our direct measure on firm's expectations helps us disentangle how distance affects information flow from the effect of economic volatility on the formation of firm's expectations.

In the study of forecasting models (Mishkin (1983), Dominguez (1986), Ito (1990), Coibion and Gorodnichenko (2012), Andrade and Le Bihan (2013), Coibion and Gorodnichenko (2015)), whether FEs made in different periods are correlated is used to detect the existence of information rigidity.[22] Intuitively, as FIRE models imply that agents have perfect information, errors made by the forecast in the current period (for the values of variable in the next period) are all caused by *unexpected and contemporaneous* shocks that happen next period (i.e., innovations in the next period). Thus, FEs made at two different periods are serially uncorrelated in FIRE models, as the unexpectedly contemporaneous shocks are uncorrelated by definition. Therefore, if the data of FEs exhibit serial correlation between FEs made in two different periods, we can confidently reject the null hypothesis that agents know information perfectly. Moreover, the validity of this test is robust to different functional form and distributional assumptions we make in the model (e.g., whether the variance of the contemporaneous shock is age dependent and whether the fundamental shock is log normal). In total, the test on the serial correlation of FEs made in different periods provides direct and clean evidence for the existence of information rigidity.

We proceed our analysis in two steps. First, we present the (raw) correlation coefficients between FEs made in different periods in Table 6. The first two columns show that the correlation coefficient between FEs made in two consecutive years are positively and significantly correlated when we look at all the affiliates and all the affiliates in the manufacturing (or in the wholesale and retail) sector. Next, when we focus on entering affiliates in the manufacturing (or in the wholesale and retail) sector and/or affiliates in the manufacturing (or in the wholesale and retail) sector that have survived for at least five years, the correlation coefficient is still positively significant. In short, the positive autocorrelation of FEs rejects the assumptions made by FIRE models.

Table 6: Serial correlation of forecast errors made in two consecutive years

	1	2	3	4	5
corr. ($FE^{\log}_{t-1,t}$, $FE^{\log}_{t,t+1}$)	0.124***	0.121***	0.145***	0.153***	0.146***
Manufacturing firms only?	No	Yes	Yes	Yes	Yes
Type of firms included	all firms	all manufacturing	entrants	survivors	entrants and survivors
N	178140	108135	11013	19968	9799

Notations: $FE^{log}_{t-1,t}$ is the log deviation of the realized sales in year t from the projected sales in year $t-1$, while $FE^{log}_{t,t+1}$ is the log deviation of the realized sales in year $t+1$ from the projected sales in year t. Top and bottom one percent observations of forecast errors are trimmed. Manufacturing firms including firms in wholesalers as well. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Manufacturing survivors refer to manufacturing affiliates that have survived for at least five years. Manufacturing entrants refers to manufacturing affiliates that entered the destination markets during our sample period.

[22]The correlation of FEs over time refers to the serial correlation between $FE^{\log}_{t-1,t}$ and $FE^{\log}_{t,t+1}$, where $FE^{\log}_{t-1,t}$ refers to the error in period $t+1$ made by the forecast in period t. It is called the the correlation between "rolling horizon" FEs (Andrade and Le Bihan (2013)).

Interestingly, the serial correlation of FEs shrinks with firm age. When we divide affiliates into four age groups, the correlation coefficient decreases as we move from a younger age cohort to an old age cohort, as shown by Table 7. As the serial correlation of FEs is indicative of information rigidity, Table 7 hints that information rigidity gets resolved over firm's life cycle. This piece of evidence motivate us to use the sticky information model in the next section.

Table 7: Serial correlation of forecast errors for different age groups

	age: 2-5	age: 6-8	age: 9-12	age≥13
corr. ($FE^{\log}_{t-1,t}$, $FE^{\log}_{t,t+1}$)	0.157***	0.123***	0.103***	0.109***
Manufacturing firms only?	Yes	Yes	Yes	Yes
N	13985	14278	18995	54021

Notations: $FE^{log}_{t-1,t}$ is the log deviation of the realized sales in year t from the projected sales in year $t-1$, while $FE^{log}_{t,t+1}$ is the log deviation of the realized sales in year $t+1$ from the projected sales in year t. Top and bottom one percent observations of forecast errors are trimmed. Manufacturing affiliates including those in retail and wholesale sectors as well. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, we run panel regressions to confirm the above finding. Specifically, the regression we run is

$$FE^{\log}_{i,t,t+1}(sales) = \beta FE^{\log}_{i,t-1,t}(sales) + FE_{industry*year} + FE_{country*year} + \varepsilon_{it},$$

where i refers to the affiliate; t refers to year; FE refers to the fixed effects. Note that as we explore cross-affiliate variation in the serial correlation of FEs, we cannot include affiliate fixed effects into the regression. Instead, we include industry-year and country-year fixed effects into the regression. Regression results in Table 8 show that even after we have controlled for a battery of fixed effects, FEs made next year are still positively and statistically significantly related to FEs made in the current year. This is true for both the whole sample (i.e., all manufacturing affiliates) and subsamples (e.g., the sample of survivors or entrants only). In addition, the conditional correlation coefficient is around 0.12, which is similar to the raw correlation coefficient reported in Table 6. This shows that industry-level and country-level fixed effects are not the dominant factors that cause the serial correlation of FEs in our data. In total, our data show that FEs made in two consecutive years are indeed positively correlated. This is the evidence that substantiates the existence of imperfect information in the international market. In the next section, we will propose a learning model that features imperfect information to rationalize all the three empirical facts documented above.

As a robustness check, we add parent firm fixed effects into the above regression. Regression results are reported in Table 9 show that although the estimated correlation coefficient becomes smaller in magnitude (i.e., $0.06-0.07$), the significance level is still extremely high. Furthermore,

Table 8: Regression for the serial correlation of forecast errors

	(1)	(2) $FE^{\log}_{t,t+1}(sales)$	(3)
$FE^{\log}_{t-1,t}(sales)$	0.106***	0.131***	0.120***
	(0.00689)	(0.0138)	(0.0187)
Type of firms included	manufacturing firms	manufacturing survivors	manufacturing entrants
Industry-year Fixed Effect	Yes	Yes	Yes
Country-year Fixed Effect	Yes	Yes	Yes
N	67790	13160	6787
adj. R^2	0.148	0.169	0.219

Notations: $FE^{log}_{t-1,t}$ is the log deviation of the realized sales in year t from the projected sales in year $t-1$, while $FE^{log}_{t,t+1}$ is the log deviation of the realized sales in year $t+1$ from the projected sales in year t. Top and bottom one percent observations of forecast errors are trimmed. Standard errors are in parentheses and clustered at the affiliate level. Manufacturing firms including firms in wholesalers as well. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Manufacturing survivors refer to manufacturing affiliates that have survived for at least five years. Manufacturing entrants refers to manufacturing affiliates that entered the destination markets during our sample period.

the estimated coefficient is stable, irrespective of which sample we use and which measure we use for firm-level FE. In total, the data strongly display positively correlated FEs over time.

Finally, we investigate how distance affects the variance and serial correlation of FEs for Japanese affiliates in various destination economies. When a Japanese affiliate forecasts its future sales in the host country, more volatile and uncertain economic conditions would cause imprecise forecasts and larger variance of FEs, which is not related to the distance from Japan per se. At the same time, longer distance from Japan to the host countries hinders information flows with the Japanese MNE and therefore increases the severity of information imperfect. In the data, we find that the variance of FEs is negatively related to the distance from Japan. In other words, Japanese affiliates in China and Southeast Asia made less *precise* forecasts compared to those in North America and Europe. To the contrary, the serial correlation of FEs (for a given affiliate) which is our key measure for the existence of imperfect information is positively related to the distance from Japan. I.e., Japanese affiliates in China and Southeast Asia made less *systematic* forecast errors compared to those in North America and Europe.

We think the above two findings are reasonable and show the important difference between imperfect information and volatility. Specifically, economies close to Japan (i.e., China and Southeast Asian countries) are emerging markets which probably have more volatile economic environment than countries that are far away from Japan (e.g., the U.S.and European countries). This causes less precise forecasts for Japanese affiliates in economies closer to Japan. However, distance hinders flows of information.[23] Therefore, the empirical measure related to the degree

[23]There are two reasons for why distance negatively affects information flows (and especially within MNEs).

Table 9: Regression for the serial correlation of sales forecast errors (including parent firm fixed effects)

	(1) $FE^{pct}_{t,t+1}$	(2) $FE^{\log}_{t,t+1}$	(3) $\hat{\epsilon}_{FE^{log}_{t,t+1}}$	(4) $FE^{pct}_{t,t+1}$	(5) $FE^{\log}_{t,t+1}$	(6) $\hat{\epsilon}_{FE^{log}_{t,t+1}}$
$FE^{pct}_{t-1,t}$	0.0656***			0.0703***		
	(0.00600)			(0.00757)		
$FE^{\log}_{t-1,t}$		0.0642***			0.0631***	
		(0.00526)			(0.00665)	
$\hat{\epsilon}_{FE^{log}_{t-1,t}}$			0.0641***			0.0629***
			(0.00526)			(0.00665)
Type of firms	all	all	all	manufacturing	manufacturing	manufacturing
Parent firm FE Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Country-year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	112766	109775	109765	74353	72792	72789
R^2	0.170	0.191	0.088	0.186	0.209	0.095

FE^{log} is the log deviation of the realized sales from the projected sales, while FE^{pct} is the percentage deviation of the realized sales from the projected sales. The last variable, $\hat{\epsilon}_{FE^{log}}$, is the residual forecast error, which we obtain by regressing FE^{log} on a set of industry-year and country-year fixed effects. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Top and bottom one percent observations of forecast errors are trimmed. Standard errors are in parentheses and clustered at the affiliate level. Manufacturing affiliates including those in retail and wholesale sectors as well.

of information imperfection (i.e., the correlation term) should be positively related to distance, which is exactly what we find from the data. For details, see Appendix 7.3.

4 An Industry Equilibrium Model of Firm Learning and Market Entry

In this section, we propose a dynamic industry equilibrium model of trade and MP to study how imperfect information and learning impacts aggregate productivity and welfare. Specifically, we focus on how the variance of the time-invariant demand draws and that of the transitory shocks, which generate different sources of uncertainty, impact aggregate productivity and welfare *differently*. The key channel we emphasize is the *dynamic selection* into MP and into staying in

First, MNEs send employees from the headquarters to their foreign affiliates in order to facilitate intra-firm coordination and communication, as face-to-face communication is important (see Startz (2017)). This is especially true for Japanese MNEs. MNEs probably send fewer employees (and send them less frequently) from the headquarters to their affiliates located in remote foreign countries than those located in adjacent foreign economies. Second, there is probably more news coverage on economies that are closer to Japan in Japanese media (e.g., China, Taiwan and south Korea). When Japanese managers who are sent from the headquarters to the foreign affiliates, they have more information about adjacent economies than about remote economies. Therefore, they make fewer systematic mistakes when filling out the survey.

the market (i.e., exporting or MP). In the counterfactual exercise, We find that an increase in the variance of the transitory demand shocks reduces aggregate productivity and welfare, while an increase in the variance of the time-invariant demand draws increases them.

Economically speaking, MP is a more productive technology than exporting, as it helps firms save on the variable cost and requires one-time sunk costs. Furthermore, firms with good time-invariant demand draws would stay in the market if there were no imperfect information. Due to the existence of imperfect information, firms that do MP are not necessarily those with the best time-invariant demand draws, and firms that exit are not necessarily those with the worst time-invariant demand draws in the economy. An increase in the variance of the transitory demand shocks reduces the signal-to-noise ratio and the effectiveness of learning. As a result, such an increase prevents the economy from allocating the most efficient firms to do FDI and the least efficient firms to exit, which leads to lower aggregate productivity and welfare. To the contrary, an increase in the variance of the time-invariant demand draws increases the effectiveness of learning, and therefore helps the economy select the most efficient firms to do FDI and the least efficient firms to exit.

We build up a dynamic industry equilibrium model of heterogeneous firms a la Arkolakis et al. (2017) to rationalize the empirical findings documented above. Similar to Arkolakis et al. (2017), the firm learns about its fundamental foreign demand by selling its products in the destination market. Different from Arkolakis et al. (2017) (and also Jovanovic (1982)), we allow the firm to make an endogenous and *dynamics* choice on its entry model into the foreign market (i.e., exporting v.s. MP). In particular, the firm can export its products to the foreign market before setting up an affiliate there, as exporting entails smaller sunk costs and generates information value. In addition, we introduce sticky information a la Mankiw and Reis (2002) into the Jovanovic-type firm dynamics model (Jovanovic (1982)) in order to match the positive serial correlation of FEs observed in the data. The spirit of our model is close to the two-period model studied in Conconi et al. (2016). However, we make key departures from Conconi et al. (2016) by focusing on the difference between the two types of shocks the firm faces and by emphasizing the life cycle feature of uncertainty and information imperfection at the firm level.

4.1 Setup: Demand and Supply

This section considers a dynamic industry equilibrium model in which each Japanese firm produces a differentiated variety and has to decide between exporting and FDI in order to serve the foreign country (i.e., the rest of the world). For simplicity and the data constraint, we abstract from Japanese firms' domestic activities and focus on their overseas activities only. Specifically, the total expenditure of foreign consumers is assumed to be fixed and exogenous to Japanese firms' activities in the foreign market. This is a reasonable assumption, as Japanese products (Japanese MNEs' local sales plus Japanese exports) only account for a small share of the total consumption in any major economy in the world (e.g., the U.S., China, E.U. etc.). Therefore, Japanese exports and its MNEs' activities should generate small general equilibrium effects in destination countries. Labor is the only input in production. We assume that Japanese affiliates only employ a small fraction of the labor force in destination economies and therefore cannot affect the wage there. In addition, we also abstract from the analysis on how trade and FDI affect the domestic labor market in Japan and assume domestic wage is fixed.

We introduce the demand side structure of the model. In the foreign country, the representative consumer has the following nested-CES preferences where the first nest is among composite goods produced by firms from different countries, indexed by i,

$$U_t = \left(\sum_i \chi_i^{\frac{1}{\delta}} Q_{it}^{\frac{\delta-1}{\delta}} \right)^{\frac{\delta}{\delta-1}},$$

and the second nest is among varieties $\omega \in \Sigma_{it}$ produced by firms from each country i,

$$Q_{it} = \left(\int_{\omega \in \Sigma_{it}} e^{\frac{a_t(\omega)}{\sigma}} q_t(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}. \tag{1}$$

In the first nest, the parameter χ_i is the demand shifter for country i goods, and the parameter δ is the Armington elasticity between goods produced by firms from different countries. In the second nest, the parameter σ is the elasticity between different varieties, and $a_t(\omega)$ is the demand shifter for variety ω. We assume that firms differ in their demand shifter, $a_t(\omega)$.

After denoting foreign consumers' total expenditure as $\tilde{Y}_t$, we can express the demand for a particular Japanese variety, ω, as:

$$q_t(\omega) = \frac{\tilde{Y}_t}{\tilde{P}_t^{1-\delta}} \chi_{jp} P_{jp,t}^{\sigma-\delta} e^{a_t(\omega)} p_t(\omega)^{-\sigma}, \tag{2}$$

where $\tilde{P}_t$ is the aggregate price index for all goods, and $P_{jp,t}$ is the ideal price index for Japanese goods. When the Armington elasticity δ equals 1, the first nest is Cobb-Douglas, and the expenditure on Japanese goods no longer depend on $P_{jp,t}$. When $\sigma = \delta$, the elasticities in the two CES nests are the same, which is the case in prominent trade models such as Eaton and Kortum (2002) and Melitz (2003). In our calibration, we set δ to be a value between 1 and σ.

In our industry equilibrium model, we treat $\tilde{Y}_t$ and $\tilde{P}_t$ as exogenous. Therefore, we combine the exogenous terms in expression (2), $\tilde{Y}_t \tilde{P}_t^{\delta-1} \chi_{jp}$ into one variable, Y_t, and call it the aggregate demand shifter. In addition, since we only focus on Japanese firms, we suppress the subscript jp in the following analysis. The CES preference over different varieties of Japanese goods implies the ideal price index as:

$$P_t \equiv \left(\int_{\omega \in \Sigma_t} e^{a_t(\omega)} p_t(\omega)^{1-\sigma} d\omega \right)^{1/(1-\sigma)}. \tag{3}$$

We use the term, $A_t \equiv Y_t P_t^{\sigma-\delta}$ to denote the aggregate demand condition faced by all firms in period t and rewrite the firm-level demand function as

$$q_t(\omega) = A_t e^{a_t(\omega)} p_t(\omega)^{-\sigma}. \tag{4}$$

We specify firm-level behavior in what follows. First, we assume that demand uncertainty comes from the firm-specific demand shifter, $a_t(\omega)$, for each firm. Specifically, Japanese firms differ in the firm-specific demand shift, $a_t(\omega)$, and we assume that $a_t(\omega)$ is the sum of a time-invariant fundamental demand draw $\theta(\omega)$ and a transitory shock $\varepsilon_t(\omega)$ as in Jovanovic (1982) and Arkolakis et al. (2017):

$$a_t(\omega) = \theta(\omega) + \varepsilon_t(\omega),\ \varepsilon_t(\omega) \overset{i.i.d.}{\sim} N\left(0, \sigma_\varepsilon^2\right). \tag{5}$$

Firms understand that $\theta(\omega)$ is drawn from a normal distribution $N\left(\bar{\theta}, \sigma_\theta^2\right)$, and the independent and identically distributed (i.i.d.) transitory shock, $\varepsilon_t(\omega)$, is drawn from another normal distribution $N\left(0, \sigma_\varepsilon^2\right)$. Importantly, we assume that the firm does not know the value of its time-invariant demand draw. Each period, although the firm observes the realize demand, $\theta(\omega)$, it cannot distinguish between $\theta(\omega)$ and $\varepsilon_t(\omega)$. Instead, the firm forms an posterior belief about the distribution of θ.

Next, we assume that there are two types of firms in the economy in the same spirit as in sticky information models a la Mankiw and Reis (2002): the informed firms and the uninformed firms. Initially, all entering firms are uninformed in the sense that they all use the prior distribution of θ (i.e., $N(\bar{\theta}, \sigma_\theta^2)$) to form the expectation for the fundamental demand draw. At the end of each period, $1-\alpha$ fraction of the remaining uninformed firms become informed. From the time when they become informed, they begin to update the beliefs for $\theta(\omega)$ by utilizing realized overall demand shocks and will never become uninformed again. The remaining uninformed firms still use the prior distribution of θ to make their forecasts. When time elapses, more and more firms become informed, and all firms become informed when they live long enough.

Different from the demand side, we assume that firms are homogenous in labor productivity for simplicity. Specifically, in order to produce q units of output, the firm has to employ the same amount of workers. This simplification is motivated by recent work that emphasizes the importance of demand heterogeneity for understanding firm heterogeneity (e.g., Hottman et al. (2016)).

The industry structure is characterized by monopolistically competition. There is an exogenous mass of potential entrants J (from Japan) that decide whether or not to enter the foreign market every period. Each entrant draws a time-invariant demand shifter θ from a normal distribution, $N\left(\bar{\theta}, \sigma_{\theta}^{2}\right)$. Every entrant does not know its fundamental demand draw and has to use the prior belief for θ to decide whether to enter the foreign market. If the firm chooses to enter the market, it also has to decide how to serve the foreign market. A potential entrant can either serve the foreign market via exporting, which involves a sunk cost of f_x^e, or serve the foreign market by setting up an affiliate with an entry cost of f_m^e. Both sunk costs are paid in units of domestic labor. If neither mode is profitable, the potential entrant simply exits and obtains zero payoff.

Similar to entrants, incumbents do not know the exact value of θ. However, the informed incumbents have better information for the fundamental demand than entrants, as they can utilize information on past sales to update the beliefs for the fundamental demand draw. The uninformed incumbents have the same information concerning the fundamental demand as the entrants, as they have not figured out how to utilize information on past sales to update their beliefs. In each period, the incumbents first receive an exogenous death shock with probability η. For surviving firms, they have to decide whether to change their mode of service. They can keep their service mode unchanged. Alternatively, they can switch to another mode of service (i.e., from exporting to MP or from MP to exporting). In addition, they can also choose to permanently exit the market. We assume that for exporters, they have to pay a one-time entry cost, f_x^e, in order to start exporting. However, incumbent MNEs can switch to exporting without paying this sunk cost. Firms also have to pay a fixed cost each period in order to remain exporting (with a fixed cost of f_x) or doing FDI (with a fixed cost of f_m). Therefore, firms with low demand draws will choose to exit.

For firms that serve the foreign market, they decide how much to produce in period t before the overall demand shock a_t is realized. After the overall demand shock in period t, a_t, is realized, they choose the price p_t in order to sell all the products they have produced, as there is no storage technology and firms cannot accumulate inventories. For informed incumbent firms, they update their beliefs about the fundamental demand θ after observing the overall demand shock in period t: a_t. Additionally, a randomly selected $1-\alpha$ fraction of uninformed firms become informed at the end of each period.

In the calibration exercise, we normalize the sunk entry cost into exporting, f_x^e, to zero, as we do not use the information on domestic production of Japanese firms to calibrate this parameter. Additionally, we follow the literature on exporter/MP dynamics (Ruhl and Willis (2016), Das et al. (2007) etc.) to assume that the sunk entry cost into FDI, f_m^e, is drawn from a log normal distribution. As a result, the sunk entry cost into FDI becomes a state variable for the firm's dynamic optimization decision.[24] Finally, the fixed per-period operation cost of MP, f_m, is set to be zero, as there is a flat profile of exit rate (with firm age) over MNEs' affiliates' life cycles.

4.2 Belief Updating and Serially Correlated Forecast Errors

In this subsection, we show that our model of firm learning described above can rationalize all the three empirical findings documented in Section 3. In particular, both FIRE models and the original Jovanovic model (i.e., Jovanovic (1982)) do not yield positively correlated FEs overtime. We proceed our analysis in the following three steps.

4.2.1 Full Information Rational Expectation Models

First, we show that FIRE models which assume that firms know their time-invariant demand draws yield serially uncorrelated FEs, which are inconsistent with our empirical finding. Specifically, as the firm knows its time-invariant demand shifter, $\theta\left(\omega\right)$, in FIRE models, it chooses the level of output to maximize:

$$\max_{q_t} E_{\varepsilon_t} A_t^{\frac{1}{\sigma}} e^{\frac{\theta+\varepsilon_t}{\sigma}} q_t^{\frac{\sigma-1}{\sigma}} - wq_t,$$

where w is the wage rate. Thus, the optimal output choice is

$$q_t(\theta) = A_t e^{\theta+\frac{\sigma_\varepsilon^2}{2\sigma}} \left(\frac{(\sigma-1)}{\sigma w}\right)^{\sigma},$$

[24] Another reason for assuming that firms make random draws of the entry costs into FDI is to match the productivity hierarchy among first-time entrants (into the destination markets) documented in Table 20. The table shows that experienced affiliates are more productive than non-experienced affiliates. In the model, non-experienced affiliates choose to enter the FDI market (after entry) based on the entry costs (i.e., not based on the information concerning the fundamental demand draw), as all entrants have the same prior belief about the fundamental demand draw. In other words, the selection into FDI is random in the dimension of the fundamental demand draws for non-experienced affiliates. However, experienced affiliates are a selected sample of firms that have better fundamental demand draws than the ex ante average, as only firms that have better ex post beliefs for their fundamental demand draws choose to enter the FDI market. This leads to the theoretical prediction that experienced affiliates are more productive than non-experienced affiliates in terms of revenue productivity, which is true in the data. If we introduce ex ante heterogeneity in labor productivity instead of the entry cost into FDI, non-experienced affiliates are also a selected sample of firms that have higher productivity than the ex ante average. Therefore, the productivity hierarchy pattern among first-time entrants cannot be rationalized by the theory.

and the resulting FE is[25]

$$FE^{\log}_{t-1,t}(sales) = \frac{\varepsilon_t}{\sigma} - \frac{\sigma^2_\varepsilon}{2\sigma^2}. \tag{6}$$

It is clear that the covariance of FEs made in two consecutive periods is

$$cov(FE^{\log}_{t-1,t}, FE^{\log}_{t,t+1}) = cov\left(\frac{\varepsilon_t}{\sigma}, \frac{\varepsilon_{t+1}}{\sigma}\right) = 0,$$

as the transitory shock is uncorrelated over time. Moreover, even if the fundamental demand draw, θ, is time-varying and follows an AR(m) processes ($m = 1, 2, ...$), we still have the result of non-correlated FEs over time as the innovation in the demand process is unpredictable.[26] This result is true for FIRE models in general (see Mishkin (1983)). A final remark is that even if we allow for the endogenous exit by firms over time, the implied serial correlation of FEs will become negative. The detailed discussion is relegated to Appendix 6.2 which consider the case in which the fundamental demand draw follows an AR(1) process. In total, FIRE models cannot be used to rationalize the positively correlated of FEs over time observed in our data.

4.2.2 Jovanovic Model: Jovanovic (1982)

In this subsection, we discuss how the firm forms its ex post belief for the fundamental demand draw in the Jovanoic model (Jovanovic (1982)), which is a special case of our full model with $\alpha = 0$. In the Jovanovic model, the firm does not directly observe its time-invariant demand $\theta(\omega)$, although it knows the prior distribution of $\theta(\omega)$. In the beginning of period $t+1$, the firm knows the realizations of the overall demand shifters up to period t,[27] as it has observed t signals before (i.e., a set of $\{a_i\}_{i=1,2...,t}$). Since both the prior distribution of θ and the distribution of the noise ε are normal, the Bayes' rule implies that the posterior belief about θ (after observing t signals) is also normal with mean μ_t and variance σ^2_t, where

$$\mu_t = \frac{\sigma^2_\varepsilon}{\sigma^2_\varepsilon + t\sigma^2_\theta}\bar{\theta} + \frac{t\sigma^2_\theta}{\sigma^2_\varepsilon + t\sigma^2_\theta}\bar{a}_t, \tag{7}$$

[25] Readers are referred to Appendix 6.1 for the detail.

[26] A digression here is that the first two empirical patterns documented above can be rationalized by the perfect information model with age-dependent volatility. In particular, if the variance of the i.i.d. demand shock goes down with firm age and market experience, older affiliates and affiliates whose parent firms have previous export experience have smaller variance and absolute value of FEs. However, even if we allow for age-dependent volatility, FIRE models still cannot rationalize the positive serial correlation between FEs, as this prediction is independent of distributional assumptions and functional form we impose on ε_t and on the demand/productivity processes.

[27] For age one firms, they do not know any realized overall demand shock, as they just enter the market.

and

$$\sigma_t^2 = \frac{\sigma_\varepsilon^2 \sigma_\theta^2}{\sigma_\varepsilon^2 + t\sigma_\theta^2}. \tag{8}$$

The history of signals $(a_1, a_{2,} \ldots, a_t)$ is summarized by age t and the average

$$\bar{a}_t \equiv \frac{1}{t}\sum_{i=1}^{t} a_i \text{ for } t \geq 1; \quad \bar{a}_0 \equiv \bar{\theta}.$$

Therefore, the firm believes that the overall demand shock at age t, $a_t = \theta + \varepsilon_t$, has a normal distribution with mean μ_{t-1} and variance $\sigma_{t-1}^2 + \sigma_\varepsilon^2$. For a firm of age t with previous history $\bar{a}_{t-1}$, $(\bar{a}_{t-1}, t)$ summarizes all necessary information concerning the firm's belief about the value of θ. For age one firm, its belief for the mean and variance of θ is the same as the prior beliefs.

Next, we state the firm's optimization problem. The objective function now becomes

$$\max_{q_t} E_{\theta,\varepsilon_t} A_t^{\frac{1}{\sigma}} e^{\frac{\theta+\varepsilon_t}{\sigma}} q_t^{\frac{\sigma-1}{\sigma}} - wq_t,$$

which leads to the result that

$$q_t = A_t \left(\frac{\sigma - 1}{\sigma}\right)^{\sigma} \left(\frac{b\left(\bar{a}_{t-1}, t-1\right)}{w}\right)^{\sigma}, \tag{9}$$

where

$$\begin{aligned} b\left(\bar{a}_{t-1}, t-1\right) &= E_{a_t|\bar{a}_{t-1},t-1}\left(e^{a_t/\sigma}\right) \\ &= \exp\left\{\frac{\mu_{t-1}}{\sigma} + \frac{1}{2}\left(\frac{\sigma_{t-1}^2 + \sigma_\varepsilon^2}{\sigma^2}\right)\right\}. \end{aligned} \tag{10}$$

The next proposition shows that the FEs in two consecutive periods are uncorrelated:

Proposition 1 *Forecast errors made in two consecutive periods by the same firm are uncorrelated.*

Proof. See Appendix 6.6. ■

There are three components in the expression of FE that are correlated over time. First, there is a positive correlation between $\theta - \mu_{t-1}$ and $\theta - \mu_t$, as both μ_t and μ_{t-1}) only contain a fraction of the true θ.[28] Second, the firm includes the i.i.d. shocks up to period $t-1$ (i.e., $\{\varepsilon_i\}_{i=1,2,\ldots t-1}$) into the forecast made in both periods $t-1$ and t. As these shocks do not affect the realization

[28] In other words, as the firm *partially* includes the true time-invariant demand into its forecast, there is a difference between the true time-invariant demand and the prior mean in the FE (i.e., $(1 - \zeta(t-1, \lambda))(\theta - \bar{\theta})$) every period, which causes a positive correlation.

of the transitory demand shock after period $t-1$, this causes another positive correlation of FEs over time. Finally, since the transitory shock in period t positively affects the FE in period t and negatively affects the FE in period $t+1$[29], there is a negative correlation coming from the transitory shock in period t (i.e., ε_t). This negative part of correlation perfectly cancels out the (first two) positive parts of correlation, which leads to zero serial correlation of FEs over time. Undoubtedly, this property is a result coming form the assumption that the learning object (i.e., θ) is fixed overtime. In Appendix 6.3, we show that even when the fundamental demand draw follows a random walk over time, the serial correlation of FEs is not necessarily zero.

Although the Jovanovic model cannot generate the positive correlation of FEs over time, it can explain the fact that the variance of FEs goes down with firm age and market experience. Based on equation (42), we can derive the variance of FEs at age t as

$$\begin{aligned} var(FE^{\log}_{t-1,t}(sales)) &= \frac{var(\varepsilon_t + \theta - \mu_{t-1})}{\sigma^2} \\ &= \frac{var(\varepsilon_t) + var(\theta) + var(\mu_{t-1}) - 2cov(\theta, \mu_{t-1})}{\sigma^2}, \end{aligned}$$

as ε_t is independent of θ and μ_{t-1}. The next proposition shows that this variance decreases with firm age and previous experience in the market:

Proposition 2 *Variance of the forecast errors declines with years of experience t.*

Proof. See Appendix 6.6.1. ■

Thanks to the accumulation of experience, the variance of FEs (and the absolute value of FEs) becomes smaller, when the affiliate becomes older and when the affiliate's parent firm has export experience to the region where the affiliate is set up afterwards. In summary, the Jovanovic model can explain the first two empirical facts documented above, but not the third one. This motivates us to extend the Jovanovic model *at the minimum level* to rationalize all the three empirical findings.[30]

4.2.3 Learning Model with Information Rigidity

In this subsection, we show how our full model with $\alpha > 0$ can rationalize all the three empirical findings documented above. First, we use the following proposition to show that the modified Jovanovic model presented in Subsection 4.1 still implies declining variance of FEs with firm age and market experience.

[29] Remember that it enters into the firm's experience when the firm make the forecast in period $t+1$.

[30] Jovanovic model has implications for age-dependent volatility of growth rate of output. Specifically, the model predicts that the volatility of growth rate of output decreases with firm age, which is a salient feature of our data. For details, see Appendix 6.4.

Proposition 3 *Variance of the forecast errors declines with years of experience t.*

Proof. See Appendix 6.6.2. ■

In the modified learning model, we have two forces that push down the imprecision of forecasts over firm's life cycle. First, informed firms accumulate more experience and have clearer information about their fundamental demand, when they operate in the market for a longer period of time. Next, as more firms become informed over time and informed firms make more accurate forecasts (compared to the uninformed firms), the variance of FEs goes down with firm's market experience.[31]

Next, we characterize the serial correlation of FEs in our full model using the following proposition:

Proposition 4 *Forecast errors made in two consecutive periods by the same firm are positively correlated.*

Proof. See Appendix 6.6.3. ■

The above proposition rationalizes our last empirical finding concerning the positive correlation between FEs made in two consecutive periods. First, FEs of informed firms are serially uncorrelated, which is the same as in the Jovanovic model. Moreover, FEs of the switching firms (i.e., firms that become informed during the two periods) are uncorrelated.[32] Finally, it is the uninformed firms that generate positively correlated FEs over time, as their forecasts do not change across two consecutive periods. In total, our extended Jovanovic model with sticky information in Subsection 4.1 rationalizes the three facts concerning FEs documented in the empirical section. This explains why we choose this setup.[33]

4.3 Static Optimization of Firm Profit

We study the firm's static optimization problem in the steady state in this subsection. As all aggregate variables such as wages, the ideal price index and expenditure on Japanese goods

[31] This is the term related to $1-\alpha^{t-1}$.

[32] For this type of firms, there are two offsetting forces that determine the serial correlation of FEs. First, as the fundamental demand draw always shows up in the overall demand shock every period, there is a positive correlation between FEs made in two consecutive period due to the imperfect inclusion of the true fundamental demand draw into the forecasts. However, as the firm "wakes up" in period t, it is going to include the transitory demand shock in period t into its forecast made at the end of period t. Therefore, the transitory shock, ε_t, positively affects FE made in period t (i.e., only affecting the realized value) and negatively affects FE made in period $t+1$ (i.e., only affecting the forecasted value), which creates a negative correlation. The two opposite forces perfectly offset each other, which leads to zero serial correlation of FEs across periods for switching firms.

[33] This sticky information component of our model is also motivated by the evidence that the positive serial correlation of FEs decreases when firms become older (see Table 7), which is consistent with our theoretical prediction in Appendix 6.6.3.

are constant in the steady state, we omit the subscript t whenever possible. In each period, conditional on the mode of service, a firm's decision about how much to produce is a static problem. Firms hire labor and produce q_t quantity of output to maximize expected per-period profit given its belief about the demand shock a_t. The realized per-period profit for an affiliate is

$$\pi_{m,t} = p_t(a_t)q_t - w^* l_t - w f_m,$$

where

$$q_t = l_t,$$

and price depends on the realized demand a_t as in equation (2). Foreign and domestic wage rates are denoted by w^* and w respectively.

The MNE chooses optimal quantity q_t to maximize expected per-period profit $E_{a_t|\bar{a}_{t-1},t}(\pi_{m,t})$. For the informed MNEs, the output choice is determined by equation (9). The equilibrium price

$$p_{m,t}(a_t) = \frac{\sigma}{\sigma-1} e^{a_t/\sigma} \frac{w^*}{b(\bar{a}_{t-1}, t-1)} \tag{11}$$

and

$$q_{m,t} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{b(\bar{a}_{t-1}, t-1)}{w^*}\right)^{\sigma} \frac{Y}{P^{\delta-\sigma}}, \tag{12}$$

The resulting per-period profit function is

$$E\pi_{m,t} = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} \frac{b(\bar{a}_{t-1}, t-1)^{\sigma}}{w^{*\sigma-1}} \frac{Y}{P^{\delta-\sigma}} - w f_m. \tag{13}$$

For the uninformed MNEs, we have the equilibrium price and output as

$$p_{m,t}(a_t) = \frac{\sigma}{\sigma-1} e^{a_t/\sigma} \frac{w^*}{b(\bar{a}_0, 0)} \tag{14}$$

and

$$q_{m,t} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{b(\bar{a}_0, 0)}{w^*}\right)^{\sigma} \frac{Y}{P^{\delta-\sigma}}, \tag{15}$$

where $b(\bar{a}_0, 0)$ is the ex ante prior for the overall demand shock a_t and defined as

$$\begin{aligned} b(\bar{a}_0, 0) &= E_{a_t|\bar{a}_0,0}\left(e^{a_t/\sigma}\right) \\ &= \exp\left\{\frac{\bar{\theta}}{\sigma} + \frac{1}{2}\left(\frac{\sigma_\theta^2 + \sigma_\varepsilon^2}{\sigma^2}\right)\right\}. \end{aligned} \tag{16}$$

The resulting per-period profit function is

$$E\pi_{m,t} = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} \frac{b(\bar{a}_0, 0)^{\sigma}}{w^{*\sigma-1}} \frac{Y}{P^{\delta-\sigma}} - wf_m, \tag{17}$$

Similarly, for the informed exporters, we can derive the optimal output choice as

$$q_{x,t} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{b(\bar{a}_{t-1}, t-1)}{\tau w}\right)^{\sigma} \frac{Y}{P^{\delta-\sigma}}, \tag{18}$$

in which the marginal cost depends on the iceberg trade cost $\tau > 1$ and the domestic wage rate w instead of the foreign wage w^*. The equilibrium price is

$$p_{x,t}(a_t) = \frac{\sigma}{\sigma-1} e^{a_t/\sigma} \frac{\tau w}{b(\bar{a}_{t-1}, t-1)}. \tag{19}$$

The resulting expected per-period profit is

$$E\pi_{x,t} = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} \frac{b(\bar{a}_{t-1}, t-1)^{\sigma}}{(\tau w)^{\sigma-1}} \frac{Y}{P^{\delta-\sigma}} - wf_x. \tag{20}$$

For the uninformed exporters, the equilibrium output and the equilibrium price are

$$q_{x,t} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{b(\bar{a}_0, 0)}{\tau w}\right)^{\sigma} \frac{Y}{P^{\delta-\sigma}}, \tag{21}$$

and

$$p_{x,t}(a_t) = \frac{\sigma}{\sigma-1} e^{a_t/\sigma} \frac{\tau w}{b(\bar{a}_0, 0)} \tag{22}$$

respectively. The resulting per-period profit function is

$$E\pi_{x,t} = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} \frac{b(\bar{a}_0, 0)^{\sigma}}{(\tau w)^{\sigma-1}} \frac{Y}{P^{\delta-\sigma}} - wf_x. \tag{23}$$

4.4 Dynamic Choice of Market Entry

In each period, an entrant or incumbent firm can choose among three different service modes: exiting, exporting (denoted as x) or FDI (denoted as m). To become an exporter or MNE, a firm must pay a sunk cost. A firm's state variables include its mode of service in previous period, o, the draw of sunk entry cost into FDI, f_m^e, its current market experience, t, the history of demand shocks, $\bar{a}_{t-1}$ (from the period when the firm becomes informed), and whether or not the firm is informed, $in \in \{0, 1\}$. Since firms make optimal decisions based on their belief about θ rather than the true value of θ, these variables are sufficient to characterize the value functions and policy functions of the firm.

An incumbent exporter can choose to stay exporting, become an MNE or exit. If it wants to be an MNE, it has to pay the sunk cost f_m^e in units of domestic labor.[34] We derive the value function for the informed incumbent firm first. For an informed exporting firm, the value function prior to choosing the mode of service (and after the death shock) in period t is given by

$$V\left(x, f_m^e, t, \bar{a}_{t-1}, in=1\right) = \max_{o' \in \{x,m,exit\}} E_t \left\{ \begin{array}{c} \pi_{x,t} + \beta(1-\eta)V\left(x, f_m^e, t+1, \bar{a}_t, in=1\right), \\ \pi_{m,t} - wf_m^e + \beta(1-\eta)V\left(m, f_m^e, t+1, \bar{a}_t, in=1\right), \\ V_{exit} \end{array} \right\}, \tag{24}$$

where $t \geq 2$ and the value of exiting, V_{exit}, is normalized to zero. We denote the optimal choice of the service mode that maximizes equation (24) as $o'\left(x, f_m^e, t, \bar{a}_{t-1}, in=1\right) \in \{x, m, exit\}$. All expectations in equation (24) are calculated using the firm's subjective belief about the distribution of the demand shock a_t in the current period. A note here is that $\bar{a}_{t-1}$ is calculated from the time when the firm becomes informed. In other words, it equals $\frac{1}{t-t_0+1}\Sigma_{i=t_0}^t a_i$ where $t_0(\leq t)$ is the period when the firm switches from being uninformed to being informed. In particular, it does not necessarily equal $\frac{1}{t}\Sigma_{i=1}^t a_i$. Since a multinational affiliate does not need to pay the sunk cost when switching to exporting, the value of being an informed incumbent MNE prior to the endogenous choice of service mode (and after the death shock) in period t is given by

$$V\left(m, f_m^e, t, \bar{a}_{t-1}, in=1\right) = \max_{o' \in \{x,m,exit\}} E_t \left\{ \begin{array}{c} \pi_{x,t} + \beta(1-\eta)V\left(x, f_m^e, t+1, \bar{a}_t, in=1\right), \\ \pi_{m,t} + \beta(1-\eta)V\left(m, f_m^e, t+1, \bar{a}_t, in=1\right), \\ V_{exit} \end{array} \right\}. \tag{25}$$

We denote the optimal choice of the service mode for such a firm as $o'\left(m, f_m^e, t, \bar{a}_{t-1}, in=1\right) \in \{x, m, exit\}$.

Now, we derive the value functions for the uninformed incumbent firms. For an uninformed exporting firm, the value function prior to choosing the mode of service (and after the death

[34] As we abstract from the analysis of the labor market, whether the MNE uses domestic labor to pay the entry cost is irrelevant.

shock) in period t is given by

$$V\left(x, f_m^e, t, \bar{a}_0, in=0\right) = \max_{o' \in \{x,m,exit\}} E_t \left\{ \begin{array}{c} \pi_{x,t} + \beta(1-\eta)[\alpha V\left(x, f_m^e, t+1, \bar{a}_0, in=0\right) \\ +(1-\alpha)V\left(x, f_m^e, t+1, a_t, in=1\right)], \\ \pi_{m,t} - wf_m^e + \beta(1-\eta)[\alpha V\left(m, f_m^e, t+1, \bar{a}_0, in=0\right) \\ +(1-\alpha)V\left(m, f_m^e, t+1, a_t, in=1\right)], V_{exit} \end{array} \right\}, \tag{26}$$

and we denote the optimal choice of the service mode for such a firm as $o'\left(x, f_m^e, t, \bar{a}_0, in=0\right) \in \{x, m, exit\}$. Note that if the firm is uninformed at the beginning of period t, it will become informed at the end of period t with probability $1-\alpha$. In addition, the history of demand shocks changes from $\bar{a}_0$ (i.e., the prior belief) to a_t when the firm becomes informed at the end of period t, as it utilizes past information on sales only from the period when it becomes informed. All expectations in equation (26) are calculated using firms' subjective belief about the distribution of the demand shock a_t in the current period. Since a multinational affiliate does not need to pay the sunk cost in the case of switching to exporting, the value of being an uninformed incumbent MNE prior to the endogenous choice of service mode (and after the death shock) in period t is

$$V\left(m, f_m^e, t, \bar{a}_0, in=0\right) = \max_{o' \in \{x,m,exit\}} E_t \left\{ \begin{array}{c} \pi_{x,t} + \beta(1-\eta)[\alpha V\left(x, f_m^e, t+1, \bar{a}_0, in=0\right) \\ +(1-\alpha)V\left(x, f_m^e, t+1, a_t, in=1\right)], \\ \pi_{m,t} + \beta(1-\eta)[\alpha V\left(m, f_m^e, t+1, \bar{a}_0, in=0\right) \\ +(1-\alpha)V\left(m, f_m^e, t+1, a_t, in=1\right)], V_{exit} \end{array} \right\}. \tag{27}$$

We denote the optimal choice of the service mode in period t for an uninformed incumbent MNE as $o'\left(m, f_m^e, t, \bar{a}_0, in=0\right) \in \{x, m, exit\}$.

For the entrant, it is always uninformed and simply chooses the service mode that yields the highest value:

$$o'\left(ent, f_m^e, 1, \bar{a}_0, in=0\right) = \arg\max_{o' \in \{x,m,exit\}} E_1 \left\{ \begin{array}{c} \pi_{x,t} - wf_x^e + \beta(1-\eta)[\alpha V\left(x, f_m^e, 2, \bar{a}_0, in=0\right) \\ +(1-\alpha)V\left(x, f_m^e, 2, a_1, in=1\right)] \\ \pi_{m,t} - wf_m^e + \beta(1-\eta)[\alpha V\left(m, f_m^e, 2, \bar{a}_0, in=0\right) \\ +(1-\alpha)V\left(m, f_m^e, 2, a_1, in=1\right)], V_{exit} \end{array} \right\}. \tag{28}$$

4.5 Steady-state Recursive Competitive Equilibrium

We discuss the stationary equilibrium of the model in this subsection as follows.

1. value functions $V\left(o, f_m^e, t, a_{t-1}, in\right)$, $o \in \{x, m\}$ that satisfy equations (24), (25), (26) and

(27);

2. policy functions of the mode choice $o'(o, f_m^e, t, \bar{a}_{t-1}, in)$ ($o \in \{ent\}$ if $t=1$ while $o \in \{x, m\}$ if $t \geq 2$) that maximize value functions defined in equations (24), (25), (26) and (27);

3. policy functions of optimal output $q_o, o \in \{m, x\}$ that satisfy equations (12), (15), (18), and (21).

4. prices given the demand shock in the current period (age=t) $p_o(a_t), o \in \{m, x\}$ that satisfy equations (11), (14), (19), (22);

5. a measure function of firms $\lambda(o, f_m^e, t, \bar{a}_t, \theta, in)$, $o \in \{x, m, ent\}$ that is consistent with the aggregate law of motion. This measure function of firms is defined at the beginning of each period and after the exogenous exit takes place. In particular, an exogenous mass J of entrants draw θ from a log-normal distribution $G_\theta(\cdot)$ each period, respectively. Therefore, the measure of entrants with state variables θ is

$$\lambda(ent, f_m^e, 1, \bar{a}_0, \theta, in=0) = J g_\theta(\theta) g_{f_m^e}(f_m^e),$$

where $g_\theta(\cdot)$ and $g_{f_m^e}(\cdot)$ are the density functions of the log normal distribution for θ and f_m^e respectively. The cumulative demand shock $\bar{a}_0$ for entrants is defined to be the same as the prior mean of θ. All entrants are uninformed in the first period. The measure function of the exporters (and that of MNEs) is the fixed point of the law of motion of this measure function. Given any Borel set of $\bar{a}_t$, Δ_1, measures of uninformed and informed firms with service mode $o' \in \{x, m\}$ at the beginning of period $t+1$ satisfy

$$\begin{aligned} & \lambda(o', f_m^e, t+1, \Delta_1, \theta, in=0) \\ = \; & \alpha \sum_{o \in \{x,m,ent\}} \int \begin{array}{c} \mathbf{1}(\bar{a}_t \in \Delta_1, o'(o, f_m^e, t, \bar{a}_{t-1}, in=0) = o') \\ \times (1-\eta) \Pr(\bar{a}_t | \bar{a}_{t-1}, \theta) \lambda(o, f_m^e, t, d\bar{a}_{t-1}, \theta, in=0) \end{array} \end{aligned}$$

and

$$\begin{aligned} & \lambda(o', f_m^e, t+1, \Delta_1, \theta, in=1) \\ = \; & \sum_{o \in \{x,m,ent\}} \int \begin{array}{c} \mathbf{1}(\bar{a}_t \in \Delta_1, o'(o, f_m^e, t, \bar{a}_{t-1}, in=1) = o') \\ \times (1-\eta) \Pr(\bar{a}_t | \bar{a}_{t-1}, \theta) \lambda(o, f_m^e, t, d\bar{a}_{t-1}, \theta, in=1) \end{array} \\ & +(1-\alpha) \sum_{o \in \{x,m,ent\}} \int \begin{array}{c} \mathbf{1}(\bar{a}_t \in \Delta_1, o'(o, f_m^e, t, \bar{a}_{t-1}, in=0) = o') \\ \times (1-\eta) \Pr(\bar{a}_t | \bar{a}_{t-1}, \theta) \lambda(o, f_m^e, t, d\bar{a}_{t-1}, \theta, in=0) \end{array}, \end{aligned}$$

where $\mathbf{1}(...)$ is an indicator function. Note that at the beginning of the first period (i.e., $t=1$), all firms' service modes are defined to be *ent* (i.e., entrants). Therefore, there are no exporters or MNEs at age one in the stationary distribution, i.e., $\lambda\left(o, f_m^e, 1, \bar{a}_0, \theta, in\right) = 0$ for $o \in \{x, m\}$. In contrast, at the beginning of each later period ($t \geq 2$), all incumbents' modes of service are either exporting or FDI (i.e., x or m). Thus, there are no entrants at $t \geq 2$, i.e., $\lambda\left(o, f_m^e, t, \bar{a}_{t-1}, \theta, in\right) = 0$ for $o = ent$ and $t \geq 2$.

6. the price index P is constant over time and must be consistent with consumer optimization (3):

$$P^{1-\sigma} = \sum_{t\geq 1} \sum_{\substack{in\in\{0,1\} \\ o\in\{x,m,ent\}}} \int_{f_m^e, \bar{a}_{t-1}, \theta, a_t} \begin{array}{c} e^{a_t} p_o\left(a_t, q_o\left(b\left(\bar{a}_{t-1}, t-1\right), in\right)\right)^{1-\sigma} \\ \times \lambda\left(o, df_m^e, t, d\bar{a}_{t-1}, d\theta, in\right) d\Pr\left(a_t|\theta\right) \end{array}.$$

Given each guess of P, we can solve for the value functions and policy functions, as well as the measure function for firms, λ. We iterate on the value of P until it converges in the simulation nd calibration.

4.6 Calibration and Counterfactual Analysis

In this section, we describe the procedures for calibrating the dynamic model proposed above. The calibrated model is able to capture the decline in absolute value of FEs over affiliates' life cycle, as well as the smaller absolute value of FEs for affiliates with previous export experience. It is also able to capture other salient features of the data, such as growth in exporters' sales and the decline in exit rates over their life cycles, which we do not directly target in the calibration. After calibrating the model, we consider two counterfactual experiments with respect to the variance of the fundamental demand draw and with respect to the variance of the transitory demand shock.

4.6.1 Calibration

We first normalize a set of model primitives which are not identified since our model is not a general equilibrium model. We normalize the exogenous aggregate demand shifter Y, the wage rate in Japan, w, and the wage rate in the foreign countries, w^* to one. The mean of the log of the fundamental demand draw, μ_θ, is normalized to zero. We also normalize the entry costs into exporting, f_x^e, to zero, as we abstract from Japanese domestic firms in the model. Specifically, moments that can be used to pin down f_x^e, such as the share of exporters relative to domestic firms, are not available. In this case, we should interpret the entry costs into FDI, f_m^e, as the entry costs into FDI *relative to exporting*.

Next, we calibrate a set of parameters without solving our model, as listed in Table 10. We set the elasticity of substitution between varieties, σ, to 4, a common value in the literature (see

Bernard et al. (2003); Arkolakis et al. (2013)). The Armington elasticity among goods from different countries, δ, is set to 2, an intermediate value between the Cobb-Douglas case ($\delta = 1$) and the elasticity between different varieties σ. We set the discount factor, β, to 0.96, which implies a real interest rate of four percent.

The exogenous death rate η and the FDI per-period fixed costs f_m are crucial for the exit rates of multinational affiliates. Because there is strong selection in the model, affiliates' exit rate would decline over their life cycles if the FDI per-period fixed costs are positive. However, we did not find a significant decline for affiliates' exit rate over their life cycle, even for affiliates without export experience.[35] Therefore, we postulate that $f_m = 0$ and set η to 0.03 so that the model can match the average exit rate of affiliates (3%). Appendix 7.4 provides evidence.

Table 10: Parameters calibrated without solving the model

Parameters	Description	Value	Source
σ	Elasticity of substitution between Japanese goods	4	Bernard et al. (2003)
δ	Armington elasticity between goods from different countries	2	
β	Discount factor	0.96	4% real interest rate
η	Exogenous death rate	0.03	Average exit rates of multinational affiliates
f_m	FDI per-period fixed costs	0	Flat profile of affiliates' exit rate over their life cycles

Three parameters that govern information rigidity and learning can also be backed out without calibrating the model. Since we have shut down the endogenous exit for multinational affiliates, there is no selection on the fundamental demand draw, θ, among multinational affiliates after entry. Also, as entrants have the same prior belief for their fundamental demand shocks, they choose to become MNEs based on the realized entry cost of FDI, f_m^e (i.e., not based on realized θ) and do not endogenously exit after entry. Thus, the formulas derived in section 4.2.3 can be directly applied to calculated variance and auto-covariance of FEs for non-experienced multinationals. In particular, we target the variance of FEs at age one and age ten of non-experienced MNEs, since they are most informative about σ_θ and σ_ε, respectively. We also target the covariance of FEs at age one and two, since the positive autocovariance is caused by information rigidity in our model, which is governed by the parameter α.[36] The calibrated value of α is 0.21, which implies that 79% of uninformed firms become informed each period. After three years in the market, less than one percent of the firms are still uninformed.

[35] See Appendix 7.4 for details.

[36] In practice, due to partial-year effects, age-one firms in the data may have less information than age-one firms in the model. We therefore assume that age-one firms in the data correspond to a mixture of age-zero and age-one firms in the model (with equal weights), and age-two firms in the data correspond to a mixture of age-one and age-two firms in the model (with equal weights). We then adjust the formulas derived in Section 4.2.3 accordingly.

Table 11: Parameters related to forecast errors and moments

Parameters	Value	Description	Moments	Data	Model
σ_θ	2.05	Std of time-invariant shock	Var. of FE at age 1	0.48	0.48
σ_ε	0.90	Std of transitory shock	Var. of FE at age 10	0.24	0.24
α	0.21	prob of awaking	Cov of $FE_{1,2}$ and $FE_{2,3}$	0.034	0.034

The remaining four parameters are jointly calibrated by solving the equilibrium and matching four moments. The parameters are: the per-period fixed cost of exporting, f_x, the mean and standard deviation of log FDI entry cost, $\mu_{f_m^e}$ and $\sigma_{f_m^e}$, and the iceberg trade cost τ. The four targeted moments are the average exit rate of exporters, the fraction of exporters among active firms, the fraction of experienced affiliates at age one and the share of exports in total sales (i.e., total exports plus total sales of MNEs' affiliates).

In Table 12, we list the moments in an order such that, loosely speaking, each moment is the most informative about the parameter in the same row. A higher export per-period fixed cost raises the exporter exit rate, while a higher average FDI entry cost increases the fraction of exporters among all firms selling in the foreign market. In the model, only firms with small enough FDI entry costs become non-experienced MNEs in the first period. Therefore, $\sigma_{f_m^e}$ affects the share of non-experienced MNEs positively. Finally, the iceberg trade costs will have a large impact on the intensive margin of export, and thus the sales share of exporters among all active firms.

Table 12: Parameters calibrated by solving the model and matching moments

Parameters	Value	Description	Moments	Data	Model
f_x	0.0056	export fixed cost	average exit rate of exporters	0.10	0.11
$\mu_{f_m^e}$	1.58	mean of log FDI entry cost	fraction of exporters among active firms	0.70	0.69
$\sigma_{f_m^e}$	2.45	Std of log FDI entry cost	fraction of experienced MNEs at age one	0.73	0.75
τ	1.46	iceberg trade cost	Exporter sales share	0.21	0.21

4.6.2 Untargeted Moments

We now turn to untargeted moments of the calibrated model. We first examine the dynamics of FEs for affiliates with and without export experience. We then consider the dynamics of exporters and affiliates in terms of sales growth and endogenous exit over their life cycles.

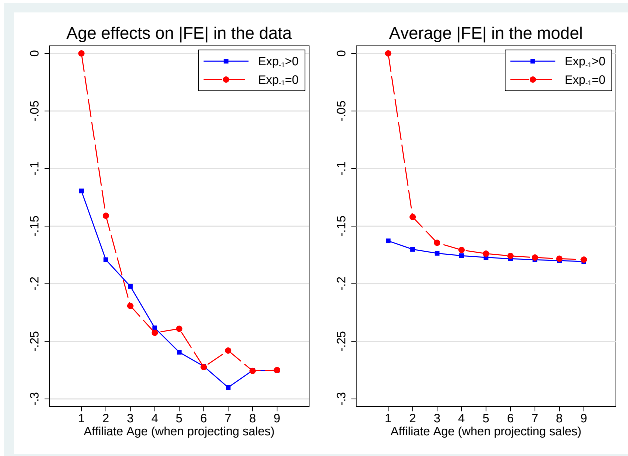
Dynamics of Forecast Errors We examine the changes in $\left|FE^{\log}\right|$ over affiliates' life cycles in Figure 2. We first estimate the age effects on $\left|FE^{\log}\right|$ for affiliates that enter a host country for the first time. We interact the age fixed effects with a dummy variable indicating whether the parent firm has previous export experience in the same region. We plot the estimated fixed effects for experienced and non-experienced MNEs in the left panel of Figure 2, using the age-one non-experienced MNEs as the base group. In the right panel, we plot the average $\left|FE^{\log}\right|$ by affiliate age predicted by the calibrated model, again normalizing the average $\left|FE^{\log}\right|$ to zero for non-experienced MNEs at age one.

Consistent with the data, the model predicts that average $|FE^{\log}|$ declines over affiliates' life cycles and that the initial $\left|FE^{\log}\right|$ is lower for affiliates whose parent firms have export experience. However, the model predicts a much smaller decline in $\left|FE^{\log}\right|$ for experienced MNEs and a larger difference between experienced MNEs and non-experienced MNEs at age one. For example, in the model, average $\left|FE^{\log}\right|$ of experienced MNEs drops by 0.02 over their life cycles, while the corresponding empirical moment is 0.16. The main reason for this discrepancy is that firms in the model learn very fast - there is almost no uncertainty about θ after four periods. This implies experienced firms will start with very precise forecast about θ and the main source of FEs is the transitory transitory shock, ε. A possible improvement we can make is to introduce learning about both demand and supply and assume that exporting only helps the firm learn foreign demand. This modification would reduce the information generated by exporting (relative to MP). However, we do not pursue here in order to keep our model simple.

Dynamics of Sales In Figure 3, we compare the age profile of exports in the model to that in the data. The red dashed line represents the average log of sales by exporter age predicted by the model, while the blue solid line represents the corresponding moments in the data. The two lines are very well aligned. Note that learning and information rigidity per se do not generate growth in sales, since firms may receive either better or worse signals than their time-invariant demand. The growth of average firm size is a result of learning *together with selection* on θ in the model. In contrast, the model does not capture the growth of average log sales of the multinational affiliates. The reason is that we shut down endogenous exits of affiliates to match the flat profile of exit rate (with firm age) over their life cycles. Other mechanisms, such as the accumulation of customer capital, is needed to match the dynamics of sales for multinational affiliates (see, for example, Fitzgerald et al. (2016)).

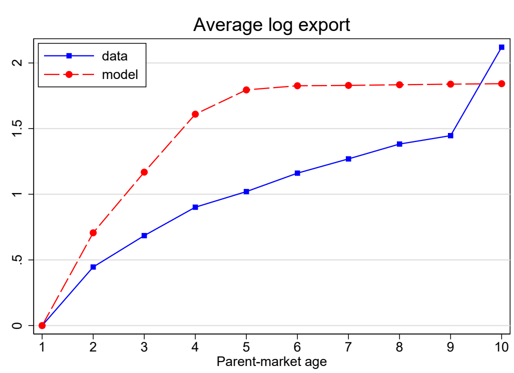
Dynamics of Exits Figure 4 compares the exporter exit rates by their ages in the model to those in the data. Consistent with the data, the model predicts a declining trend in the exit rates of exporters when they become older. In the model, the exporter exit rates decline from 47% to 3% over their life cycles, while the exporter exit rates decline from 16% to 4% in the data. Overall, the model predicts higher exporter exit rates (by each age group), even though the model is able to match the average exporter exit rate in the data. This occurs as

Figure 2: Forecast error - age profile: data v.s. model



Note: The left panel shows the estimated age effects on average $|FE^{log}|$ for affiliates in the data, while the right panel shows the average $|FE^{log}|$ by affiliate age in the model. To calculate the average $|FE^{log}|$ at age t in the model, we adjust the partial-year effects by averaging the forecast errors of affiliates at age $t-1$ and age t, since most affiliates enter into the destination market in the middle of each fiscal year. The blue solid line shows the estimated age effects for affiliates whose parent firms have previous export experience, i.e., $Exp_{-1} > 0$, while the red dashed line shows the estimated age effects for affiliates without previous export experience, i.e., $Exp_{-1} = 0$. The age effect of the affiliates without previous export experience is normalized to zero.

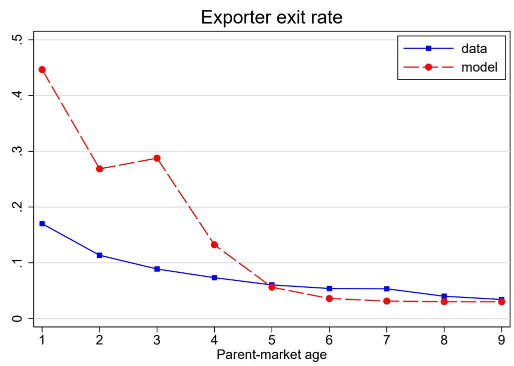
Figure 3: Export-age profile: data v.s. model



Note: The blue solid line represents average log(exports) by exporter age in the data, while the red dashed line represents the average log of exports by exporter age in the model.

the distribution of exporters is more skewed towards old firms in the model compared to that in the data.

Figure 4: Exit rate - age profile: data v.s. model



Note: The blue solid line represents the estimated age effects on the probability of exiting the export market in the data, while the red dashed line represents the average exit rate of exporters by age in the model.

In summary, the calibration of our parsimonious model is able to capture the qualitative patterns of the exporter dynamics and the FE dynamics, which are not targeted in the calibration.

4.6.3 Counterfactuals: Ex ante Uncertainty and Ex post Volatility

In this section, we use the calibrated model to perform counterfactual analysis. The analysis illustrates how the ex ante uncertainty (captured by σ_θ) and ex post volatility (captured by σ_ε) affect trade and MP patterns, the dynamic selection and aggregate productivity. In particular, we show that ex ante demand uncertainty and ex post demand volatility have qualitatively different effects on aggregate productivity via their different impact on the dynamic selection (into different production modes) in our industry equilibrium model.

We motivate our counterfactual analysis with respect to σ_θ and σ_ε by documenting the variation in these parameters across regions. Following the discussion of the calibration of parameters related to forecast errors, one immediate implication is that, conditional on values of α and σ, we can calibrate σ_θ and σ_ε without solving the model. Here, we do so for four regions separately: Asia (excluding China), China, North America and Europe. Table 13 shows the corresponding moments and calculated parameters. There is considerable variation in the standard deviation of the time-invariant demand draw, θ, across regions. The standard deviation, σ_θ, is the largest in China (2.78), and smallest in Europe (1.60). This could be due to the fact that China and other Asian economies are emerging markets, and the ex-ante uncertainty about the fundamental demand draw is quite high. In contrast, there is much smaller variation in the standard deviation of the transitory demand shock, ε. The largest σ_ε is 1.08 for China, while the smallest value is 0.87 (North America). In the remaining part of this subsection, we try to explore how σ_θ and σ_ε affect trade and MP patterns, dynamic selection and welfare.

Table 13: Cross-country difference in variance of shocks

Region/Country	Asia (non-China)	China (P.R.C.)	North America	Europe
Moments				
Std. dev. of $FE_{1,2}$	0.48	0.62	0.45	0.42
Std. dev. of FE_{10+}	0.24	0.28	0.23	0.26
Parameters				
σ_θ	2.09	2.78	1.91	1.60
σ_ϵ	0.91	1.08	0.87	0.98

Although our model assumes that uncertainty and volatility come from the demand side, implications of the model can also be applied to an alternative setup in which firms differ in productivity (i.e., supply-side heterogeneity) and learn their fundamental productivity over the life cycle. In fact, this is the original setup adopted by Jovanovic (1982). In what follows, we interpret the ex post volatility, σ_ε, as the volatility of both demand and supply conditions and related this to policy variables. First, similar to our analysis in Section 3.2, we regress absolute value of FEs on BMI risk index (at the country level) and a set of control variables using observations of Japanese affiliates who are at least eight years old.[37] As Table 14 shows, country-level risks such as the probability of an economic crisis and the stability of government policies positively affect firm-level volatility. This result indicates that macro stabilization policies and rule-based policies (instead of discretionary policies) at the aggregate level probably reduce the volatility of firm-level demand and supply conditions.

Next, we obtain data on economic policy uncertainty (EPU) for 19 economies for years between 1996 and 2007 and calculate the average EPU for these 19 economies over the 12 years. Then, we correlate the variance of FEs made by old enough affiliates (i.e., affiliates that are at least ten years old) in each of those 19 economies to the EPU index. Table 15 shows that there is a strong positive correlation between the EPU index and the variance of FEs constructed by us. This shows that country-level policy uncertainty seems to be positively associated with firm-level volatility. In total, we conclude that volatility of firm-level demand and supply conditions seems to be correlated to economic policies at the aggregate or industry level.

In our counterfactual experiment, we first change the dispersion of the transitory shock σ_ε in

[37]The variance of FEs made by old enough affiliates solely reflects the volatility of transitory (demand and supply) shocks according to our model.

Table 14: Firm-level forecast errors and country-level risks

	(1) $\lvert FE^{log}\rvert$	(2) $\lvert FE^{pct}\rvert$	(3) $\lvert\hat{\epsilon}_{FE^{log}}\rvert$
Country risk index	0.0702**	0.0547**	0.0846**
	(0.0302)	(0.0272)	(0.0357)
log($sales$)	-0.0209***	-0.0197***	-0.0162***
	(0.00113)	(0.00105)	(0.00102)
N	65280	65224	65379
R^2	0.198	0.175	0.202
Firm Age	≥ 8	≥ 8	≥ 8
Industry-year Fixed Effect	Yes	Yes	Yes
Parent Fixed Effect	Yes	Yes	Yes
Age Fixed Effect	Yes	Yes	Yes

Standard errors are clustered at the country level, * 0.10 ** 0.05 *** 0.01. Each column head lists the dependent variable of the regressions. $\lvert FE^{log}\rvert$ is the absolute log deviation of the realized sales from the projected sales; $\lvert FE^{pct}\rvert$ is the absolute percentage deviation of the realized sales from the projected sales; $\lvert\hat{\epsilon}_{FE^{log}}\rvert$ is the absolute value of the residual forecast error, which we obtain by regressing FE^{log} on a set of industry-year and country-year fixed effects. Country risk index (BMI research database) is an index from zero to one that measures the overall risk of the economy, such as an economic crisis or a sudden change in the political environment , with one being the most risky environment.

Table 15: Correlation between EPU and variance of forecast errors at the destination country level

	$Var(FE^{pct})$	$Var(FE^{log})$	$Var(\hat{\epsilon}_{FE^{log}})$
Economic Policy Uncertainty Index	0.2910	0.1740	0.1873
Type of Firms	all	all	all
obs.	19	19	19

FE^{log} is the log deviation of the realized sales from the projected sales; FE^{pct} is the percentage deviation of the realized sales from the projected sales; $\hat{\epsilon}_{FE^{log}}$ is the value of the residual forecast error, which we obtain by regressing FE^{log} on a set of industry-year and country-year fixed effects. Economic Policy Uncertainty Index is obtained from EPU website. The 19 economies included here are Australia, Brazil, Canada, Chile, China, Germany, Spain, France, UK, India, Ireland, Italy, Korea, Mexico, Netherland, Russia, Singapore, Sweden and the U.S.

the range from 0.90 to 1.51. The range of these values are well in line with the variation across the four regions in Table 13. Since changing σ_ε affects the mean of the demand shifter $e^{(\theta+\varepsilon)/\sigma}$, we subtract $\Delta\sigma_\varepsilon^2/2\sigma^2$ from $\bar{\theta}$ (note that mean of θ is set to zero in the baseline calibration) to ensure that it is a mean-preserving spread when $\Delta\sigma_\varepsilon > 0$. Similarly, we add $\Delta\sigma_\varepsilon^2/2\sigma^2$ to $\bar{\theta}$ to ensure that it is a mean-preserving contraction when $\Delta\sigma_\varepsilon < 0$.[38]

Figure 5 shows four equilibrium outcomes for different values of σ_ε. A larger σ_ε implies a lower signal-to-noise ratio, $\sigma_\theta^2/\sigma_\varepsilon^2$, which leads to less effective learning and thus weaker incentives to use exporting to obtain information about the fundamental demand. Therefore, more entrants choose to do MP directly, instead of entering the exporting market first and then doing MP. In other words, the share of non-experienced affiliates among entrants increases when the ex post volatility increases. This effect negatively affects the dynamic selection into MP from exporting, as firms that do MP eventually have less information about their fundamental demand draws and therefore make more mistakes.[39] This is reflected by a smaller positive (and even negative) correlation between θ and being an MNE among active firms (panel c).[40] The second effect on the dynamic selection into market entry comes from the result that firms that choose to produce (exporting or doing FDI) know less about their fundamental demand draws and therefore make more mistakes when deciding whether to exit the market.[41] This is reflected by a lower (positive) correlation between θ and staying in the market among all firms (panel d).[42]

Eventually, the two types of changes in the dynamic selection translate into lower aggregate labor productivity (defined as the aggregated composite CES good divided by the total labor used for variable, fixed and entry costs) as shown in panel (a). Since our model is partial equilibrium in nature, it is not ideal for welfare analysis. We think aggregate labor productivity is a better measure of welfare than the ideal price index, since it takes into account the resources drawn into the "foreign market sector" by payment of fixed and entry costs. With this caveat in mind, we see a sizable effect of an increase in σ_ε on aggregate productivity. For example, increasing σ_ε from 0.90 to 1.05 lowers aggregate productivity by 1.5%.

[38]We choose to implement this adjustment, as we want to make sure that the change in σ_ε does not change the mean of the demand shifter distribution in the eyes of the consumer in equation (1). After this adjustment, the distribution of the demand shifter in the CES preference function has the same mean as before.

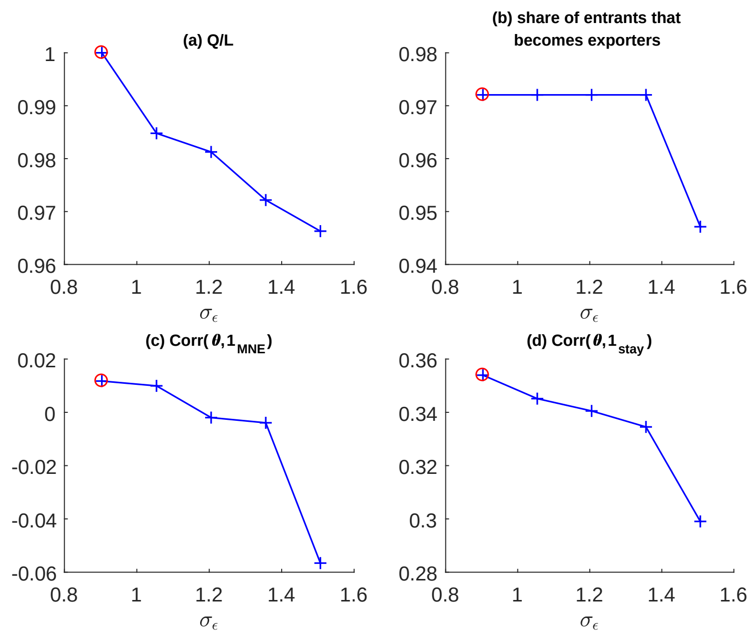
[39]Mistake here means that a firm with a medium value of θ chooses to do MP, while it should have chosen exporting if it knew its true fundamental demand draw perfectly.

[40]When σ_ε is sufficiently large the correlation turns to be negative, as there is no endogenous exits among MNEs after they begin to do MP.

[41]Mistake here means that a firm with a low level of θ chooses to exporting, while it should have chosen to exit if it knew its true fundamental demand draw perfectly.

[42]The third impact on production allocation is in the static sense. Namely, as firms know their fundamental demand draws less (via learning) when σ_ε increases, they choose (static) output less closely based on their true time-invariant demand. In other words, firms that truly receive good fundamental demand draws are less likely to capture larger market shares when σ_ε increases. This affects aggregate productivity as well.

Figure 5: Counterfactuals with respect to σ_ε



Note: The value of σ_ε is 0.90 in the baseline equilibrium, which is marked with a red circle in all panels.

One point worth mentioning here is that a larger variance of ex post demand volatility (or ex ante demand uncertainty) leads to more heterogeneous products in terms of quality. This *improves* aggregate productivity and welfare through the variety effect. That is, consumers obtain higher levels of utility when they face more heterogeneous products (with the mean of quality fixed), as they can allocate more consumption on better products (i.e., love of variety) which leads to a lower ideal price index.[43] However, the negative effect on the dynamic selection dominates the positive variety effect, which leads to lower aggregate productivity and welfare.

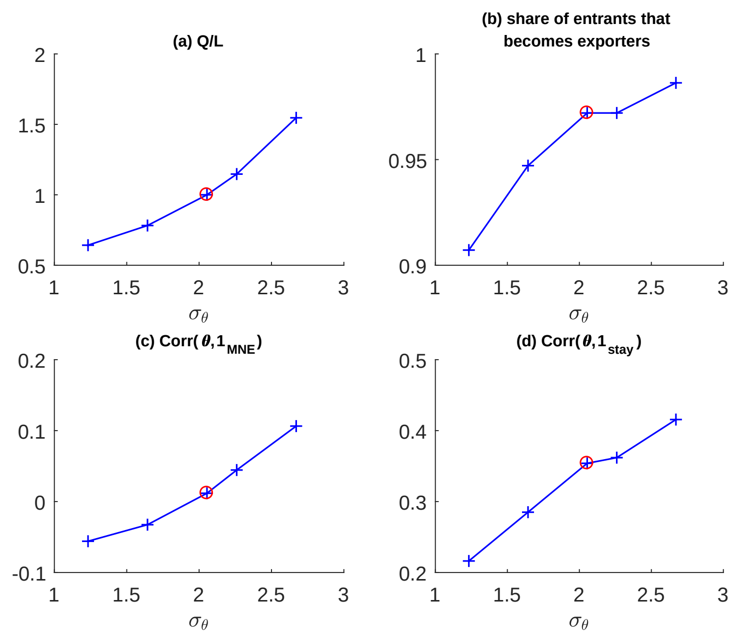
We now change the variance of the time-invariant demand draws by varying σ_θ in the range from 1.03 to 2.67, which is reasonable given the range of σ_θ across the four regions shown in Table 13. We again subtract $\Delta\sigma_\theta^2/2\sigma^2$ from $\bar{\theta}$ to ensure that these are mean-preserving spreads for the demand shifter $e^{(\theta+\varepsilon)/\sigma}$. A caveat here is that the variance of the time-invariant demand draws reflects the heterogeneity of producers in an economy. It is driven by production technologies and consumer preferences in the economy and not directly related to any macro or industry policies we can think of. However, we still implement such a counterfactual analysis, as we want to contrast the impact of ex ante uncertainty (i.e., the variance of θ) on the dynamic selection

[43]In the CES framework, the ideal price index is negatively affected by the variance of the product quality distribution.

with the effect of ex post volatility (i.e., the variance of ε).

Broadly speaking, the effect of an increase in ex ante uncertainty on the dynamic selection is exactly the opposite to the effect of an increase in ex post volatility, as it implies a higher signal-to-noise ratio and therefore increases the effectiveness of learning. In short, the dynamic selection is positively affected by such an increase, as both the (positive) correlation between θ and being a multinational firm among active firms (panel c) and the (positive) correlation between θ and staying in the market (panel d) increase with the variance of the time-invariant demand draws. Eventually, these effects translate into higher aggregate productivity when the variance of ex ante uncertainty increases, which is the opposite to the effect of an increase in ex post volatility.

Figure 6: Counterfactuals with respect to σ_θ



Note: The value of σ_θ is 2.05 in the baseline equilibrium, which is marked with a red circle in all panels.

In summary, both the uncertainty of ex ante fundamental demand (or productivity) draws and the volatility of ex post transitory shocks contribute to firm-level uncertainty in our model. However, the effects of these two types of uncertainty on dynamic trade/MP patterns, the dynamic selection and aggregate productivity are different. Therefore, in order to understand the effect of uncertainty on aggregate and dynamic economic outcomes, it is important to distinguish between these two sources of uncertainty.

5 Conclusion

In this paper, we use a unique dataset of Japanese multinational affiliates, which contains information on sales forecasts, to detect information imperfection and learning in the international market. We document three stylized facts concerning affiliates' forecasts. First, FEs of sales decline with the age of affiliate. Second, if the parent firm has previous export experience to the region where its affiliate is set up, the entering affiliate starts with a smaller variance of FEs. Third, FEs of sales are positively correlated over time and this positive correlation becomes stronger when the affiliates are located further away from Japan, which are inconsistent with predictions from FIRE models. In total, We view these facts as direct evidence for the existence of imperfect information and learning in the international market. We then build up a dynamic industry equilibrium model of trade and FDI, which features information rigidity and learning, in order to explain the documented facts.

To quantify the role of learning and demand uncertainty in exporters and multinational firms' dynamics, we extend the standard firm learning model (Jovanovic (1982); Arkolakis et al. (2017)) into an international setting. Specifically, we add sticky information a la Mankiw and Reis (2002) and the endogenous choice between exporting and MP (for serving the foreign market) into the canonical firm learning model and calibrate the extended model to match moments related to FEs and aggregate trade/MP variables. The calibrated model is able to replicate the new facts about affiliates' FEs, as well as other salient features of the data.

We then conduct counterfactual analysis regarding firm-level uncertainty. We find that changing the variance of the time-invariant demand draws and that of the temporary demand shocks have different implications for the entry margins of trade and MP, dynamic selection and aggregate productivity. In particular, a higher variance of time-invariant demand draws implies a higher signal-to-noise ratio. This leads to more effective learning and stronger incentives to use exporting to obtain information. To the contrary, a higher variance of the transitory shocks implies a lower signal-to-noise ratio and leads to less effective learning. As a result, dynamic selection is negatively affected by ex post volatility, which leads to lower aggregate productivity and welfare. In short, our exercises show that when we analyze how uncertainty affects aggregate outcomes, it is crucial to distinguish between the two sources of uncertainty discussed above.

6 Theory Appendix

6.1 Full Information Rational Expectation Models

In this subsection, we derive the FE in FIRE models in detail. Base on the optimal output choice derived in the main text we have the log of *realized* sales as

$$\log(R_t(\theta)) = \log(A_t) + \frac{\sigma\theta + \varepsilon_t + \frac{(\sigma-1)\sigma_\varepsilon^2}{2\sigma}}{\sigma} + (\sigma-1)\Big[\log\Big(\frac{\sigma-1}{\sigma w}\Big)\Big].$$

Since the firm knows θ in FIRE models, its best estimate for a_t is θ as ε_t is a transitory i.i.d. shock. Therefore, the conditional distribution of a_t in any period is $N\left(\theta, \sigma_\varepsilon^2\right)$, and the log of forecasted sales is

$$\log\Big(E_{t-1}^S(R_t)\Big) = \log(A_t) + \frac{\sigma\theta + \frac{\sigma_\varepsilon^2}{2}}{\sigma} + (\sigma-1)\Big[\log\Big(\frac{\sigma-1}{\sigma w}\Big)\Big],$$

which leads to

$$FE_{t-1,t}^{\log}(sales) = \frac{\varepsilon_t}{\sigma} - \frac{\sigma_\varepsilon^2}{2\sigma^2}. \tag{29}$$

Note that when the firm forecasts its sales one period in advance, it still faces an *unpredictable* random shock (i,e., ε_t) which causes FEs even in the full information model. Note that as the contemporaneous transitory shock in demand follows the log normal distribution, higher variance of the transitory shock pushes up the forecasted sales, price and output.

6.2 Full Information Rational Expectation Models with Endogenous Exit

We discuss how the endogenous exit would change full information rational expectation (FIRE) model's prediction on the serial correlation of FEs. In order to generate endogenous exit, we consider the case in which the fundamental demand, θ, evolves according to an AR(1) process:

$$\theta_{t+1} = \rho_1\theta_t + \zeta_{t+1}, \tag{30}$$

where ζ_t is a draw from a normal distribution $N\left(0, \sigma_\zeta^2\right)$ and serially uncorrelated. The resulting FE and serial correlation of FEs are

$$FE_{t-1,t}^{\log}(sales) = \frac{\varepsilon_t}{\sigma} - \frac{\sigma_\varepsilon^2}{2\sigma^2} + \frac{\zeta_t}{\sigma} - \frac{\sigma_\zeta^2}{2\sigma^2}. \tag{31}$$

and

$$cov(FE_{t-1,t}^{\log}, FE_{t,t+1}^{\log}) = cov\Big(\frac{\varepsilon_t + \zeta_t}{\sigma}, \frac{\varepsilon_{t+1} + \zeta_{t+1}}{\sigma}\Big)$$

respectively. Different from the case without selection, now we have endogenous selection in the sense that firms with the fundamental demand shocks below a certain cutoff, $\bar{\theta}_t$, exit the market in period t. Therefore, survivors in both periods t and $t+1$ must have

$$\rho_1\theta_{t-1} + \zeta_t \geq \bar{\theta}_t \quad \rho_1(\rho_1\theta_{t-1} + \zeta_t) + \zeta_{t+1} \geq \bar{\theta}_{t+1}, \tag{32}$$

as firms choose whether or not to exit based on the realization of θ_t in period t and forecast is made in the end of period $t-1$. Conditional on θ_{t-1} and survival in both periods, there is a negative correlation between ζ_t and ζ_{t-1} implied by equation (32). The intuition is that a better contemporaneous fundamental demand shock last period makes survival in this period easier. This leads to a negative correlation between the contemporaneous fundamental shocks in two consecutive periods, conditioning on survival.

6.3 Time-varying Fundamental Demand Shocks

In this subsection of the appendix, we discuss the implication of the Jovanovic model for the serial correlation of FEs. As shown in Section 4.2.2, FEs are serially uncorrelated. There are three components in the expression of FE that are correlated over time. First, there is a positive correlation between $\theta - \mu_{t-1}$ and $\theta - \mu_t$, as both μ_t and μ_{t-1}) only contain a fraction of the true θ.[44] Second, the firm includes the i.i.d. shocks up to period $t-1$ (i.e., $\{\varepsilon_i\}_{i=1,2,...t-1}$) into the forecast made in both periods $t-1$ and t. As these shocks do not affect the realization of the transitory demand shock after period $t-1$, this causes another positive correlation of FEs over time. Finally, since the transitory shock in period t positively affects the FE in period t and negatively affects the FE in period $t+1$[45], there is a negative correlation coming from the transitory shock in period t (i.e., ε_t). This negative part of correlation perfectly cancels out the (first two) positive parts of correlation, which leads to zero serial correlation of FEs over time. Undoubtedly, this property is a result coming form the assumption that the object of learning (i.e., θ) is fixed overtime. In what follows, we show that even when the fundamental demand draw follows a random walk over time, the serial correlation of FEs is not necessarily zero:

Proposition 5 *Suppose the fundamental demand draw follows a random walk over time. I.e., $\theta_{i,t} = \theta_{i,t-1} + \zeta_{i,t}$, the serial correlation of forecast errors is non-zero. However, it is not necessarily positive.*

[44] In other words, as the firm *partially* includes the true time-invariant demand into its forecast, there is a difference between the true time-invariant demand and the prior mean in the FE (i.e., $(1 - \zeta(t-1,\lambda))(\theta - \bar{\theta})$) every period, which causes a positive correlation.

[45] Remember that it enters into the firm's experience when the firm make the forecast in period $t+1$.

Proof. We consider the following learning model:

$$\theta_{i,t} = \theta_{i,t-1} + \zeta_{i,t}$$

and

$$a_{i,t} = \theta_{i,t} + \varepsilon_{i,t},$$

where $a_{i,t}$ is the realized overall demand shock which is observable, while $\theta_{i,t}$ is the time-variant fundamental demand draw which is unobservable.

We solve the steady state first. Standard argument leads to the result that

$$\Sigma_{ss} = \frac{\sigma_\zeta^2 + K^2\sigma_\varepsilon^2}{1-(1-K)^2}$$

and

$$K = \frac{\Sigma_{ss}}{\sigma_\varepsilon^2 + \Sigma_{ss}},$$

where Σ_{ss} is the variance of filtering error of θ_i in the steady state, and K is the Kalman gain (i.e., the weight put on the new signal when updating the belief) in the steady state. After solving these two equations, we obtain

$$K(\lambda) = \frac{1}{2}(-\lambda + \sqrt{\lambda^2 + 4\lambda}), \tag{33}$$

where $\lambda \equiv \frac{\sigma_\zeta^2}{\sigma_\varepsilon^2}$ is the signal-noise ratio (i.e., the precision of the signal).

Next, we consider non-steady state forecasting. In order to forecast $a_{i,t+1}$, the firm needs to predict $\theta_{i,t}$ as $E_t a_{i,t+1} = E_t\theta_{i,t+1} = E_t\theta_{i,t}$. The prediction for $\theta_{i,t}$ at the end of period t is denoted by $\hat{\theta}_{i,t}$ (i.e., filtering). Based on the timing assumption of our model, $\hat{\theta}_{i,0} = \bar{\theta}_0$ which is the prior belief. Suppose firms start from different fundamental demand shocks but have the same prior belief for $\theta_{i,0}$: $N(\bar{\theta}_0, \Sigma_0)$. As we are not in the steady state, the Kalman gains are time-variant. In particular, the forecasting rule is as follows:

$$\hat{\theta}_t = (1-K_t)\hat{\theta}_{t-1} + K_t a_t, \tag{34}$$

FE of $\theta_{i,t+1}$ in period $t+1$ is

$$
\begin{aligned}
e_{t+1} &= \theta_{t+1} - \hat{\theta}_{t+1} \\
&= \theta_{t+1} - (1 - K_{t+1})\hat{\theta}_t - K_{t+1}\left(\theta_{t+1} + \varepsilon_{t+1}\right) \\
&= (1 - K_{t+1})\left(\theta_t + \zeta_{t+1} - \hat{\theta}_t\right) - K_{t+1}\varepsilon_{t+1} \\
&= (1 - K_{t+1})\left(e_t + \zeta_{t+1}\right) - K_{t+1}\varepsilon_{t+1}
\end{aligned}
$$

The equation that governs the movement of variance of FEs is

$$
\Sigma_{t+1} = (1 - K_{t+1})^2 \left(\Sigma_t + \sigma_\zeta^2\right) + K_{t+1}^2 \sigma_\varepsilon^2, \tag{35}
$$

where $\Sigma_t = var(e_t)$, we start with Σ_0 which is the ex ante variance of of θ_0. Minimizing Σ_{t+1} leads to the result that

$$
K_{t+1} = \frac{\rho^2 \Sigma_t + \sigma_\zeta^2}{\Sigma_t + \sigma_\zeta^2 + \sigma_\varepsilon^2} \qquad K \geq 0. \tag{36}
$$

Now, we can calculate the serial correlation of FEs over the firm's life cycle. The expression for $FE_{t,t+1}^{log}(sales)$ can be expressed as

$$
\frac{\theta_{t+1} + \varepsilon_{t+1} - \hat{\theta}_t}{\sigma} - \frac{\Sigma_t + \sigma_\zeta^2 + \sigma_\varepsilon^2}{2\sigma^2},
$$

Since u_t is uncorrelated over time, the stochastic term that is correlated over time is

$$
\begin{aligned}
&\frac{1}{\sigma}\Big[\theta_{t+1} + \varepsilon_{t+1} - \big[K_t(\theta_t + \varepsilon_t) + (1 - K_t)K_{t-1}(\theta_{t-1} + \varepsilon_{t-1}) \\
&+ ...(1 - K_{t-1})(1 - K_{t-2})...(1 - K_2)[K_1(\theta_1 + \varepsilon_1) + (1 - K_1)\bar{\theta}_0]\big]\Big].
\end{aligned}
$$

Since the above expression is hard to calculate in general, let us focus on age one firms and age two firms first:

$$
\begin{aligned}
cov(FE_{1,2}^{\log}, FE_{2,3}^{\log}) \quad = \quad & \frac{1}{\sigma^2} cov\Big((\varepsilon_2 - K_1\varepsilon_1) + (\zeta_2 + (1 - K_1)\zeta_1), \\
& (\varepsilon_3 - K_2\varepsilon_2 - (1 - K_2)K_1\varepsilon_1) + (\zeta_3 + (1 - K_2)\zeta_2 + (1 - K_2)(1 - K_1)\zeta_1)\Big).
\end{aligned}
$$

which equals

$$
(1 - K_2)[\sigma_\varepsilon^2 K_1^2 + \sigma_\zeta^2(1 + (1 - K_1)^2)] - \sigma_\varepsilon^2 K_2,
$$

which can be either positive or negative. In particular, if K_2 (i.e., the Kalman gain in period two) is close to one, the whole term becomes negative which is inconsistent with our empirical finding. ■

6.4 Volatility of Output Growth

In this subsection of the appendix, we show that the Jovanovic model predicts that the volatility of growth rate of output decreases with firm age, which is a salient feature of our data. The learning model provides a rationale for this, even in the case in which the volatility of productivity or demand shocks does not vary with age.

Proposition 6 *Growth volatility of output decreases with firm age. Growth volatility of sales decreases with firm age at least when the firm is young.*

Proof. Based on equation (41), we know that log firm output at age t is proportional to (after omitting constants and aggregate variables which are constant in the steady state)

$$\sigma \log(b(\bar{a}, t-1)), \tag{37}$$

and it is proportional to

$$\sigma \log(b(\bar{a}, t)), \tag{38}$$

at age t+1. Therefore, the growth rate of output or quantity (or the log difference) is proportional to[46]

$$\Big(\frac{\lambda(\theta-\bar{\theta}) + (1+\lambda(t-1))\lambda\varepsilon_t - \lambda^2\Sigma_{i=1}^{t-1}\varepsilon_i}{(1+\lambda t)(1+\lambda(t-1))}\Big).$$

The variance of the growth rate at age t ($t \geq 2$) is

$$var(growth\ rate)_t = \Big[\frac{\lambda^2\sigma_\theta^2 + \lambda^4\sigma_\varepsilon^2(t-1)}{(1+\lambda t)^2(1+\lambda(t-1))^2} + \Big(\frac{\lambda}{(1+\lambda t)}\Big)^2\sigma_\varepsilon^2\Big],$$

which can be reduced to

$$var(growth\ rate)_t = \Big(\frac{\lambda^2\sigma_\varepsilon^2}{(1+\lambda t)(1+\lambda(t-1))}\Big).$$

Thus, the growth volatility of output decreases with firm age.

Next, we explore how the growth volatility of sales varies with firm age. Based on equation (41), we know that log firm sales at age t are proportional to (after omitting constants and

[46]Here, we omit the term related to $\frac{1}{2}\left(\frac{\sigma_{t-1}^2+\sigma_\varepsilon^2}{\sigma}\right)$ and $\frac{1}{2}\left(\frac{\sigma_t^2+\sigma_\varepsilon^2}{\sigma}\right)$, as they do not vary across firms.

aggregate variables which are constant in the steady state)

$$(\sigma-1)\log(b(\bar{a},t-1))+\frac{a_t}{\sigma}, \tag{39}$$

and it is proportional to

$$(\sigma-1)\log(b(\bar{a},t))+\frac{a_{t+1}}{\sigma} \tag{40}$$

at age $t+1$. Therefore, the growth rate of sales (or the log difference) is proportional to

$$\Big(\frac{\sigma-1}{\sigma}\Big)\Big(\frac{\lambda(\theta-\bar{\theta})+(1+\lambda(t-1))\lambda\varepsilon_t-\lambda^2\Sigma_{i=1}^{t-1}\varepsilon_i}{(1+\lambda t)(1+\lambda(t-1))}\Big)+\frac{\varepsilon_{t+1}-\varepsilon_t}{\sigma}.$$

Note that there is an additional term of $\frac{\varepsilon_{t+1}-\varepsilon_t}{\sigma}$ due to the shock to the price. The variance of the growth rate at age t ($t\geq 2$) is

$$\begin{aligned} var(growth\ rate)_t &= \Big(\frac{\sigma-1}{\sigma}\Big)^2\Big[\frac{\lambda^2\sigma_\theta^2+\lambda^4\sigma_\varepsilon^2(t-1)}{(1+\lambda t)^2(1+\lambda(t-1))^2}+\Big(\frac{\lambda}{(1+\lambda t)}-\frac{1}{\sigma-1}\Big)^2\sigma_\varepsilon^2\Big] \\ &\quad +\frac{\sigma_\varepsilon^2}{\sigma^2}, \end{aligned}$$

which can be further reduced to

$$\Big(\frac{\sigma-1}{\sigma}\Big)^2\Big[\frac{\lambda^3\sigma_\varepsilon^2}{(1+\lambda t)^2(1+\lambda(t-1))}+\Big(\frac{\lambda}{(1+\lambda t)}-\frac{1}{\sigma-1}\Big)^2\sigma_\varepsilon^2\Big]+\frac{\sigma_\varepsilon^2}{\sigma^2}.$$

In general, we do not have a result concerning how the growth volatility of sales evolves with firm age, as the term of $\Big(\frac{\lambda}{(1+\lambda t)}-\frac{1}{\sigma-1}\Big)^2$ can either increase or decrease with firm age. However, when λ is not too small and firm is young. the growth volatility of sales also goes down with firm age. However, the term of $\Big(\frac{\lambda}{(1+\lambda t)}-\frac{1}{\sigma-1}\Big)^2$ increases with firm age when the firm is old enough. ■

Several things are worth mentioning. First, the declining profile of the volatility of output (and sales) growth ceases to exist when $\lambda=0$ (i.e., the fundamental uncertainty disappears). This verifies that if there is no need to learn which is true when the fundamental uncertainty goes to zero, there is no age-dependent volatility of output growth. Therefor, it is exactly the learning mechanism that triggers the declining volatility of firm growth. Second, as the cross derivative of $\frac{\lambda^2\sigma_\varepsilon^2}{(1+\lambda t)(1+\lambda(t-1))}$ with respect to λ and t is negative, the reduction in the level of growth volatility is larger when the signal-to-noise ratio is higher. Economically speaking, a bigger λ implies faster learning and a quicker convergence to the volatility of sales growth at the steady state level.

Now, the question is why the growth volatility declines with firm age. A quick glance at equations (37) and (38) shows that two components contribute to the growth volatility of output. The first term is related to the change in the average experience (i.e., $\log(b(\bar{a},t)) - \log(b(\bar{a},t-1))$ which goes down with firm age. Intuitively, firm's belief and average experience fluctuate substantially when it is young, as there is not too much experience there. However, when the firm is old enough, its average experience stops fluctuating significantly. The second term is the contemporaneous productivity shock which is age independent. In short, the declining volatility of firm belief with age triggers the declining volatility of firm's output growth. And, the learning mechanism generates the declining volatility of output growth endogenously.

The final question is why the growth volatility of *sales* does not always go down with firm age. The key is that the shock to the price in the period t (i.e., ε_t) is correlated with the belief formed at the end of period t, which is used to forecast sales in period $t+1$. And, the volatility of this term (i.e., ε_t) does not always decrease with firm age. This makes deriving an unambiguous result on how age affects the growth volatility of sales impossible.

6.5 Proofs

6.6 Proof for Proposition 1

Proof. We derive realized sales and forecasted sales first. The log of realized sales and the log of forecasted sales are

$$\log(R_t(\theta)) = \log(A_t) + \frac{\theta+\varepsilon_t}{\sigma} + (\sigma-1)b\left(\bar{a}_{t-1},t-1\right) + (\sigma-1)\Big[\log\Big(\frac{\sigma-1}{\sigma w}\Big)\Big], \tag{41}$$

and

$$\log\Big(E^S_{t-1}(R_t)\Big) = \log(A_t) + \sigma b\left(\bar{a}_{t-1},t-1\right) + (\sigma-1)\Big[\log\Big(\frac{\sigma-1}{\sigma w}\Big)\Big]$$

respectively. The resulting FE becomes

$$FE^{\log}_{t-1,t}(sales) = \frac{\varepsilon_t + (\theta-\mu_{t-1})}{\sigma} - \frac{\sigma^2_{t-1}+\sigma^2_{\varepsilon}}{2\sigma^2}. \tag{42}$$

Surprisingly, the Jovanovic model also predicts that FEs made in two consecutive periods are uncorrelated. To see this, we rewrite the FE as

$$\begin{aligned} FE^{\log}_{t-1,t}(sales) &= \frac{(1-\zeta(t-1,\lambda))(\theta-\bar{\theta}) + \varepsilon_t - \zeta(t-1,\lambda)\frac{\Sigma_{i=1}^{t-1}\varepsilon_i}{t-1}}{\sigma} \\ &\quad -\frac{\sigma^2_{t-1}+\sigma^2_{\varepsilon}}{2\sigma^2}, \end{aligned}$$

where the signal-to-noise ratio is defined as

$$\lambda \equiv \frac{\sigma_\theta^2}{\sigma_\varepsilon^2}; \quad \zeta(t-1,\lambda) \equiv \frac{(t-1)\lambda}{1+(t-1)\lambda}.$$

The implied covariance of FEs in two consecutive periods is

$$cov(FE_{t-1,t}^{\log}, FE_{t,t+1}^{\log}) = \frac{1}{\sigma^2}\left[\frac{\lambda\sigma_\varepsilon^2}{(1+\lambda t)(1+\lambda(t-1))} - \frac{\lambda t\sigma_\varepsilon^2}{t(1+\lambda t)} + \frac{\lambda t\lambda(t-1)\sigma_\varepsilon^2}{t(1+\lambda t)(1+\lambda(t-1))}\right] = 0.$$

Readers are referred to Appendix 6.3 for the discussion of time-varying fundamental demand draw. ■

6.6.1 Proof for Proposition 2

Proof. We can rewrite the expression of the variance of FE derived in the main text as:

$$var(FE_{t-1,t}^{\log}(sales)) = \frac{(1+\frac{\zeta(t-1,\lambda)^2}{t-1})\sigma_\varepsilon^2}{\sigma^2} + \frac{(1-\zeta(t-1,\lambda))^2\sigma_\theta^2}{\sigma^2}, \tag{43}$$

where

$$\zeta(t-1,\lambda) \equiv \frac{(t-1)\lambda}{1+(t-1)\lambda}.$$

Differentiating equation (43) with respect to t leads to

$$-\frac{\partial\zeta(t-1,\lambda)}{\partial t}\sigma_\varepsilon^2\Big[2(1-\zeta(t-1,\lambda))\lambda - \frac{2\zeta(t-1,\lambda)}{t-1}\Big] - \sigma_\varepsilon^2\frac{\zeta(t-1,\lambda)^2}{(t-1)^2},$$

which equals

$$-\sigma_\varepsilon^2\frac{\zeta(t-1,\lambda)^2}{(t-1)^2} < 0.$$

Therefore, variance of FEs declines with t. ■

6.6.2 Proof for Proposition 3

Proof. The variance of FEs at age t now becomes

$$\begin{aligned}
& var(FE_{t-1}^{\log})_{sticky} \\
= \; & \frac{\sigma_\theta^2 + \sigma_\varepsilon^2 + (1-\alpha^{t-1})\zeta(t-1,\lambda)^2\Big(\sigma_\theta^2 + \frac{\sigma_\varepsilon^2}{t-1}\Big) - 2(1-\alpha^{t-1})\zeta(t-1,\lambda)\sigma_\theta^2}{\sigma^2} \\
= \; & \frac{[1-(2\zeta(t-1,\lambda)-\zeta(t-1,\lambda)^2)(1-\alpha^{t-1})]\sigma_\theta^2 + \Big(1+\frac{(1-\alpha^{t-1})\zeta(t-1,\lambda)^2}{t-1}\Big)\sigma_\varepsilon^2}{\sigma^2} \\
= \; & (1-\alpha^{t-1})\Big(var(FE_{t-1}^{\log})) - \frac{\sigma_\theta^2+\sigma_\varepsilon^2}{\sigma^2}\Big) + \frac{\sigma_\theta^2+\sigma_\varepsilon^2}{\sigma^2},
\end{aligned}$$

where $var(FE_{t-1}^{\log})$ is the variance of FEs at age t in the original Jovanovic model. As we have shown that $var(FE_{t-1}^{\log})$ declines with firm age in Proposition 2, we have that

$$var(FE_{t-1}^{\log}) - \frac{\sigma_\theta^2+\sigma_\varepsilon^2}{\sigma^2}$$

also decreases with firm age. Furthermore, its value is negative. Thus, the absolute value of it increases with firm age. As $(1-\alpha^{t-1})$ increases with firm age, we have that

$$(1-\alpha^{t-1})\Big(\frac{\sigma_\theta^2+\sigma_\varepsilon^2}{\sigma^2} - var(FE_{t-1}^{\log})\Big),$$

increases with firm age t, and this term is always positive. Therefore, $var(FE_{t-1}^{\log})_{sticky}$ decreases with firm age. ■

6.6.3 Proof for Proposition 4

Proof. The correlation of FEs in two consecutive periods (i.e., period t and period $t+1$) can be decomposed into three parts. First, there are α^t fraction of firms that are still uninformed by the end of period t. Second, there are $1-\alpha^{t-1}$ fraction of firms that are informed by the end of period $t-1$. The third type of firms is the firm that switches from being uninformed to being informed with the fraction of $\alpha^{t-1}(1-\alpha)$ among all firms. As in the original Jovanovic model, the serial correlation (and covariance) of FEs is zero for $1-\alpha^{t-1}$ fraction of firms that are informed by the end of period $t-1$. For firms that are still uninformed by the end of period t, the correlations is

$$cov(FE_{t-1}^{\log}, FE_t^{\log}) = cov\Big(\frac{\varepsilon_t + \theta - \bar{\theta}}{\sigma}, \frac{\varepsilon_{t+1} + \theta - \bar{\theta}}{\sigma}\Big) = \frac{\sigma_\theta^2}{\sigma^2},$$

as they use the prior mean, $\bar{\theta}$, to forecast the fundamental demand in both periods. For the switchers, the correlation is

$$\begin{aligned}
& cov(FE^{\log}_{t-1}, FE^{\log}_{t}) \\
= \; & cov\Big(\frac{\varepsilon_t + \theta - \bar{\theta}}{\sigma}, \frac{\varepsilon_{t+1} + \theta - \mu_t}{\sigma}\Big) \\
= \; & \frac{1}{\sigma^2} cov\Big(\varepsilon_t + \theta - \bar{\theta}, \theta - \mu_t\Big) \\
= \; & \frac{1}{\sigma^2} cov\Big(\varepsilon_t + \theta - \bar{\theta}, \frac{\theta - \bar{\theta}}{1+t\lambda} - \frac{\lambda \sum_{t=1}^{t} \varepsilon_t}{1+t\lambda}\Big) \\
= \; & \frac{1}{\sigma^2} \Big(\frac{\sigma_\theta^2}{1+t\lambda} - \frac{\lambda \sigma_\varepsilon^2}{1+t\lambda}\Big) = 0.
\end{aligned}$$

Therefore, the average (total) covariance of $FE^{\log}_{t-1,t}$ and $FE^{\log}_{t,t+1}$ is

$$\frac{\alpha^t \sigma_\theta^2}{\sigma^2},$$

which is strictly positive and decreases when firms become older. This is consistent with the evidence presented in Table 7. ■

7 Empirical Appendix

7.1 Validation of Firm-level Forecasts

In this subsection, we show that the projected sales reported by Japanese MNEs' affiliates' and FEs constructed by us are reliable and make intuitive sense for three reasons. First, the FDI survey is mandated by METI and not imposed by the parent firms of these affiliates. As a result, the affiliate reports the projected sales to the government and not to the parent firm. Therefore, the strategical communication is not likely to be a concern here.[47]

Second, we show that the projected sales have statistically significant and economically strong impact on realized sales, employment and investment in the future. Specifically, we regress the realized sales in year t on projected sales in year $t-1$ (for sales in year t) and a set of fixed effects, and the results are reported in Table 16. The first three columns show that the sales forecast positively and statistically significantly predicts the realized sales next year. Importantly, the predictive power of the sales forecast is much stronger than the realized sales in previous years (i.e., last year or two years ago). These results validate that the sales forecast contains useful and reliable information for firm sales in the future. In addition, even if we focus on a subset of Japanese affiliates such as those in the manufacturing industries or those that have survived for at least five years consecutively, the same empirical result holds. Finally, when we focus on how the sales forecast affects employment and investment (or the probability of investment) in the future, Table 17 shows that sales forecast positively predicts future employment and investment. This empirical result further verifies the reliability and usefulness of the information on firm-level sales forecast.[48]

Finally, we show that the constructed FEs are positively correlated with aggregate-level risk or volatility, which makes intuitive sense. Specifically, we regress the absolute value of FEs on aggregate-level risk or volatility (and a set of fixed effects), and the results are reported in Table 18. We obtain the Country Risk Index from the BMI research database. This index measures the overall risk of an economy, such as an economic crisis or a sudden change in the political environment.[49] After controlling for common trends at the industry-year level using the fixed effects and parent firm fixed effects, we find the absolute value of FEs is positively correlated with country-level risk in the *destination country* (columns 1 and 2). However, if the country risk indices capture the fluctuations in the macro-economy or government policies well,

[47] Specifically, the affiliate should not have the incentive to over-report the projected sales in order to impress the parent firm.

[48] If the affiliates randomly or non-rationally reported their projected sales, the projected sales should have no or weak predictable power for future sales, employment and investment.

[49] The original index S provides a composite score from 0 (high risk) to 100 (low risk). We transform it into $1 - S/100$ so that our index lies between 0 to 1, with 1 representing the highest risk.

Table 16: Projected sales and realized sales

	Dependent Variable: $log(Sales)_t$					
Sample:	all	all	all	manufacturing	service	survivors
$log(SalesForecast)_{t-1}$	0.713***	0.618***	0.592***	0.588***	0.590***	0.623***
	(0.010)	(0.012)	(0.014)	(0.014)	(0.020)	(0.017)
$log(Sales)_{t-1}$		0.128***	0.082***	0.127***	0.112***	0.113***
		(0.008)	(0.014)	(0.008)	(0.015)	(0.011)
$log(Sales)_{t-2}$			0.047***			
			(0.006)			
N	126501	125145	104967	74684	49668	21449
R^2	0.960	0.962	0.965	0.965	0.961	0.959
Affiliate Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Country-year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at parent firm level, * 0.10 ** 0.05 *** 0.01. The first three columns use all observations. The fourth column uses observations (i.e., affiliate-year) whose parent firms are in manufacturing sectors. The fifth column uses observations whose parent firms are in service sectors. The last column use affiliates who have survived for at least five consecutive years.

Table 17: Projected sales and realized investment and employment

Dependent Var:	$log(Employment)_t$	$log(Investment)_t$	$Investment_t > 0$
$log(SalesFore)_{t-1}$	0.266***	0.509***	0.059***
	(0.014)	(0.024)	(0.004)
$log(Sales)_{t-1}$	0.081***	-0.129***	-0.011***
	(0.005)	(0.014)	(0.003)
N	123887	77217	105535
R^2	0.958	0.779	0.615
Affiliate Fixed Effect	Yes	Yes	Yes
Country-year Fixed Effect	Yes	Yes	Yes
Industry-year Fixed Effect	Yes	Yes	Yes

Standard errors are clustered at parent firm level, * 0.10 ** 0.05 *** 0.01. All columns use all observations.

it is not surprising that unexpected aggregate shocks lead to less precise forecasts. To eliminate uncertainty induced by aggregate fluctuations, we focus on the absolute value of residual FEs in column 3. The residual FEs, which represent firms' idiosyncratic uncertainty, are also positively correlated with country-level risk. Our interpretation is that macro-level and micro-level subjective uncertainty may be closely related. For example, a government that frequently changes macroeconomic policies may also engage in policies targeting at a particular set of firms, inducing micro-level uncertainty. In columns 4-6, we confirm this pattern using the standard deviation of real GDP growth rates as an alternative measure of aggregate volatility. A caveat here is that this paper is *not* about aggregate risks or volatility. We use the above regressions, only because we want to show the reliability of our constructed FEs.

Table 18: Affiliates' uncertainty and country risk index

	(1) $\lvert FE^{log}\rvert$	(2) $\lvert FE^{pct}\rvert$	(3) $\lvert\hat{\epsilon}_{FE^{log}}\rvert$	(4) $\lvert FE^{log}\rvert$	(5) $\lvert FE^{pct}\rvert$	(6) $\lvert\hat{\epsilon}_{FE^{log}}\rvert$
Country risk index	0.275***	0.261***	0.264***			
	(0.042)	(0.041)	(0.049)			
$\sigma(\Delta log(GDP))$				1.061**	1.076***	0.991**
				(0.406)	(0.378)	(0.433)
N	129886	130388	129625	129807	130309	129559
R^2	0.149	0.151	0.140	0.146	0.150	0.137
Industry-year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Parent Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Mean of X	0.291			0.027		
Std. Dev. of X	0.061			0.010		

Standard errors are two-way clustered at country and parent firm level, * 0.10 ** 0.05 *** 0.01. Each column head lists the dependent variable of the regressions. $|FE^{log}|$ is the absolute log deviation of the realized sales from the projected sales; $|FE^{pct}|$ is the absolute percentage deviation of the realized sales from the projected sales; $|\hat{\epsilon}_{FE^{log}}|$ is the absolute value of the residual forecast error, which we obtain by regressing FE^{log} on a set of industry-year and country-year fixed effects. Country risk index (BMI research database) is an index from zero to one that measures the overall risk of the economy, such as an economic crisis or a sudden change in the political environment , with one being the most risky environment. $\sigma(\Delta log(GDP))$ is the standard deviation of real GDP growth rate of the host country since 1990, calculated from Penn World Table 9.0.

The empirical regularities described above reassure us that the projected forecast for sales provided by the Japanese affiliates abroad and the absolute value of FEs constructed by us contain reliable and useful information concerning micro-level uncertainty faced by Japanese MNEs. In the next three subsections, we examine how firm-level uncertainty gets resolved over the firm's life cycle and how it is related to the parent firms' previous export experience. In the last subsection, we present key evidence that substantiates the existence of imperfect information in the international market, which cannot be rationalized by FIRE models such as the AR(1) model with perfect information.

7.2 Robustness Checks for Learning from Exporting

In this subsection, we provide several robustness checks for the baseline regression described in Subsection 3.4. Specifically, Table 19 presents the same pattern as in Table 5, when we restrict our sample to first-time entrants into regions instead of countries. The effect of export experience is larger but at the same time more noisy due to the reduced size of our sample. To be conservative, we prefer to use estimates from the sample of first-time entrants into countries in our quantitative exercises.

Table 19: Learning from exporting at the continent level

	Dependent Variable: $\lvert FE^{log}\rvert$			
	(1)	(2)	(3)	(4)
$Exp_{-1} > 0$	-0.266**			
	(0.115)			
$Exp_{-1} > 0$ or $Exp_{-2} > 0$		-0.211*		
		(0.119)		
$Exp \quad Expe. > 0$			-0.196	
			(0.127)	
$Exp \quad Expe.$				-0.018
				(0.015)
Industry FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
N	180	180	218	218
R^2	0.528	0.569	0.515	0.504

Standard errors are clustered at parent firm level, * 0.10 ** 0.05 *** 0.01. We only include affiliates that are first-time entrants into a particular continent.

The relationship between previous export experience and FEs at age one is robust to controlling for firm size. As we discussed in the previous section, bigger firms may have smaller subjective uncertainty. In addition, Table 20 shows that experience MNEs tend to set up bigger and more productive (in terms of sales per worker) affiliates upon FDI entry relative to inexperienced MNEs. Therefore, firm size and productivity are also correlated with previous export experience of first-time entrants. In order to address these concerns, we control for parent firm's employment (or sales) and employment (or sales) of its affiliate in Table 21. Previous export experience still has a significantly negative impact on the initial subjective uncertainty, and the magnitude of the effect does not vary much. Consistent with the evidence in Table 3, parent firm size is not strongly correlated with affiliate subjective uncertainty while affiliate size is negatively associated with its subjective uncertainty.

Our final robustness checks are related to the type of FDI and exports measured in our data. Learning about uncertain foreign demand through exporting is more relevant for horizontal than vertical FDI. In columns 1-3 of Table 22, we try to exclude possible affiliates of firms doing vertical FDI by restricting our sample to affiliates that never export more than 1/3 of their

Table 20: Export experience is related to characteristics of affiliates

	(1) $log(\frac{sales}{employment})_{sub}$	(2) $log(sales)_{sub}$	(3) $log(employment)_{sub}$
$Exp_{-1} > 0$	0.568**	0.471	0.0665
	(0.280)	(0.333)	(0.149)
N	778	811	1241
R^2	0.759	0.699	0.613
Industry-year Fixed Effect	Yes	Yes	Yes
Country-year Fixed Effect	Yes	Yes	Yes

Std. err. clustered at the affiliate level. * 0.10 ** 0.05 *** 0.01. First time entrant is defined at the country level. Exporting experience is defined as whether the parent firm exported one year prior to FDI entry. The sample includes patent firms in the manufacturing sector and affiliates that are in the manufacturing or (wholesale and retail) sector.

Table 21: Learning from exporting and firm size

	Dependent Variable: $\lvert FE^{log}\rvert$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{-1} > 0$	-0.151**	-0.115*				
	(0.063)	(0.062)				
$Exp_{-1} > 0$ or $Exp_{-2} > 0$			-0.147**	-0.121*		
			(0.063)	(0.064)		
$Exp \quad Expe. > 0$					-0.113*	-0.077
					(0.065)	(0.063)
log(Parent Employment)	0.017		0.021		0.009	
	(0.023)		(0.022)		(0.021)	
log(Affiliate Employment)	-0.031		-0.020		-0.045**	
	(0.020)		(0.018)		(0.018)	
log(Parent Domestic Sales)		0.018		0.021		0.018
		(0.017)		(0.016)		(0.016)
log(Affiliate Sales)		-0.054***		-0.052***		-0.058***
		(0.014)		(0.013)		(0.014)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	549	534	557	543	654	625
R^2	0.493	0.535	0.503	0.541	0.485	0.532

Standard errors are clustered at parent firm level, * 0.10 ** 0.05 *** 0.01.

sales back to Japan. This does not affect the estimated effect of previous export experience. In columns 4-6, we refine our measure of parent firms' export experience. Specifically, we redefine export experience to be zero, if all of the parent firm's exports to a certain region are intra-firm trade. The estimated effects are less significant than other specifications, but the magnitude remains stable.

Table 22: Learning from exporting and horizontal FDI

	Dependent Variable: $\lvert FE^{log} \rvert$					
	Exclude vertical FDI			Exclude affiliated export		
	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{-1} > 0$	-0.166**			-0.099		
	(0.073)			(0.067)		
$Exp_{-1} > 0$ or $Exp_{-2} > 0$		-0.155**			-0.141**	
		(0.072)			(0.067)	
$Exp \quad Expe. > 0$			-0.159**			-0.114
			(0.078)			(0.071)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	456	464	551	441	446	551
R^2	0.542	0.549	0.529	0.545	0.554	0.524

Standard errors are clustered at parent firm level, * 0.10 ** 0.05 *** 0.01. In columns 1-3, we exclude affiliates whose sales share back to Japan is larger than one third in at least one year. In columns 4-6, in addition to excluding vertical FDI, we further refine our measure of exporting experience by excluding intra-firm exports from parent firm to affiliates in a particular continent.

7.3 Uncertainty, Information Imperfection and Distance

In this subsection, we show that the degree of information rigidity is positively related to gravity variables such as the (physical) distance. International trade literature has studied how distance between countries affects trade costs and trade/FDI flows extensively (Anderson and Van Wincoop (2003), Redding and Venables (2004), Irarrazabal et al. (2013) etc.). In particular, physical distance between countries can generate trade costs through deterring information flows between countries. For instance, the fact that remote countries do trade as much as nearby countries can be rationalized by the argument that firms have less information about their demand conditions in remote markets than in adjacent markets. In our context, Japanese affiliates abroad probably need to coordinate and communicate with their parent firms in Japan. Therefore, physical distance between the parent firm (i.e., Japan) and the affiliate (i.e., the destination country) can deter information flows within the MNE and affects the level of information rigidity. In what follows, we relate several of our key data moments of FEs (e.g., the variance and the serial correlation coefficient of FEs) to the physical distance between the parent firm and the affiliate to show that the distance is indeed positively correlated with the level of information rigidity.

We start off by showing several simple graphs. Specifically, we calculate the variance of FEs for all Japanese affiliates in a given economy at age one (i.e., $FE^{\log}_{1,2}$) and above age ten (i.e., $FE^{\log}_{t,t+1}$ where $t \geq 10$) respectively. Since only a handful destination economies have enough observations for us to calculate the variance of FEs for affiliates at age one, we end up with Japanese affiliates in twenty major economies (excluding tax heaven economies) in our graph.[50] We plot the variance of FEs for the two age cohorts in various economies against the weighted distance from Japan (the data is obtained from CEPII) in Figures 7 and 8. It seems that the initial uncertainty at the economy level is *negatively* related to the distance from Japan, while the eventual uncertainty is uncorrelated to the distance.

The finding on the relationship between the initial uncertainty and distance is puzzling, as the reader would think that Japanese affiliates in adjacent economies might have better information about the destination markets and therefore have more precise forecasts than the affiliates in remote economies. However, the fundamental volatility of the destination economy (e.g., economic policy uncertainty, the probability of economic crisis and political uncertainty etc.) probably plays a more important role than the level of information rigidity in determining the precision of these affiliates' forecasts. Note that economies close to Japan (e.g., China, Taiwan and Southeast Asian countries) are emerging markets whose economic environment is less stable than economies that are far away from Japan (e.g., the U.S., Canada, Australia and European countries).[51] This probably causes less precise forecasts made by Japanese affiliates in Asian economies than those in north America and Europe.

What is interesting is that when we focus on the serial correlation coefficient of FEs over time, which is a measure of the degree of information rigidity (and not for the fundamental volatility of the economy), there is a strong positive association between the distance from Japan and the level of the correlation for the destination economy. Figures 9 and 10 clearly show this pattern. In other words, Japanese affiliates in China and Southeast Asia made less *systematic* FEs compared to those in North America and Europe. In summary, the two empirical findings above help us distinguish imperfect information across borders from volatility (or risks) of the destination economies. This difference is economically important, as volatility is fundamentally different from barriers to information flows.

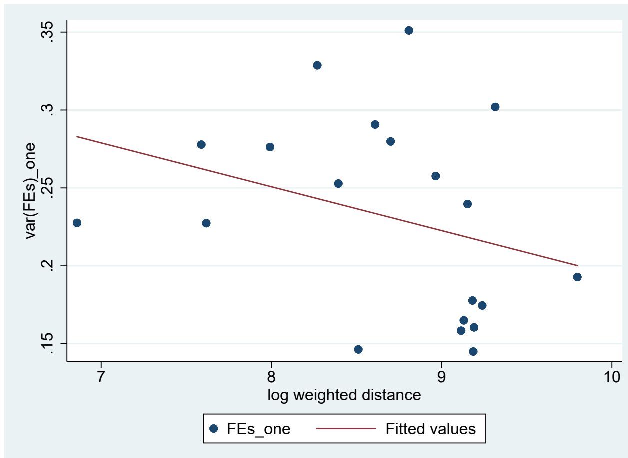
Finally, we run the following panel regressions to confirm our finding on the relationship between distance and the degree of information rigidity:

$$|FE^{\log}|_{it} = distance_c + \log(sales)_{it} + \delta_c + \delta_{st} + HQ_{j(i)} + \delta_t + \varepsilon_{it}$$

[50] We want to have enough observations in the calculation, as otherwise the law of large numbers would not hold for each destination country. The twenty economies we pick have at least twenty observations of Japanese affiliates' FEs at age one.

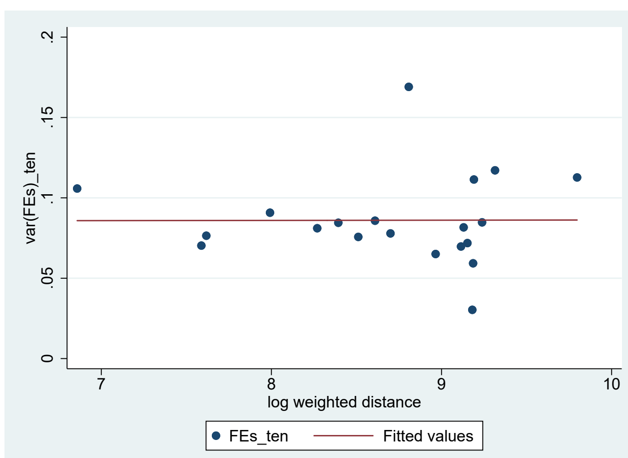
[51] We do not have many observations from economies in the middle east, Africa and South America.

Figure 7: Initial Uncertainty (age-one) and Distance



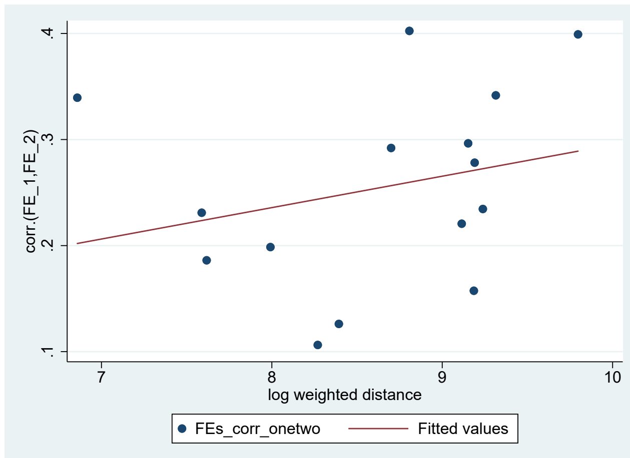
Note: Each point represents a destination economy. Twenty economies with enough observations of FEs at age one are included.

Figure 8: Eventual Uncertainty (age-ten or above) and Distance



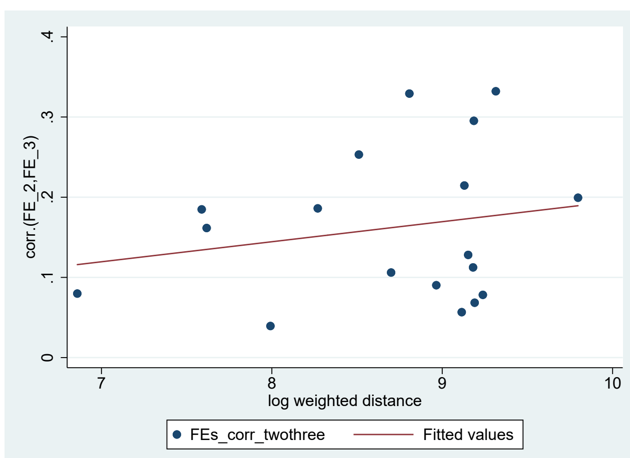
Note: Each point represents a destination economy. Twenty economies with enough observations of FEs at age one are included.

Figure 9: Information Rigidity and Distance: correlation of $FE^{log}_{1,2}$ and $FE^{log}_{2,3}$



Note: Each point represents a destination economy. Economies with more than fifteen observations are included.

Figure 10: Information Rigidity and Distance: correlation of $FE^{log}_{2,3}$ and $FE^{log}_{3,4}$



Note: Each point represents a destination economy. Economies with more than fifteen observations are included.

and

$$Corr(FE^{\log}_{it}, FE^{\log}_{it+1}) = distance_c + \log(sales)_{it} + \delta_c + \delta_{st} + HQ_{j(i)} + \delta_t + \varepsilon_{it},$$

where δ_{st} represents the industry-year fixed effects, and $HQ_{j(i)}$ is the parent firm fixed effect. In order to control firm-level factors that affect the variance and serial correlation of FEs, we include δ_t (a vector of age dummies) and $\log(sales)_{it}$ (log sales of the affiliate) into the regressions. $Corr(FE^{log}_{i,t}, FE^{log}_{i,t+1})$ is defined to be 1 if FEs made in two consecutive years have the same sign and -1 otherwise. The key interest of our analysis is how the distance between Japan and the destination economy ($distance_c$: weighted distance) affects the variance and the serial correlation of FEs for a given affiliate. In order to control for other confounding factors at the destination economy level, we also include other variables such as the culture distance and religious distance into some of our regressions.[52] These variables are denoted by δ_c.

In Tables 23 and 24, we run the first regression for affiliates at age one or two and for affiliates that are at least ten years old respectively. The regression result indicates that distance negatively affects the imprecision of FEs in the destination economy for young affiliates (i.e., age one or two). Interestingly, the regression results also show that cultural difference positively affects the imprecision of FEs in the destination economy for young affiliates. The result that firm size negatively affects the imprecision of FEs reconciles our previous finding documented in Subsection 3.4. In total, we conclude that distance from Japan is negatively related to the imprecision of FEs made by young affiliates abroad. However, this only reflects the fact that economies closer to Japan are mainly emerging and developing economies which have more volatile economic environment.

In Table 25, we run the second regression. Interestingly, after we have controlled for cultural distance and religious distance between Japan and the destination economy (and other firm-level characteristics), the positive relationship between distance and the serial correlation of FEs become even stronger. This confirms our previous argument that physical distance acts as a barrier to information flows and positively affect the degree of information rigidity. In total, the richness of our forecasting data enables us to disentangle the effect of distance on information rigidity from other confounding factors such as the fundamental volatility of the economy. This is particularly important, as economies closer to Japan probably have more volatile economic environment and economies far away from Japan probably have less frequent information flows from Japan.[53]

[52] Data on cultural and religious distance between Japan and other economies are obtained from Prof. Enrico Spolaore's website: `https://sites.tufts.edu/enricospolaore/research/`.

[53] There are two reasons for why distance negatively affects information flows. First, MNEs send employees from the headquarters to their foreign affiliates in order to facilitate intra-firm coordination and communication, as face-to-face communication is important. This is especially true for Japanese MNEs. MNEs probably send fewer

Table 23: Distance from Japan and FEs made by manufacturing entrants (age one or two)

	Dependent Variable: $\lvert FE^{log}\rvert$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(distance)_{weighted}$	-0.0227	-0.0155*	-0.0198	-0.0209**	-0.0295	-0.0253**
	(0.0144)	(0.00633)	(0.0193)	(0.00724)	(0.0290)	(0.00841)
$\log(sales)_{sub}$	-0.0777***	-0.0615***	-0.0753***	-0.0586***	-0.0716***	-0.0582***
	(0.0102)	(0.00454)	(0.0105)	(0.00464)	(0.0103)	(0.00475)
cultural distance			0.000354	0.000858**	0.000344	0.000709*
			(0.000841)	(0.000294)	(0.000967)	(0.000325)
religious distance					0.124	0.0801^{+}
					(0.111)	(0.0456)
Type of affiliate	first-time entrants	all	first-time entrants	all	first-time entrants	all
Parent firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2564	5201	2198	4594	2123	4459
R^2	0.660	0.483	0.689	0.502	0.694	0.506

Standard errors are clustered at the destination country level, + 0.10 * 0.05 ** 0.01 *** 0.001. We only include manufacturing and wholesale/retail affiliates whose parent firms in Japan are in manufacturing sectors.

Table 24: Distance from Japan and FEs of manufacturing entrants (age above ten)

	Dependent Variable: $\lvert FE^{log}\rvert$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(distance)_{weighted}$	-0.00431	-0.00314	-0.00557	-0.00537^{+}	-0.00511	-0.00663
	(0.00305)	(0.00322)	(0.00350)	(0.00302)	(0.00461)	(0.00395)
$\log(sales)_{sub}$	-0.0233***	-0.0205***	-0.0226***	-0.0205***	-0.0225***	-0.0206***
	(0.00177)	(0.00122)	(0.00191)	(0.00130)	(0.00203)	(0.00137)
cultural distance			0.000110	0.000155	0.0000992	0.000143
			(0.000141)	(0.000110)	(0.000153)	(0.000131)
religious distance					-0.00159	0.00983
					(0.0143)	(0.0160)
Type of affiliate	first-time entrants	all	first-time entrants	all	first-time entrants	all
Parent firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
N	40750	56390	34044	47229	31857	44423
R^2	0.230	0.197	0.246	0.209	0.250	0.213

Standard errors are clustered at the destination country level, + 0.10 * 0.05 ** 0.01 *** 0.001. We only include manufacturing and wholesale/retail affiliates whose parent firms in Japan are in manufacturing sectors.

Table 25: Distance from Japan and correlation of FEs made by manufacturing MNEs

	Dependent Variable: $Corr(FE_t^{log}, FE_{t+1}^{log})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(distance)_{weighted}$	0.00949	0.0156**	0.0203***	0.0243***	0.0243**	0.0294***
	(0.00578)	(0.00518)	(0.00516)	(0.00542)	(0.00824)	(0.00733)
$\log(sales)_{sub}$	0.00164	-0.00398*	0.000816	-0.00438*	0.000421	-0.00478*
	(0.00337)	(0.00167)	(0.00397)	(0.00172)	(0.00418)	(0.00182)
cultural distance			-0.00101**	-0.000997**	-0.00104**	-0.00105**
			(0.000312)	(0.000306)	(0.000339)	(0.000313)
religious distance					-0.0278	-0.0360
					(0.0379)	(0.0313)
Type of affiliate	first-time entrants	all	first-time entrants	all	first-time entrants	all
Parent firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
N	103561	159226	87555	136302	82987	129896
R^2	0.149	0.136	0.152	0.138	0.154	0.139

Standard errors are clustered at the destination country level, + 0.10 * 0.05 ** 0.01 *** 0.001. We only include manufacturing and wholesale/retail affiliates whose parent firms in Japan are in manufacturing sectors. $Corr(FE_t^{log}, FE_{t+1}^{log})$ is defined to be 1 if FEs in two two consecutive years have the same sign and -1 otherwise.

7.4 Flat Age-profile of Exits

In this section, we show that previous export experience (before FDI entry) and the affiliate age do not seem to affect the exit rates of the affiliates after entry. In Table 27, we regress the exit dummy on the affiliate age and a set of fixed effects. The empirical result shows that irrespective of which subsample we use (all entrants or manufacturing plus wholesale/retail entrants) and which firm fixed effects (parent or affiliate) we include into the regression, firm age does not seem to be related to the exit probably. This stands in contrast to the prediction of firm learning model with endogenous exits, as this type of model would predict declining exit rates with firm age, if there is a per-period fixed operating cost.

Next, we investigate how previous export experience affects the exit rates after entry into the FDI market. In Table 26, we regress the exit dummy on the affiliate age, its previous export experience and a set of fixed effects. The empirical result shows that neither previous export experience nor firm age affects the exit probability after entry into the FDI market. This stands in contrast to the prediction of firm learning model with endogenous exits. Firm learning models with endogenous exits would predict that positive previous export experience helps firms learn

employees (and send them less frequently) from the headquarters to their affiliates located in remote economies than those that are located in adjacent economies. Second, there is probably more news coverage on economies that are closer to Japan in Japanese media (e.g., China, Taiwan and South Korea). When Japanese managers who are sent from the headquarters to the foreign affiliates make the forecats, they have more information about adjacent economies than about remote economies. Therefore, they make less systematic mistakes when filling out the survey.

Table 26: Age profile of affiliates' exiting

	Dependent Variable: exit dummy			
	(1)	(2)	(3)	(4)
affiliate age	0.0000382	0.0000312	-0.0000612	-0.0000668
	(0.0000551)	(0.0000562)	(0.0000570)	(0.0000582)
Affiliate type	manuf.+wholesale/retail	manuf.+wholesale/retail	all	all
Affiliate FE	Yes	No	Yes	No
Parent firm FE	No	Yes	No	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
N	94273	94271	125947	125941
R^2	0.099	0.101	0.107	0.108

Standard errors are clustered at the affiliate level, + 0.10 * 0.05 ** 0.01 *** 0.001. Only first-time entrants into the destination markets are included.

about their demand and reduce exit rates after entry, if there is a per-period fixed operating cost which triggers endogenous exits.

Table 27: Export experience and exiting probability of the affiliates

	Dependent Variable: exit dummy	
	(1)	(2)
$Exp_{-1} > 0$	0.00205	0.00222
	(0.0134)	(0.0132)
affiliate age	0.000527	0.000571
	(0.000777)	(0.000771)
One-parent-one-affiliate pairs included?	No	Yes
Parent firm FE	Yes	Yes
Industry-year FE	Yes	Yes
Country-year FE	Yes	Yes
N	6202	7913
R^2	0.223	0.235

Standard errors are clustered at the affiliate level, + 0.10 * 0.05 ** 0.01 *** 0.001. We only include manufacturing and wholesale/retail affiliates whose parent firms in Japan are in manufacturing sectors. Only first-time entrants into the destination markets are included.

In total, as we do not observe significant effects of previous export experience and firm age on the exit rates after FDI entry, there is no strong sign for the existence of endogenous exits among multinational affiliates in our dataset. Therefore, we set the per-period fixed operating cost of FDI, $f_m = 0$, to zero in our calibration exercise.

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