Demand Uncertainty and the Joint Dynamics of Exporters and Multinational Firms *

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Abstract

This paper uses a unique dataset of Japanese multinational affiliates, which contains information on sales forecasts, to document two new facts regarding firms' uncertainty in foreign markets. First, we find that sales forecasts become more precise over an affiliate's life cycle. Second, for first-time entrants into particular countries, those whose parent firms have previous export experience in the same region can better predict their sales than those whose parents do not have such experience. We see these facts as direct evidence on firm learning about uncertain demand in foreign markets, through both affiliate sales and exports. We then extend the dynamic model of firm learning in Arkolakis, Papageorgiou and Timoshenko (2015) to a setting in which firms can choose between exporting and FDI to serve the foreign market. The calibrated model is able to replicate the two new facts regarding firms' uncertainty, as well as other salient features of exporter and multinational dynamics. Counterfactual experiments show that incorporating learning has important implications for the pattern of trade and multinational production in response to changes in demand uncertainty and trade liberalization.

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1 Introduction

When firms enter foreign markets, they face considerable uncertainty. In addition to macroeconomic fluctuations induced by business cycles or government policies, firms face uncertainty at the microeconomic level. For instance, exporters or multinational affiliates may not know how popular their products would be in the foreign market before entry. Naturally, such demand uncertainty can be resolved by gradually discovering the popularity of their products after entry. Moreover, for firms that contemplate doing foreign direct investment (FDI), they may use the strategy of sequential entry, i.e., using exporting as an intermediate stage before FDI, since exporting involves lower entry costs but can help the firm learn about their demand. In this paper, we use a unique dataset of Japanese multinational enterprises (MNEs) which contains information on firm-level sales forecasts and study how firms resolve demand uncertainty in foreign markets and how such uncertainty affects the joint dynamics of export and multinational production.

A growing literature in international trade has started to investigate how demand uncertainty - and in general, information imperfection - affects exporter and MNE dynamics. The literature has shown that the specification of the firm's information set has important implications for trade and FDI patterns (Conconi et al. (2016)), as well as the estimation of trade frictions and the welfare impact of trade reforms (Dickstein and Morales (2016)). However, since none of the papers have direct measures on firms' expectations, there is debate about how to specify firms' information set based on indirect information, such as data on firm sales, entries and exits. For example, some researchers emphasize the role of self-discovery about consumer demand[1], while others claim selection and persistent productivity shocks alone can account for the dynamics of exporters and MNEs (Gumpert et al. (2016)). Our first contribution in this paper is to construct a new dataset on Japanese multinational firms, which contains a direct measure of firms' expectations, i.e., forecasts on future sales, and provide evidence that multinational firms learn about their idiosyncratic demand in the foreign markets over their life cycles and through previous exporting experience.

In particular, we construct a measure of "forecast error" in sales, which is defined as the percentage deviation of the forecasted sales from the realized sales. We then treat

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

the absolute forecast errors as measures of uncertainty and relate them to other variables such as affiliate age and parent firms' previous export experience in the same region. Two facts emerge from the empirical analysis. First, as multinational affiliates gain experience in the foreign market, their absolute forecast errors decline, which suggests that firms learn about their demand over their life cycle.[2] Second, multinational affiliates whose parent firms have previous exports (to the region where the affiliates are located) tend to have smaller initial absolute forecast errors, which indicates that exporting helps to reduce uncertainty faced by firms that conduct multinational production eventually. In terms of magnitude, we find that on average, firms' absolute forecast errors decline by about 18 log points over the life cycle. When an MNE has previous export experience (to the region where their affiliates are located), the initial forecast error is 13 to 15 log points smaller comparing to MNEs without export experience, accounting for a large fraction of the decline in uncertainty over the affiliates' life cycles. These facts provide independent validation of the literature that emphasizes self-discovery in shaping exporter and MNE dynamics.

To understand the quantitative importance of self-discovery, we then build and quantify a dynamic heterogeneous firm model featuring learning about uncertain demand, as well as joint dynamics of exporting and multinational production. We follow Arkolakis et al. (2017) to model how firms update their beliefs about demand. In the model, firms' demand shifters consist of a time-invariant component and a transitory shock. However, firms do not directly observe the time-invariant component and only knows its distribution before entering the market. After entry, firms observe the realized demand each period, which reveals the sum of the time-invariant demand and the transitory shock (noise). Firms update their beliefs about their time-invariant demand using the Bayes' rule. Naturally, firms' uncertainty about their time-invariant demand declines as they accumulate experience in the foreign market. Were firms' experience to approach infinity, uncertainty about the time-invariant demand would be fully resolved. On the other hand, since firms learn about their demand regardless of the mode of service, firms with previous export experience will have lower initial uncertainty than those without. Therefore, our dynamic

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

model is able to capture the two facts regarding the dynamics of affiliates' forecast errors in the data.

In terms of modelling the dynamic choice of service modes in the foreign market, we allow firms to choose between exporting and multinational production (MP). MP is likely to be associated with a higher sunk cost than exporting, but affords a lower variable cost. MP becomes attractive to firms when they expect the underlying demand to be high. Therefore, exporting can be used as a way to test the market, which might eventually leads to MP. Similar to the discussion in Conconi et al. (2016) and different from Gumpert et al. (2016), our model features a dynamic complementarity between trade and MP. Moreover, as our model is a full-fledged multi-period learning model, it can generate rich predictions on how trade and MP costs as well as demand uncertainty affect the dynamics of firms in the foreign markets.

We calibrate our model to moments regarding exporter and multinational dynamics as well as moments on affiliates' forecast errors. The calibrated model can qualitatively replicate the dynamics of forecast errors, average exporter sales growth and endogenous exits, which are not directly targeted in the calibration. We are particularly interested in how demand uncertainty affects trade and MP patterns. In the model, both the variance of the time-invariant demand and the variance of the temporary demand shock contribute to demand uncertainty. As we show in our counterfactual analysis, these two types of demand uncertainty have qualitatively different implications for trade and MP patterns. Broadly speaking, a higher variance of the time-invariant demand increases the signal-to-noise ratio therefore speeds up learning. It also induces firms to start exporting and increases the share of experienced multinational affiliates. In contrast, a higher variance of the temporary demand shock makes learning less effective, reduces entries into exporting and leads to more direct entries into FDI. To understand how demand uncertainty affects aggregate outcomes, it is crucial to distinguish between these two sources of uncertainty.

In another counterfactual experiment, we study whether the dynamic complementarity between trade and MP in this model may help to generate a negative correlation between distance and MP sales. We do this by varying the iceberg trade costs, which are usually believed to be positively correlated with distance. We find that after a decline in trade costs, total exports increase and total MP sales decline. Therefore, the calibrated model features a strong substitutability between trade and MP, and it does not produce a negative correlation between trade costs and affiliate sales, as proposed in Conconi et al. (2016). However, when we reduce the effectiveness of learning, we find that exports and MP sales are even more responsive to trade costs, which confirms that the learning mechanism generates some level of complementarity, though it cannot overcome the substitution effects and reverse the effect of trade costs on MP sales. To rationalize the negative correlation between distance and FDI as we observe in the data, other mechanisms such as intra-firm trade of intermediate inputs are needed (see, e.g., Irarrazabal et al. (2013)).

In macroeconomics, researchers have long been interested in the information structure of agents and its implications (see Aghion et al. (2003) for an evaluation of the related literature). Similar to our work, some empirical studies in this field use firm/consumer survey data or analyst forecasts to measure expectation directly (Guiso and Parigi (1999); Bachmann et al. (2013); Bachmann and Bayer (2014); Baker et al. (2016); Senga (2016)). However, most of these studies cannot link forecasts data to firm activity[3] or do not observe firms repeatedly over time. We are the first to use comprehensive panel data on both realized outcomes and firm forecasts to study this issue and thus able to examine how uncertainty changes over the firms' life cycles.

A related literature studies the impact of uncertainty on firm and aggregate outcomes. Early works by Abel (1983) and Bernanke (1983) reveal how uncertainty affects firms' investment behavior.[4] 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 multinational production (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 firm uncertainty can change with their activities and emphasize the importance of the learning mechanism. We also illustrate that different sources of uncertainty have different implications for the dynamic choices of trade and FDI.

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

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

[4]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.

in export value and decline in exit rates in the first few years of exporting.[5] Garetto et al. (2016) study the dynamics of U.S. multinational firms and find little growth for affiliates of U.S. multinational firms. Gumpert et al. (2016) study the joint dynamics of exporting and multinational production under an exogenous AR(1) productivity process, which is closely related to our paper. We complement their work by focusing on learning as a mechanism of reducing firm uncertainty, and examine the quantitative relevance of the dynamic complementarity between exporting and FDI due to the possibility of testing the market through exporting.

The remainder of the paper is organized as follows. In Section 2, we document new facts regarding firms' forecast errors. We develop the quantitative model of firm learning and dynamics of export and multinational production in Section 3. In Section 4, we calibrate the model and perform counterfactuals regarding trade costs and demand uncertainty. We conclude in Section 5. All tables and figures can be found in the appendix.

2 New Facts: Uncertainty Dynamics

In this section, we present new facts regarding multinational firms' uncertainty over their life cycles. We first introduce our data and show descriptive statistics on our measure of firm-level uncertainty. We then show how this uncertainty measure changes with affiliate age and how it correlates with parent firms' previous export experience in the region.

2.1 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 of Overseas Business Activities ("FDI survey" hereafter). The firm survey provides information about business activities of Japanese firms and covers all firms that employ more than 50 workers and have more than 30 million Japanese yen in total assets. 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

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

a region before an affiliate is established. It also allows us to calculate the transition probabilities between different modes of service, i.e., export or multinational production.

The FDI survey contains information about overseas subsidiaries of Japanese multinational enterprises (MNEs). It covers direct subsidiaries that the Japanese parent firms hold at least 10% of the equity, and second-generation affiliates in which the direct subsidiaries own at least 50% of the shares. Tracing the identification codes 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.[6] Similar to other surveys of multinational firms, this dataset contains information on affiliates' location, industry, sales, employment, investment, R&D, etc.

More importantly 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 of the firm. We calculate three measures of forecast errors. 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

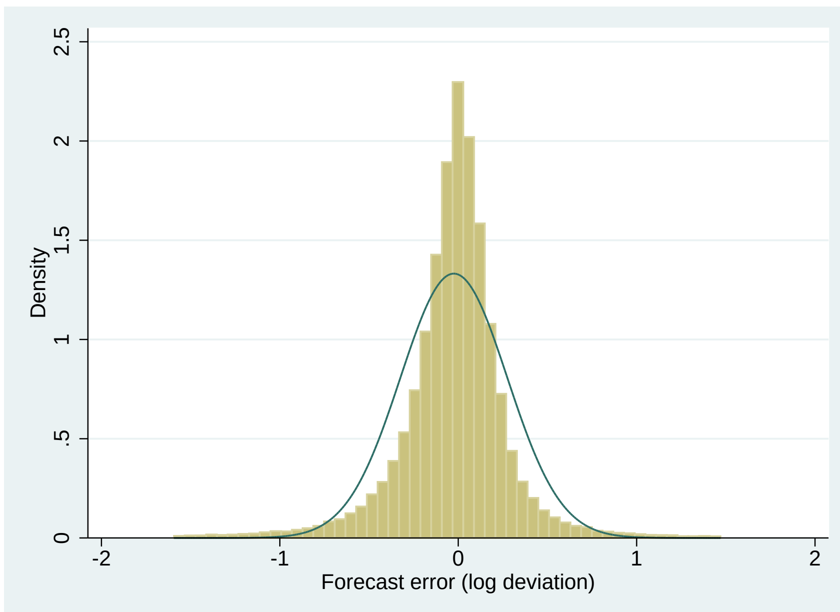
$$FE_t^{pct} = \frac{R_{t+1}}{E^S\left(R_{t+1}\right)} - 1.$$

Finally, since we focus on firms' uncertainty about idiosyncratic demand, we want to exclude systemic forecast errors 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 forecast errors. The fixed effects only account for about 11% of the variation, which suggests that micro-level uncertainty plays a large role in generating firms' forecast errors.

[6] 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 (for example, when examing 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 uncertainty.

In Figure 1, we plot the distribution of the first measure of forecast errors, $FE^{\log}$, across all affiliates in all years. The forecast errors 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.[7]

Figure 1: Distribution of forecast errors



Note: Histogram of FE^{log} with fitted normal density.

In Table 1, we report summary statistics regarding forecast errors. In the first two rows, we report the level of forecast errors, 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 these measures are very close to zero, suggesting that firms do not make systemic mistakes when making these forecasts. In the third and fourth rows, we report the summary statistics of the absolute forecast errors, which we see as measures of firms' uncertainty. On average, firms under- or over-estimate 20% of the

[7]By this assumption, the first measure of forecast errors has a log-normal distribution in our model. We focus on moments calculated using this measure, which simplifies our numerical implementation (see section 3.4).

sales. In the last row, we compute the residual forecast errors and examine their absolute values. Since the fixed effects do not account for a large fraction of the variation, the mean, standard deviation and median of the absolute residual forecast error are similar to those of $\left|FE^{\log}\right|$ and $|FE^{pct}|$.

Table 1: Summary statistics for forecast errors

	Obs.	mean	std. dev.	median
FE^{log}	132056	-0.024	0.300	-0.005
FE^{pct}	132562	0.017	0.333	-0.006
$\lvert FE^{log}\rvert$	132056	0.200	0.224	0.130
$\lvert FE^{pct}\rvert$	132562	0.204	0.264	0.131
$\lvert\hat{\epsilon}_{FE^{log}}\rvert$	131760	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.

In Table 2, we show that the absolute values of forecast errors are positively correlated with aggregate level risk or volatility. We obtain the Country Risk Index from the BMI research database. This index measures the overall risk of the economy, such as an economic crisis or a sudden change in the political environment.[8] After controlling for common trends at the industry-year level using fixed effects, we find the absolute forecast errors are positively correlated with country-level risk (columns 1 and 2). However, if the country risk indices capture well the fluctuations in the macro-economy or government policies, 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 residual forecast errors in column 3. The residual forecast errors, which represent firms' idiosyncratic uncertainty, are also positively correlated with country-level risk. Our interpretation is that macro-level and micro-level uncertainty may be closely related. For example, a government that frequently changes macroeconomic policies may also engage in policies targeting particular 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.

The empirical regularities described above reassure us that the absolute forecast errors

[8]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 2: 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**	1.081***	0.988**
				(0.405)	(0.377)	(0.431)
N	130601	131105	130342	130522	131026	130276
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	0.062			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.

contain useful information concerning firms' uncertainty. In the next two subsections, we examine how such uncertainty gets resolved over the firm's life cycle and how it is related to the parent firms' previous export experience.

2.2 Fact 1: Uncertainty declines over affiliates' life cycle

In this section, we discuss how affiliates' uncertainty regarding future sales changes over their life cycles. We measure uncertainty using the absolute value of the forecast errors. Table 3 shows the simple average of affiliates' $\left|FE^{\log}\right|$. As affiliates grow from age 1 to age 7, their forecast errors decline from 36% to 20%, which means they are better at predicting their future sales. 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 forecast error in year t

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

where δ_n is a vector of age dummies, δ_{ct} represents the country-year fixed effects and

Table 3: Average (s.e.) of absolute forecast errors by age

	1	2	3	4	5	6	7	8	9	10
$\|FE^{log}\|$	0.364	0.298	0.258	0.231	0.215	0.215	0.205	0.199	0.194	0.177
	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
$\|FE^{pct}\|$	0.367	0.299	0.260	0.231	0.220	0.217	0.207	0.202	0.201	0.181
	(0.008)	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
$\|\hat{\epsilon}_{FE^{log}}\|$	0.349	0.280	0.244	0.217	0.205	0.202	0.191	0.185	0.178	0.161
	(0.006)	(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.

δ_s represents the industry fixed effects. We also control for affiliate or parent size X_{it} in some regressions. We use age 1 as the base category, therefore the age fixed effects represent the difference in forecast errors between age n and age 1. To further control for heterogeneity in 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 4. Column 1 shows the baseline specification with industry and country-year fixed effects. We use affiliates at age 1 as the base category and group all affiliates of age 10 or above together. It is clear that as affiliates become older, absolute values of their forecast errors decline. On average, affiliates that are at least 10 years old have absolute forecast errors that are 17.6 log points lower. Most of the decline happens before age 5.

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 because 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 7 years. Endogenous exit may affect our estimates of the age effects for two reasons. First, affiliates with higher uncertainty may exit early because

Table 4: Age effects on the absolute forecast errors

	(1) All	(2) All	(3) All	(4) Survived 7 years
Age=2	-0.069	-0.065	-0.061	-0.069
	(0.007)	(0.007)	(0.008)	(0.011)
Age=3	-0.107	-0.093	-0.080	-0.087
	(0.007)	(0.008)	(0.008)	(0.011)
Age=4	-0.132	-0.116	-0.096	-0.098
	(0.007)	(0.008)	(0.008)	(0.011)
Age=5	-0.146	-0.125	-0.098	-0.114
	(0.007)	(0.007)	(0.008)	(0.011)
Age=6	-0.145	-0.124	-0.093	-0.115
	(0.007)	(0.007)	(0.009)	(0.012)
Age=7	-0.156	-0.132	-0.098	-0.127
	(0.007)	(0.007)	(0.009)	(0.011)
Age=8	-0.160	-0.134	-0.097	-0.123
	(0.007)	(0.008)	(0.009)	(0.012)
Age=9	-0.164	-0.138	-0.098	-0.120
	(0.007)	(0.007)	(0.009)	(0.013)
Age=10	-0.176	-0.139	-0.092	-0.121
	(0.007)	(0.007)	(0.009)	(0.012)
log(Parent Domestic Sales)		0.008	0.002	0.011
		(0.001)	(0.002)	(0.001)
log(Affiliate Sales)		-0.025	-0.058	-0.033
		(0.001)	(0.003)	(0.002)
N	131454	117419	111998	17157
R^2	0.097	0.128	0.382	0.148
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.

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 remaining in the foreign market (Bloom (2009)). Second, the forecast errors are censored because we do not observe the realized sales for affiliates that exit before the end of the fiscal year. To partially address these concerns, we focus on a subsample of affiliates that had survived for at least 7 years. The decline in uncertainty over the firm's life cycle is only slightly smaller than column 2, indicating that the forces discussed above might be small in the data.

2.3 Fact 2: Learning about the market through exporting

In this section, we show that for affiliates that enter the destination country for the first time, they start with lower uncertainty if their parent firms have previous export experience to the region. The reduction in uncertainty is economically significant compared to the average uncertainty across entrant affiliates and to the evolution of affiliates' uncertainty over time that we describe in the previous section.

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 since affiliates in these industries may sell the same product as what the parent firm had previously exported. As a result, previous export experience may help to reduce demand uncertainty for these affiliates as well. We obtain information on parent firms' previous export experience using the firm survey data, which is at the region level.[9] Using export information at the region level introduces additional measurement error into our proxy for export experience and can lead to attenuation bias in our regressions. One can see the estimates as a lower bound of the reduction in firm-level uncertainty through previous export.

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

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

years and then starts exporting. 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 multinational affiliates (Deseatnicov and Kucheryavyy (2017)), our sample has fewer observations (see Table 5). The main reason is that we only include first-time entrants that report sales at age 2 and project sales at age 1. However, we obtain very similar patterns regarding exporting and affiliate entry. The majority (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.[10]

Table 5: Years of exporting experience before affiliate entry

	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 6, we provide evidence that previous export experience reduces the initial uncertainty of affiliates that enter a country for the first time. We calculate the affiliates'

[10]The share of Japanese affiliates with previous exporting 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).

absolute forecast errors at age 1 (log deviation of the realized sales at age 2 from the projected sales at age 1) and regress this measure on various measures of previous export experience, controlling for industry fixed effects and country-year fixed effects. In column 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 equal one if and only if export experience is positive. These regressions show that having previous export experience reduces absolute forecast errors by 13 to 16 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 forecast error by 1.3 log points.

Table 6: Forecast error and previous exporting

	(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. Dependent variable is affiliates' initial forecast error, which is calculated as the absolute log deviation of the realized sales at age = 2 from the projected sales (predicted by an affiliate at age = 1). We only include affiliates that are first-time entrants into a particular host country. Exporting experience (Exp Expe.) is defined at the continent level for each parent firm. Each column head indicates the different measure of exporting experience used in the regression.

Table 7 presents the same pattern 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.

The relationship between previous export experience and forecast errors at age 1 is robust to controlling for firm size. As we discussed in the previous section, bigger firms

Table 7: Forecast error and previous exporting (first entrants into continents)

	(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. Dependent variable is affiliates' initial forecast error, which is calculated as the absolute log deviation of the realized sales at age = 2 from the projected sales (predicted by an affiliate at age = 1). We only include affiliates that are first-time entrants into a particular continent. Exporting experience (Exp Expe.) is defined at the continent level for each parent firm.

may have smaller uncertainty. Firm size may be also correlated with previous export experience of first-time entrants. Therefore, we control for parent firm employment (or sales) and affiliate employment (or sales) in Table 8. Previous export experience still has a significantly negative impact on the initial uncertainty, and the magnitude of the effect does not vary much. Consistent with the evidence in Table 4, parent firm size is not strongly correlated with affiliate uncertainty while affiliate size is negatively associated with its uncertainty.

Our final robustness checks are related to the type of FDI and exports measured in our data. Learning about uncertain foreign demand through exports is more relevant for horizontal than vertical FDI. In columns 1-3 of Table 9, we try to exclude possible vertical FDI affiliates by restricting our sample to affiliates that never export more than 1/3 of their 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. The estimated effects are less significant than other specifications, but the magnitude remains stable.

Taking all the evidence together, we show that previous export experience is associated with lower initial uncertainty for first-time affiliates in the host countries. This suggests that testing the market and learning about the foreign demand can provide a motive for

Table 8: Forecast error and previous exporting - control firm size

	(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. Dependent variable is the absolute log deviation of the realized sales at age = 2 from the projected sales (predicted by an affiliate at age = 1). We only include affiliates that are first-time entrants into a particular continent. Exporting experience (Exp Expe.) is defined at the continent level for each parent firm.

Table 9: Forecast error and previous exporting - exclude vertical FDI and affiliated export

	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

a Standard errors are clustered at parent firm level, * 0.10 ** 0.05 *** 0.01. Dependent variable is the absolute log deviation of the realized sales at age = 2 from the projected sales (predicted by an affiliate at age = 1). We only include affiliates that are first-time entrants into a particular continent. Exporting experience (Exp Expe.) is defined at the continent level for each parent firm.

b 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.

firms to export to a particular market before FDI. To understand how important such motive is, we turn to quantitative analysis.

3 A model of firm learning and mode choice

In this section, we propose a dynamic industry equilibrium model with heterogenous firms to capture firm learning about uncertain demand over their life cycle. The key channel we emphasize is that longer experience in a market reduces demand uncertainty faced by exporters and multinational affiliates. At the same time, since firms are endogenously choosing their mode of service (export v.s. FDI), and export features smaller sunk costs than FDI, export serves as an economical way to test the market before firms set up their production abroad. Compared to new foreign affiliates without export experience, those with export experience have smaller initial uncertainty, which is consistent with what we observe in the data.

We follow Jovanovic (1982) and Arkolakis et al. (2017) to model how firms learn about their underlying demand. In addition, firms that enter into the foreign market can choose to pay sunk costs to become exporters or multinational affiliates. The spirit of our model is the closest to the two-period model in Conconi et al. (2016). We move beyond the two-period model to allow for infinite horizons. This helps to fully characterize the dynamics of export and FDI as well as firms' forecast errors over their life cycles.

We consider an dynamic industry equilibrium model where each Japanese firm produces a different variety and has to decide whether to serve a foreign country (the rest of the world) through exporting or FDI. We abstract from domestic sales and only focus on foreign sales. The total foreign consumer expenditure on all goods is exogenous, which can be justified if Japanese firms' activities do not affect the total income in the foreign country and Japanese goods account for a small share of consumption so that their prices do not affect the aggregate price index of all goods from all countries. Production uses labor as the only input. We assume the Japanese affiliates in host countries employ only a small fraction of the labor force therefore cannot affect the wage there. We also abstract from domestic general equilibrium effects and assume that the domestic wage is exogenous.

In the foreign country, representative consumers have the following nested-CES preferences where the first nest is among composite goods produced by firms from different countries 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. Denote foreign consumer total expenditure as Y_t, we can express the demand for a particular Japanese variety as

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

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.

With an abuse of notation, we combine the terms that are exogenous in expression (2), $Y_t \tilde{P}_t^{\delta-1} \chi_{jp}$ 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 preferences over different varieties of Japanese goods imply the ideal price index

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

For each firm, the demand uncertainty comes from the demand shifter $a_t(\omega)$. We assume that $a_t(\omega)$ is the sum of a time-invariant component $\theta(\omega)$ and a transitory shock $\epsilon_t(\omega)$:

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

Firms do not directly observe their underlying demand $\theta(\omega)$. They understand that it is drawn from a normal distribution $N\left(\bar{\theta}, \sigma_\theta^2\right)$. As they observe signals $a_t(\omega)$ over time, they will update their beliefs and become better at inferring $\theta(\omega)$.

Every period there is an exogenous mass of entrants J. Each entrant draws a time-invariant productivity φ from a log-Normal distribution $N\left(\mu_\varphi, \sigma_\varphi^2\right)$ and a time-invariant demand shifter θ from $N\left(\bar{\theta}, \sigma_\theta^2\right)$. Entrants know their productivities, but do not know the level of their demand.[11] Based on φ, they have to decide whether to enter the foreign market. An entrant can either serve the foreign market via exporting, which involves a sunk cost f_x^e, or serve the foreign market by setting up an affiliate with an entry cost f_m^e. Both sunk costs are paid in units of domestic labor. If neither mode appears to be profitable, the entrant simply exits and obtains zero payoff.

Incumbents do not know the exact value of θ, but they have more information based

[11] We attribute the known component of firm heterogeneity to productivities. This assumption is not essential. In principle, we can allow a known heterogenous component in firm demand, and assume no heterogeneity in productivities.

on past realizations of demand and have different belief about θ than the entrants. In each period, they first receive an exogenous death shock with probability η. For surviving firms, they need to decide whether they want to change their mode of service. They can either keep their mode of service in the previous period, switch to another mode of service, or permanently exit the market. We assume that for exporters, they have to pay f_x^e to enter FDI but for incumbent MNEs they can switch to exporting without paying the export sunk cost f_x^e. Firms also have to pay a fixed cost each period to remain exporting (with a fixed cost f_x) or FDI (with a fixed cost f_m), which induce endogenous exits.

For firms that serve the foreign market, they decide how much to produce before a_t is realized, based on their belief about the underlying demand θ. After a_t is realized, they choose price p_t to sell all that have been produced, since there is no storage technology and firms cannot accumulate inventories. They update their beliefs about θ according to the Bayes' rule, which we discuss next.

Belief Updating

For a firm at the beginning of age $n+1$ ($n = 0, 1, 2, \ldots$), it has observed n signals before. Since both the prior distribution of θ and the distribution of the noise ϵ are normal, the Bayes' rule implies the posterior belief about θ after observing n signals is also normal with mean μ_n and variance σ_n^2, where

$$\mu_n = \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + n\sigma_\theta^2}\bar{\theta} + \frac{n\sigma_\theta^2}{\sigma_\epsilon^2 + n\sigma_\theta^2}\bar{a}_n, \tag{4}$$

and

$$\sigma_n^2 = \frac{\sigma_\epsilon^2 \sigma_\theta^2}{\sigma_\epsilon^2 + n\sigma_\theta^2}. \tag{5}$$

The history of signals $(a_1, a_2, \ldots, a_n)$ is summarized by age n and the average

$$\bar{a}_n \equiv \frac{1}{n}\sum_{i=1}^{n} a_i \text{ for } n \geq 1; \bar{a}_0 \equiv 0.$$

Therefore, the firm believes that the demand shock at each age, $a_n = \theta + \epsilon$, has a normal distribution with mean μ_n and variance $\sigma_n^2 + \sigma_\varepsilon^2$. For a firm of age n with previous history $\bar{a}_{n-1}$, $(\bar{a}_{n-1}, n)$ summarizes all pertinent information about the firm's belief about the underlying value of θ.

3.1 Per-period Profit and Static Optimization

We describe the firm's problem in the context of the steady-state equilibrium. All aggregate variables such as wages, the price index and expenditures on Japanese goods are constant, therefore 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 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

$$q_t = \varphi l_t,$$

and price depends on the realized demand a_t as in equation (2).

The MNE chooses optimal quantity q_t to maximize expected per-period profit $E_{a_n|\bar{a}_{n-1},n}\left(\pi_{m,t}\right)$. The first order condition for quantity yields

$$q_{m,t} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{\varphi b\left(\bar{a}_{n-1}, n-1\right)}{w^*}\right)^{\sigma}\frac{Y}{P^{\delta-\sigma}}, \tag{6}$$

where

$$\begin{aligned} b\left(\bar{a}_{n-1}, n-1\right) &= E_{a_n|\bar{a}_{n-1},n-1}\left(e^{a_n/\sigma}\right) \\ &= \exp\left\{\frac{\mu_{n-1}}{\sigma} + \frac{1}{2}\left(\frac{\sigma_{n-1}^2+\sigma_{\epsilon}^2}{\sigma^2}\right)\right\}. \end{aligned} \tag{7}$$

The price charged by a multinational affiliate can be re-written as

$$p_{m,t}\left(a_t\right) = \frac{\sigma}{\sigma-1}e^{a_t/\sigma}\frac{w^*}{\varphi b\left(\bar{a}_{n-1}, n-1\right)}. \tag{8}$$

The resulting expected per-period profit is

$$E\pi_{m,t} = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}}\frac{b\left(\bar{a}_{n-1}, n-1\right)^{\sigma}}{\left(w^*/\varphi\right)^{\sigma-1}}\frac{Y}{P^{\delta-\sigma}} - w f_m. \tag{9}$$

Similarly, for exporters, we can derive the quantity they produce

$$q_{x,t}=\left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{\varphi b\left(\bar{a}_{n-1},n-1\right)}{\tau w}\right)^{\sigma}\frac{Y}{P^{\delta-\sigma}}, \tag{10}$$

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

$$p_{x,t}\left(a_t\right)=\frac{\sigma}{\sigma-1}e^{a_t/\sigma}\frac{\tau w}{\varphi b\left(\bar{a}_{n-1},n-1\right)}. \tag{11}$$

The resulting expected per-period profit is

$$E\pi_{x,t}=\frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}}\frac{b\left(\bar{a}_{n-1},n-1\right)^{\sigma}}{(\tau w/\varphi)^{\sigma-1}}\frac{Y}{P^{\delta-\sigma}}-wf_x. \tag{12}$$

3.2 Dynamic choice of the mode of service

In each period, an entrant or incumbent can choose among three different modes: exit, export (denoted as x) or FDI (denoted as m). We assume that exiting firms can never come back. To become an exporter or MNE, a firm must pay a sunk cost. This creates inertia in the firm's mode of service. A firm's state variables include its mode of service in the previous period o, its current age n, the history of shocks $\bar{a}_{n-1}$, and its productivity φ. 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 a multinational firm or exit next period. If it wants to be a multinational, it has to pay a sunk cost f_m^e in units of domestic labor. Therefore, the value function right before choosing the mode of service in period n is given by

$$V\left(x,\varphi,n,\bar{a}_{n-1}\right)=\max_{o'\in\{x,m,exit\}}E\left\{\begin{array}{c}E\pi_{x,t}+\beta(1-\eta)V\left(x,\varphi,n+1,\bar{a}_n\right),\\ E\pi_{m,t}-wf_m^e+\beta(1-\eta)V\left(m,\varphi,n+1,\bar{a}_n\right),V_{exit}\end{array}\right\}, \tag{13}$$

and we denote the optimal choice of mode this period for an incumbent exporter

$$o'\left(x,\varphi,n,\bar{a}_{n-1}\right)=\arg\max_{o'\in\{x,m,exit\}}E\left\{\begin{array}{c}E\pi_{x,t}+\beta(1-\eta)V\left(x,\varphi,n+1,\bar{a}_n\right),\\E\pi_{m,t}-wf_m^e+\beta(1-\eta)V\left(m,\varphi,n+1,\bar{a}_n\right),V_{exit}\end{array}\right\}. \tag{14}$$

The value of exiting, V_{exit}, is normalized to zero. All expectations in equations (13) and (14) are calculated using firms' subjective belief about the distribution of the demand shock a_n in the current period.

Since a multinational affiliate does not need to pay a sunk cost if it decides to switch to exporting, the value of being an incumbent multinational firm right before it chooses the mode of service in period n is

$$V\left(m,\varphi,n,\bar{a}_{n-1}\right)=\max_{o'\in\{x,m,exit\}}E\left\{\begin{array}{c}E\pi_{x,t}+\beta(1-\eta)V\left(x,\varphi,n+1,\bar{a}_n\right),\\E\pi_{m,t}+\beta(1-\eta)V\left(m,\varphi,n+1,\bar{a}_n\right),V_{exit}\end{array}\right\}. \tag{15}$$

We denote the optimal choice of mode this period for an incumbent MNE

$$o'\left(m,\varphi,n,\bar{a}_{n-1}\right)=\arg\max_{o'\in\{x,m,exit\}}E\left\{\begin{array}{c}E\pi_{x,t}+\beta(1-\eta)V\left(x,\varphi,n+1,\bar{a}_n\right),\\E\pi_{m,t}+\beta(1-\eta)V\left(m,\varphi,n+1,\bar{a}_n\right),V_{exit}\end{array}\right\}. \tag{16}$$

For an entrant, it simply chooses the mode that brings the highest value

$$o'\left(ent,\varphi,1,a_0\right)=\arg\max_{o'\in\{x,m,exit\}}\left\{\begin{array}{c}V\left(x,\varphi,1,a_0\right)-wf_x^e\\V\left(m,\varphi,1,a_0\right)-wf_m^e,V_{exit}\end{array}\right\}. \tag{17}$$

3.3 Steady-state recursive competitive equilibrium

A steady-state equilibrium of the model is a set of

1. value functions $V\left(o,\varphi,n,a_{n-1}\right),o\in\{x,m\}$ that satisfy equations (13) and (15);
2. policy functions of mode choices $o'\left(o,\varphi,n,\bar{a}_{n-1}\right)$ ($o\in\{x,m,ent\}$ if $n=1$ while $o\in\{x,m\}$ if $n\geq 2$) that satisfy equations (14), (16) and (17);
3. policy functions of optimal quantities $q_o,o\in\{m,x\}$ that satisfy equations (6) and (10);

4. prices given the demand shock in the current period (age $= n$) $p_o(a_n), o \in \{m, x\}$ that satisfy equations (8) and (11);

5. a measure function of firms $\lambda(o, \varphi, n, \bar{a}_n, \theta), o \in \{x, m, ent\}$ that is consistent with the aggregate law of motion. In particular

   (a) the exogenous mass J of entrants each period draw θ and φ from log-normal distributions $G_\theta(\cdot)$ and $G_\varphi(\cdot)$, respectively. Therefore, the measure of entrants with state variables (θ, φ) is

$$\lambda(ent, \varphi, 1, \bar{a}_0, \theta) = J g_\varphi(\varphi) g_\theta(\theta),$$

   where $g_\varphi(\cdot)$ and $g_\theta(\cdot)$ are the density functions of log normal distributions. The cumulative demand shock $\bar{a}_0$ for entrants is defined to be zero.

   (b) the measure functions of the exporters and MNEs must be fixed points of the law of motion. Given any Borel set of $\bar{a}_n$, Δ, the measure of firms with service mode $o' \in \{x, m\}$ at the beginning of period $n+1$ satisfies

$$\lambda(o', \varphi, n+1, \Delta, \theta) = \sum_{o \in \{x,m,ent\}} \int \begin{array}{c} \mathbf{1}(\bar{a}_n \in \Delta, o'(o, \varphi, n, \bar{a}_{n-1}) = o') \\ \times (1-\eta) \Pr(\bar{a}_n | \bar{a}_{n-1}, \theta) \lambda(o, \varphi, n, d\bar{a}_{n-1}, \theta) \end{array}.$$

   Note that at the beginning of period $n = 1$, all firms' modes of service are defined to be entrants. Therefore, there are no exporters or MNEs at age $n = 1$, i.e., $\lambda(o, \varphi, 1, a_0, \theta) = 0$ for $o \in \{x, m\}$. In contrast, at the beginning of later periods ($n \geq 2$), all incumbents' modes of service are either exporters or MNEs. Thus, there are no entrants at $n \geq 2$, i.e., $\lambda(o, f_m^e, n, \bar{a}_{n-1}, \theta) = 0$ for $o = ent$ and $n \geq 2$.

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

$$P^{1-\sigma} = \sum_{n \geq 1} \sum_{\substack{o' \in \{x,m\} \\ o \in \{x,m,ent\}}} \int \begin{array}{c} e^{a_n} p_{o'}(a_n, q_{o'}(b(\bar{a}_{n-1}, n-1)))^{1-\sigma} \mathbf{1}(o'(o, \varphi, n, \bar{a}_{n-1}) = o') \\ \times (1-\eta) \times \lambda(o, d\varphi, n, d\bar{a}_{n-1}, d\theta) \, d\Pr(a_n | \theta) \end{array}.$$

Given each guess of P, we can solve for the value functions and policy functions, as well as the firm measure function λ. We iterate over the value of P until it is the same as the price index implied by the above expression.

3.4 Implications for forecast errors

In our model, firms cannot perfectly foresee their future sales for two reasons. First, they do not know the exact value of θ and gradually learn about it. Second, they receive a transitory demand shock ϵ each period. The uncertainty caused by θ can be resolved by learning, but the uncertainty caused by the transitory shock cannot. We briefly discuss the properties of the forecast errors in this section.

Given the model structure, we can use the model and calculate any of the three forecast error measures used in our empirical work. For example, the log deviation of realized sales from expected sales is

$$FE_{t-1}^{\log} = \log\left(\frac{p_t q_t}{E_{a_n|\bar{a}_{n-1},n-1}\left(p_t q_t\right)}\right).$$

For a typical firm at the end of period $t-1$, its state variables include its age $n-1$, the average demand shifter in the past $\bar{a}_{n-1}$, FDI entry cost f_m^e and the mode of service last period, o_{t-1}. Based on these variables, firms decide which mode to enter this period o_t and how much to produce q_t. There is no uncertainty associated with the operating mode and quantity. The only source of uncertainty is the demand shock a_n, which affects firms' prices p_t. Therefore, the forecast error can be rewritten as

$$\begin{aligned} FE_{n-1}^{\log} &= \log\left(p_t / E_{a_n|\bar{a}_{n-1},n-1}\left(p_t\right)\right) \\ &= \log\left(e^{a_n/\sigma} / E_{a_n|\bar{a}_{n-1},n-1}\left(e^{a_n/\sigma}\right)\right) \\ &= \frac{a_n - \mu_{n-1}}{\sigma} - \frac{\sigma_{n-1}^2 + \sigma_\epsilon^2}{2\sigma^2}. \end{aligned} \tag{18}$$

According to the firm's belief, a_n is distributed as $N\left(\mu_{n-1}, \sigma_{n-1}^2 + \sigma_\epsilon^2\right)$. Thus, $FE_{t-1}^{\log}$ has a normal distribution with mean $-\left(\sigma_{n-1}^2 + \sigma_\epsilon^2\right)/2\sigma^2$ and variance $\left(\sigma_{n-1}^2 + \sigma_\epsilon^2\right)/\sigma^2$ (denoted as σ_{FE}^2). Taking the expectation of $\left|FE_{t-1}^{\log}\right|$ using the subjective belief, we have[12]

[12]Here we have applied the formula for the expectation of a folded normal distribution. If a random

$$E^S \left| FE^{\log}_{n-1} \right| = \sqrt{\frac{2\sigma^2_{FE}}{\pi}} \exp\left(-\sigma^2_{FE}/8\right) + \frac{1}{2}\sigma^2_{FE}\left(1 - 2\Phi\left(-\frac{\sigma_{FE}}{2}\right)\right), \tag{19}$$

where Φ is the cumulative density function of the standard normal distribution. We can prove that the "average" absolute forecast error defined in this way declines as firms become more experienced in the destination market.

Proposition 1 $E^S \left| FE^{\log}_{t-1} \right|$ *declines with years of experience* n*.*

Proof. Taking the derivative of $E^S \left| FE^{\log}_{n-1} \right|$ with respective to σ_{FE}, we have

$$\frac{\partial E^S \left| FE^{\log}_{n-1} \right|}{\partial \sigma_{FE}} = \sqrt{\frac{2}{\pi}}\left(1 - \frac{\sigma^2_{FE}}{4}\right) e^{-\sigma^2_{FE}/8} + \sigma_{FE}\left(1 - 2\Phi\left(-\frac{\sigma_{FE}}{2}\right)\right) + \frac{\sigma^2_{FE}}{2}\phi\left(-\frac{\sigma_{FE}}{2}\right),$$

where ϕ is the density function of the normal distribution. Substituting $\phi\left(-\sigma_{FE}/2\right)$ with its analytical expression, one can show

$$\frac{\partial E^S \left| FE^{\log}_{n-1} \right|}{\partial \sigma_{FE}} = \sqrt{\frac{2}{\pi}} e^{-\sigma^2_{FE}/8} + \sigma_{FE}\left(1 - 2\Phi\left(-\frac{\sigma_{FE}}{2}\right)\right),$$

which is positive. Therefore, $E^S \left| FE^{\log}_{n-1} \right|$ increases with σ_{FE}. We also know that σ^2_{n-1} decreases with n from equation (5), thus σ_{FE} and $E^S \left| FE^{\log}_{n-1} \right|$ decline with firm experience n. ■

However, this definition of "average" absolute forecast error does not exactly correspond to what we observe in the data. This is because there is equilibrium selection based on the underlying demand θ. To calculate any moments about $FE^{\log}$, we start from the expression (18) and take weighted average over the joint distribution of $(o, \varphi, n, \bar{a}_{n-1}, \theta)$ in the steady-state equilibrium.

There is one moment of $FE^{\log}$ which we can easily compute without explicitly integrating over the joint distribution of firms' state variables. Following equation (18), we

variable Z is distributed as $N\left(\mu, \sigma^2\right)$, then

$$E\left(|Z|\right) = \sigma\sqrt{\frac{2}{\pi}} e^{-\mu^2/2\sigma^2} + \mu\left(1 - 2\Phi\left(\frac{-\mu}{\sigma}\right)\right).$$

can obtain the variance of the forecast error

$$Var\left(FE_{n-1}^{\log}\right) = Var\left(\frac{\theta - \mu_{n-1} + \varepsilon}{\sigma}\right) \tag{20}$$
$$= Var\left(\frac{\theta - \mu_{n-1}}{\sigma}\right) + \frac{\sigma_\epsilon^2}{\sigma^2}.$$

As n approaches infinity, firms perfectly recover their underlying demand θ, therefore the first term in the above expression converges to zero. We use this relationship to pin down σ_ϵ in our calibration without solving the equilibrium of the model.

4 Calibration and Counterfactuals

In this section, we describe the procedure for calibrating the dynamic model. The calibrated model is able to capture the decline in absolute values of forecast errors over affiliates' life cycles, as well as the smaller absolute forecast errors for affiliates with export experience. It is also able to capture other salient features of the data, such as growth in exporter sales and decline in exit rates over their life cycles. After we calibrate the model, we consider two set of counterfactual experiments with respect to demand uncertainty and trade costs.

4.1 Calibration

We first normalize a set of model primitives due to the partial equilibrium nature of our 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 demand shifter, μ_θ, is normalized to zero. We also normalize the entry costs into exporting, f_x^e, to zero. The entry costs into exporting are usually pinned down by the share of exporters relative to domestic firms. However, since we do not explicitly model domestic firms, we decide to normalize the entry costs into exporting, and interpret the entry costs into FDI, f_m^e, as the entry costs of FDI relative to exporting.

Next, we calibrate a set of parameters without solving our model, as listed in Table 10. We choose 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 cycles, even for affiliates without exporting experience. 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%). We follow Ghironi and Melitz (2005) and set the iceberg trade cost, τ, to 1.3. Finally, we calibrate σ_ϵ so that the variance of forecast errors of affiliates that are at least 10 years old matches the variance predicted by expression (20) when $n \to \infty$. In the data, the variance of forecast errors for affiliates that are at least 10 years old is 0.07, which implies $\sigma_\epsilon = 1.05$.

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 affilates' exit rate over their life cycles
τ	Iceberg trade costs	1.3	Ghironi and Melitz (2005)
σ_ϵ	Standard deviation of the transitory demand shock	1.05	Variance of forecast errors for affiliates that are at least 10 years old

The remaining four parameters are jointly calibrated by matching four moments. These parameters are: the export per-period fixed cost f_x, the FDI entry cost f_m^e, the standard deviation of log productivity σ_φ, and the standard deviation of the log of the demand shifter σ_θ. The four moments are the average exit rate of exporters, the fraction of exporters among active firms, the share of exports in total sales and the fraction of experienced affiliates at age 1.

In Table 11, we list the moments in an order such that, loosely speaking, each moment helps to identify the corresponding parameter. A higher export per-period fixed cost raises the exporter exit rate, while a higher FDI entry cost increases the fraction of exporters

Table 11: Parameters calibrated by solving the model and matching moments

Parameters	Value	Description	Moments	Data	Model
f_x	0.05	export fixed cost	average exit rate of exporters	0.10	0.09
f_m^e	2.73	FDI entry cost	fraction of exporters among active firms	0.70	0.66
σ_φ	0.45	std. dev. of log productivity	share of exports in total sales of Japanese goods abroad	0.21	0.21
σ_θ	0.77	std. dev. of demand shifter	fraction of experienced MNEs at age 1	0.73	0.73

among all firms selling in the foreign market. A larger dispersion in firm productivity as well as demand would increase affiliates' sales relative to exports, because the largest firms choose to become MNEs. Finally, if there is more demand uncertainty before firms enter the foreign market, more firms would be willing to test the market through exporting and the fraction of experienced affiliates would be higher. As seen in Table 11, most of the moments predicted by the calibrated model are close to what we observe in the data, with the exception of the fraction of exporters, which is slightly lower than that in the data.

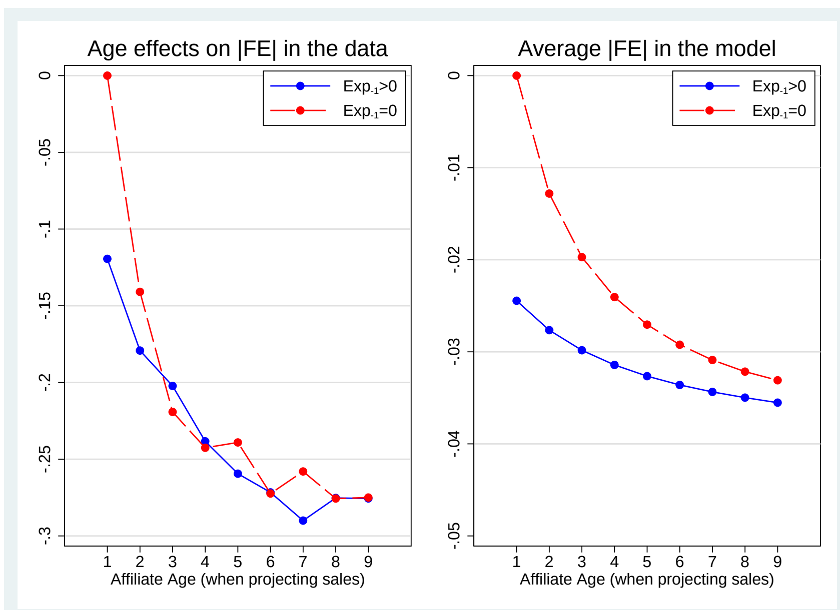
4.2 Untargeted Moments

We now turn to untargeted moments of the calibrated model. We first examine the dynamics of forecast errors for affiliates with and without exporting 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 exporting 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 exporting experience. However, the model predicts a much smaller decline as well as a much smaller difference between experienced MNEs and non-experienced MNEs. For example, in the model, average $\left|FE^{\log}\right|$ of non-experienced MNEs declines from 0.25 to 0.22 over their life cycles, while the corresponding number declines from 0.48 to 0.20 in the data. Note that in our calibration, we choose a value of σ_ϵ that matches the standard deviation of $FE^{\log}$ for affiliates that are at least 10 years old. Therefore, we are able to match the average $\left|FE^{\log}\right|$ when affiliates are old. The calibrated value of σ_θ, however, is too small to generate a large initial average $\left|FE^{\log}\right|$. Our calibrated parameters therefore provide conservative estimates of the demand uncertainty. In section 4.3.1, we change σ_θ to higher values and examine their impact on the dynamics of trade and multinational production.

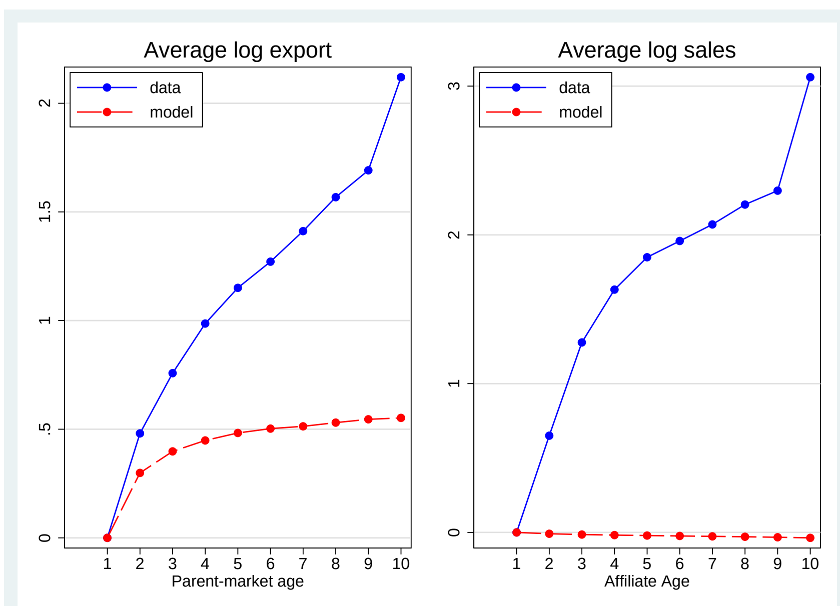
Figure 2: Forecast error - age profile: data v.s. model



Note: The left panel shows the estimated age effects on average $|FE^{log}|$ for affiliates, while the right panel shows the average $|FE^{log}|$ by affiliate age in the model. To calculate the average $|FE^{log}|$ at age n in the model, we adjust the partial-year effects by averaging the forecast error of affiliates at age n-1 and age n, since some affiliates have not finished their period at the end of the fiscal year. he blue solid line shows the estimated age effects for affiliates whose parent firms have previous exporting experience, i.e., $Exp_{-1} > 0$, while the red dashed line shows the estimated age effects for affiliates without previous exporting experience, i.e., $Exp_{-1} = 0$. The age effect of the affiliates without previous exporting experience is normalized to zero.

Dynamics of Sales In Figure 3, we compare the growth in firm sales in the model and in the data. In the left panel, we plot the average log of sales by exporter age (red dashed line) predicted by the model and the estimated age effects on log sales from our data (blue solid line). Both in the model and in the data, exporters experience persistent growth. However, the model falls short of predicting the magnitude of growth over exporters' life cycles. The growth of average firm size is a result of demand uncertainty and selection on θ in our model. This force becomes smaller as exporters becomes more informed about their underlying demand. 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 affiliates' exits to match the flat exit rate profiles over their life cycles. With only the learning mechanism, firms may receive either better or worse signals than their time-invariant demand, which, on average, does not generate growth. Given that the model falls short of predicting the growth for both the exporters and multinational affiliates, other mechanisms, such as the accumulation of customer capital, is needed to match the dynamics of sales. (see, for example, Fitzgerald et al. (2016))

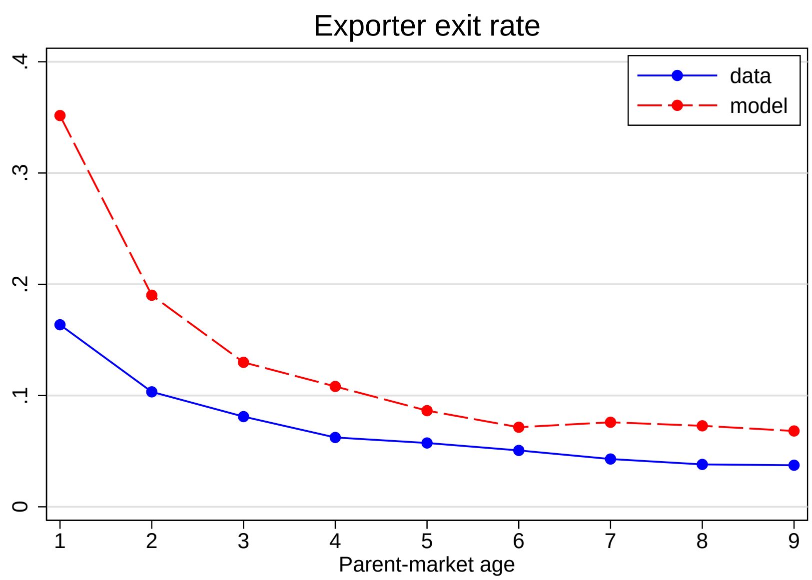
Figure 3: Sales-age profile: data v.s. model



Note: The left panel compares the average log of sales by affiliate age in the model and in the data, and the right panel compares the average log of exports by exporter age. The blue solid line represents the estimated age effects on log(sales) or log(exports) in the data, while the red dashed line represents the average log of sales or exports by age in the model.

Dynamics of Exit Figure 4 compares the exporter exit rates by their experience in the foreign market. Consistent with the data, the model predicts a decline in exit rates for older cohorts of exporters. In the model, the exporter exit rates decline from 35% to 7% 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, even though the model is able to match the average exporter exit rates in the data. This occurs because, in the model, the distribution of exporters is more skewed towards old firms 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 export in the data, while the red dashed line represents the average exit rate of exporters by age in the model.

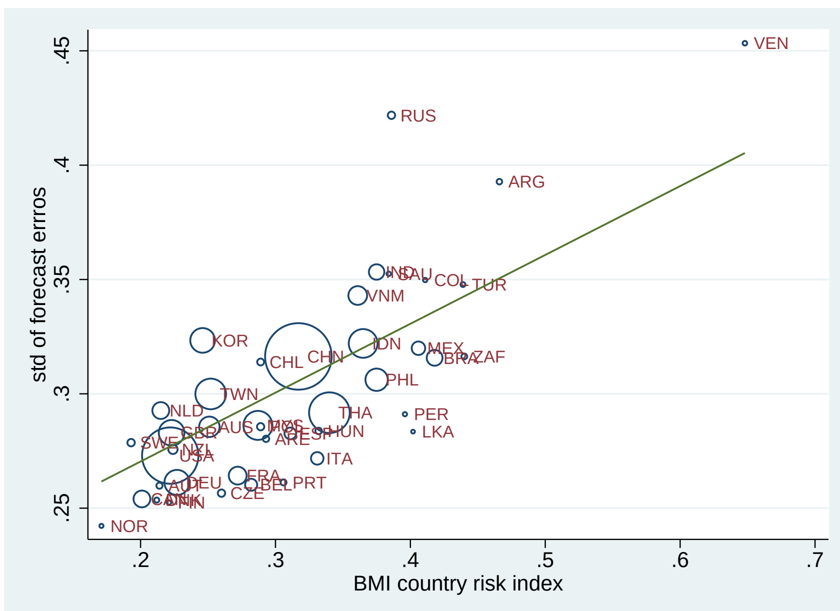
4.3 Counterfactuals

In this section, we use the calibrated model to perform counterfactual analysis. The first set of counterfactuals illustrate how demand uncertainty, captured by the dispersion of idiosyncratic demand σ_θ and σ_ϵ, affects trade and multinational production patterns. We then consider changes in trade costs, and examine whether the "dynamic complementarity" between trade and FDI in this model can help to rationalize the negative correlation between distance and FDI in the data.

4.3.1 Changes in demand uncertainty

We motivate our counterfactual analysis with respect to σ_θ and σ_ϵ by documenting the variation in demand uncertainty across countries. In Figure 5, we plot the standard deviation of the forecast errors against each host country's BMI risk index. It is clear that the level of uncertainty is positively correlated with country risk. In a country with high uncertainty such as Russia, Japanese affiliates' absolute forecast errors are about 15 percentage points higher than those of affiliates in a country with low uncertainty such as the United States.

Figure 5: Forecast errors and Country Risk



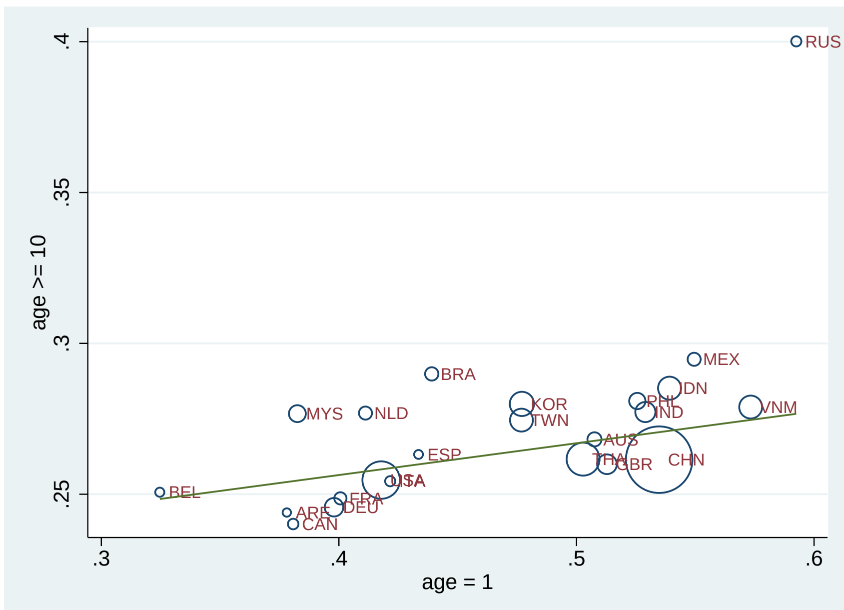
Note: We plot the standard deviation of the affiliates' forecast errors FE^{log} against the BMI country risk index of the host country. country fixed effects against the BMI country risk index. The size of the marker is proportional to number of observations in each host country. Only host countries with at least 100 affiliates are included. The line represents the fitted value of a linear regression of the standard deviation on the country risk index, weighted by the number of affiliates in the host countries.

We want to examine the effect of demand uncertainty on patterns of trade and FDI using the calibrated model. In the model, the demand uncertainty is governed by two components, the dispersion of the time-invariant demand, σ_θ, and the dispersion of the transitory shock, σ_ϵ. The latter determines the forecast errors when firms are experienced enough, while both contribute to the initial uncertainty firms face when entering the markets. Figure 6 shows the relationship between the standard deviation of forecast errors for affiliates at age 1 (young affiliates) and for affiliates that are at least 10 years old (old affiliates). Not surprisingly, there is a positive correlation between the two measures across countries, and all points are below the 45 degree line, which indicates that the firms' forecast errors are larger when they are less experienced. However, the two measures are not perfect correlated. For example, the standard deviation of the forecast errors is 0.26 for old affiliates in China, which is lower than that of old affiliates in Brazil (0.29). But when it comes to the initial uncertainty when entering the markets, affiliates in China face higher uncertainty (the standard deviation of forecast errors is 0.53) compared to that in Brazil (the standard deviation of forecast errors is 0.44). Through the lens of our model, this suggests that there is variation in both σ_θ and σ_ϵ across countries.

We first change the dispersion of the time-invariant demand by varying σ_θ in the range from 50% to 200% of the calibrated value. Holding all the other model parameters constant, this implies that the initial standard deviation of affiliates' forecast errors ranges from 0.27 to 0.47, which is reasonable given the variation across countries (see Figure 6). Figure 7 shows four equilibrium outcomes for different values of σ_θ. Since the demand shifter is log normal with variance σ_θ^2, a higher σ_θ has a direct impact on the average sales of firms if all other equilibrium variables do not change. In addition, since exporters endogenously exit when they believe their demand is low, a larger σ_θ increases the value of entering the foreign market because of the higher option value. Therefore, the probability of entering the foreign markets increases with σ_θ as is shown in panel (a). A higher σ_θ implies a larger "signal-to-noise ratio", $\sigma_\theta^2/\sigma_\epsilon^2$, and thus firms would learn about their θ faster. Therefore, it lowers the mass of relatively old exporters. In panel (b), we show that the mass of exporters aged from 7 to 9 declines with σ_θ. Overall, a higher σ_θ increases the share of young exporters and lowers the share of old exporters.

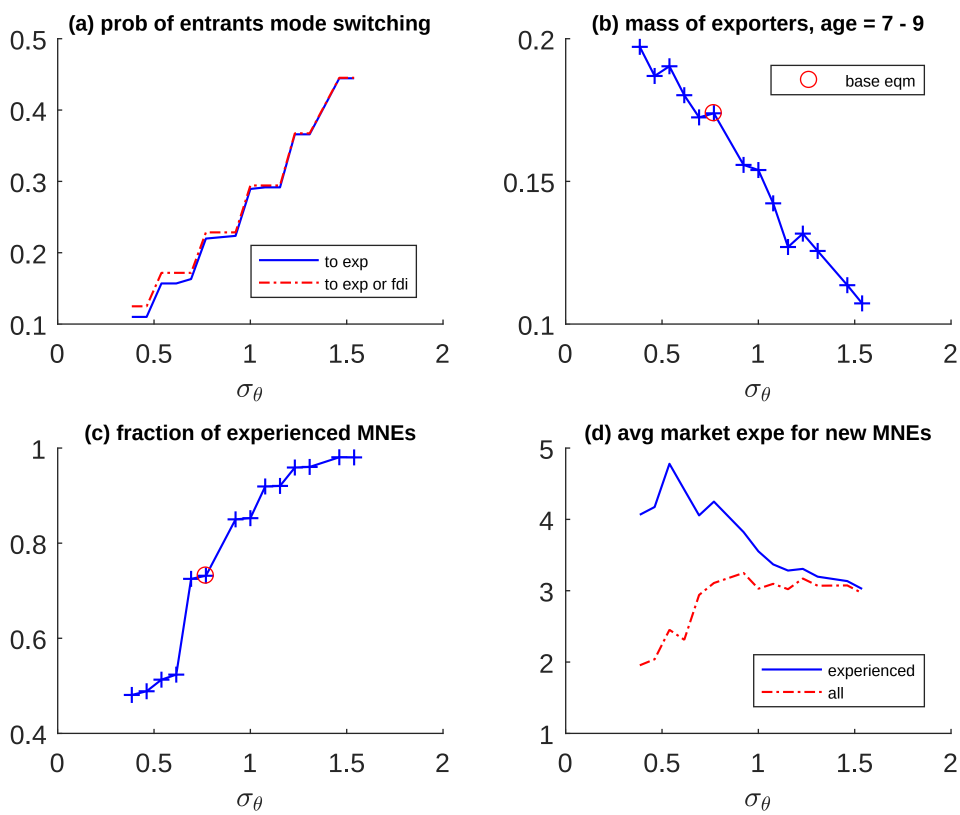
When σ_θ is high, firms are also more willing to "test the market" through exporting. In panel (c), we show that, among all new affiliates, the fraction of affiliates with exporting experience is larger when σ_θ is higher. In our calibrated model, 70% of the new MNEs have previous exporting experience. When σ_θ is twice the level of the calibrated value, which implies the initial standard deviation of affiliates' forecast errors is close to that in

Figure 6: Forecast errors and Country Risk



Note: We plot the standard deviation of forecast errors FE^{log} for affiliates in different host countries at age 10 or above against the standard deviation of FE^{log} for affiliates that are at least ten years old. The size of the marker is proportional to number of affiliates at age one in the host country. We exclude host countries that have fewer than 15 affiliates at age one year and exclude host countries with fewer than 50 affiliates at age ten or above. The line represents the fitted value of a weighted linear regression, the weights of which are the average number of affiliates in the host countries.

Figure 7: Counterfactuals w.r.t. σ_θ



Note: The value of σ_θ is 1.05 in the baseline equilibrium, which is marked with a red circle in panel (b) and (c).

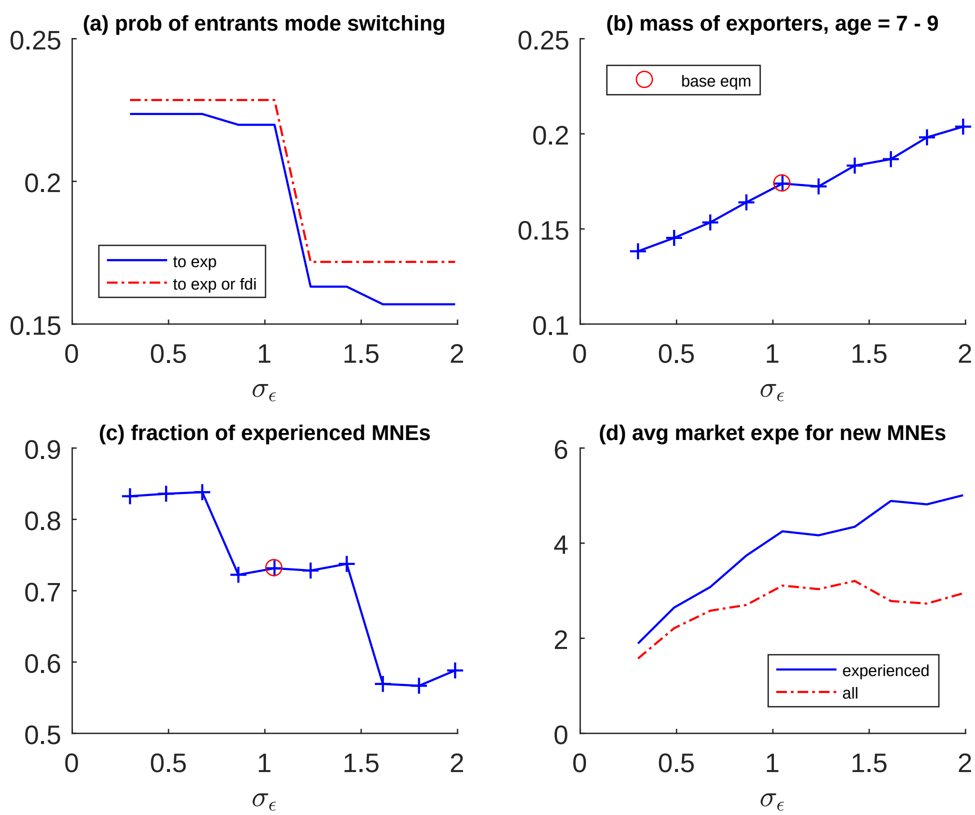
Korea or Taiwan, more than 90% of the MNEs would have accumulated market experience through exporting. In panel (d), we show the average market experience for new MNEs. Since more MNEs have exporting experience before they enter the market, the average market experience for all new MNEs increases with σ_θ for most of the values. However, for the group of experienced MNEs, because learning is faster when σ_θ is higher, the average market experience can actually *decline* with σ_θ.

When we vary the other parameter that controls for demand uncertainty, σ_ϵ, the results are quite different. In Figure 8, we again plot the probability for entrants to enter the foreign market, the mass of relatively old exporters, the fraction of experience MNEs and the average market experience. The calibrated value of σ_ϵ is 1.05, and we vary σ_ϵ between 0.3 and 2. This implies that the standard deviation of the forecast errors when firms' experience approaches infinity ranges from 0.075 to 0.5, which is roughly in line with the range of the standard deviation of forecast errors when affiliates are at least 10 years old.

Broadly speaking, a higher σ_ϵ translates into a lower signal-to-noise ratio therefore slows down learning. In contrast to the effect of raising σ_θ, raising σ_ϵ would shift the distribution of exporters towards relatively old ones. As is shown in panel (a) and (b) of Figure 8, the probability of entering exporting declines with σ_ϵ, while the mass of relatively old exporters increases. Since learning is less effective, more firms become MNEs without testing the market through exporting, which is depicted in panel (c). In panel (d), the blue solid line and the red dashed line represent the average experience for experienced new MNEs and all new MNEs, respectively. For the group of MNEs with exporting experience, they wait longer before they start multinational production. However, since more firms start multinational production without exporting experience, the average market experience for all new MNEs may decline with σ_ϵ.

In sum, both σ_θ and σ_ϵ contribute to demand uncertainty in the model. However, the effects of σ_θ and σ_ϵ on trade and MP are qualitatively different. To predict the impact of demand uncertainty on trade and MP patterns, it is important to distinguish between these two sources of uncertainty.

Figure 8: Counterfactuals w.r.t. σ_ϵ



Note: The value of σ_ϵ is 1.05 in the baseline equilibrium, which is marked with a red circle in panel (b) and (c).

4.3.2 Changes in trade costs

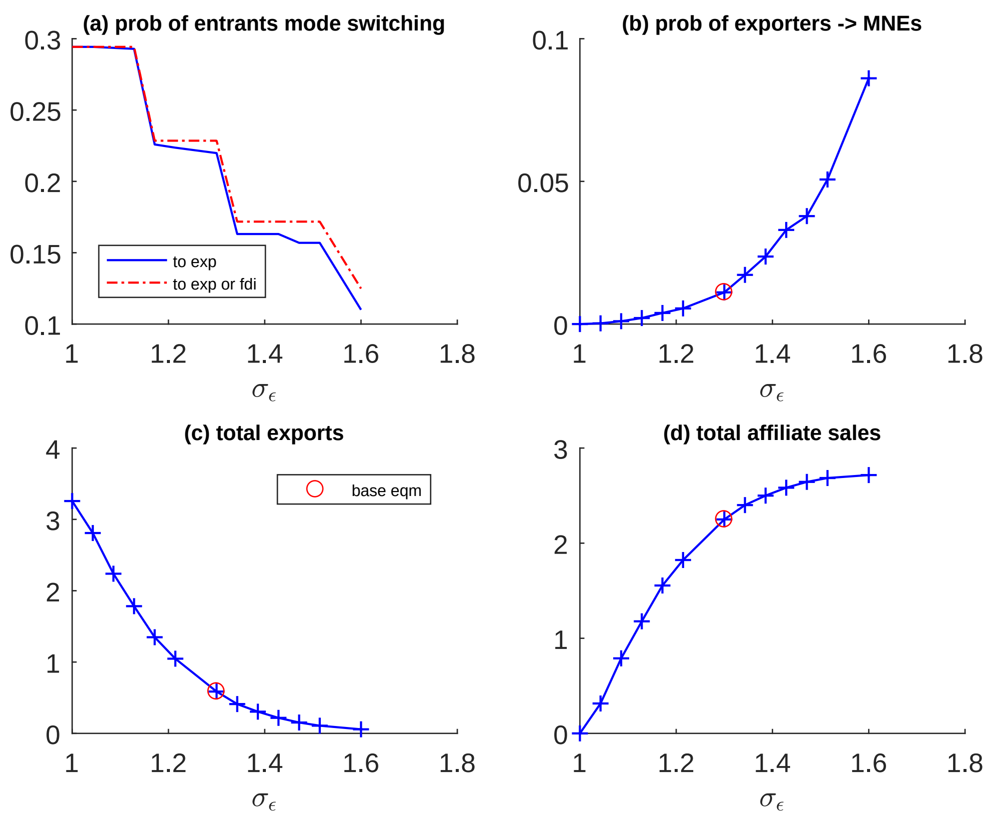
We now consider counterfactual experiments with a more standard parameter, the iceberg trade cost, τ. As Conconi et al. (2016) pointed out, learning about uncertain demand can generate a dynamic complementarity between trade and multinational production (MP). In their two period model, they show a case in which no firm enters the foreign market when trade costs are high, while lower trade costs can induce firms to export in the first period and some of them eventually become multinational firms. Therefore, lowering trade costs may promote MP as well as exporting. This mechanism can be potentially used to explain the empirical fact that FDI declines with distance. With a full-fledged dynamic model, we want to evaluate the quantitative relevance of this mechanism by varying the trade costs in our model.

We vary the value of τ between 1 (no trade cost) and 1.6, and plot four outcome variables in Figure 9. As is seen in panel (a), higher trade costs reduce the value of becoming an exporter and therefore lower the probability of entrants becoming exporters. Though higher trade costs induce more direct entries into MP, overall they lower the probability of entering the foreign markets (exporting or MP). This may eventually lead to less MP since some exporters would switch to MP later in their life cycles. However, when τ is higher, MP is more attractive than exporting, and the probability of exporters switching to MP is also higher (see panel (b)). Panel (c) and (d) show that the level of exports unambiguously decreases with τ, and that the level of affiliates' sales unambiguously increases with τ. This suggests that the dynamic complementarity due to learning is dominated by the direct competition effect between trade and MP in our calibrated model. Therefore, to explain the empirical fact that FDI declines with distance, other mechanisms such as intra-firm trade of intermediate inputs are needed (see Irarrazabal et al. (2013)).

We next show that the substitutability between export and MP depends on the effectiveness of learning. We do this by calculating the elasticity of exports or affiliates' sales with respect to τ under low and high values of σ_ϵ. A higher σ_ϵ lowers the signal-to-noise ratio, therefore reduces the speed of learning. Since learning is important in generating the dynamic complementarity between trade and MP, we conjecture that when σ_ϵ is higher, there is more substitutability between trade and MP, therefore they are more responsive to trade liberalizations.

In our baseline calibration, σ_ϵ is 1.05. We change σ_ϵ to 1.55, in order to match the

Figure 9: Counterfactuals w.r.t. τ



Note: The value of τ is 1.3 in the baseline equilibrium, which is marked with a red circle in panel (b), (c) and (d).

standard deviation of affiliates's forecast errors at age 10 or above in Russia, the country with the highest demand uncertainty in Figure 6. We also change the iceberg trade costs from 1.3 to 1.2 and 1.1. In Table 12, we report the change in the log of affiliates' sales, exports and the ratio between the two. For example, when trade costs decline from 1.3 to 1.2, MP sales increase by 26 log points when σ_ϵ is low, while MP sales increase by 28 log points when σ_ϵ is high. The elasticity of MP sales with respect to trade costs is about 7% lower when learning is more effective (3.25 v.s. 3.5). Therefore, in our calibrated model, there is a strong substitutability between trade and MP. More effective learning would reduce this substitutability. However, the reduction in the elasticity of MP sales with respect to trade costs is small and we do not find any reasonable value of σ_ϵ under which the sign of this elasticity is reversed.

Table 12: Responses to trade liberalization under different values of σ_ϵ

	$\sigma_\epsilon = 1.05$		$\sigma_\epsilon = 1.55$	
change in τ	$1.3 \to 1.2$	$1.3 \to 1.1$	$1.3 \to 1.2$	$1.3 \to 1.1$
Δ log(MP sales)	-0.26	-0.95	-0.28	-0.98
Δ log(Exports)	0.65	1.25	0.66	1.26
Δ log(Exports/MP sales)	0.91	2.20	0.94	2.23

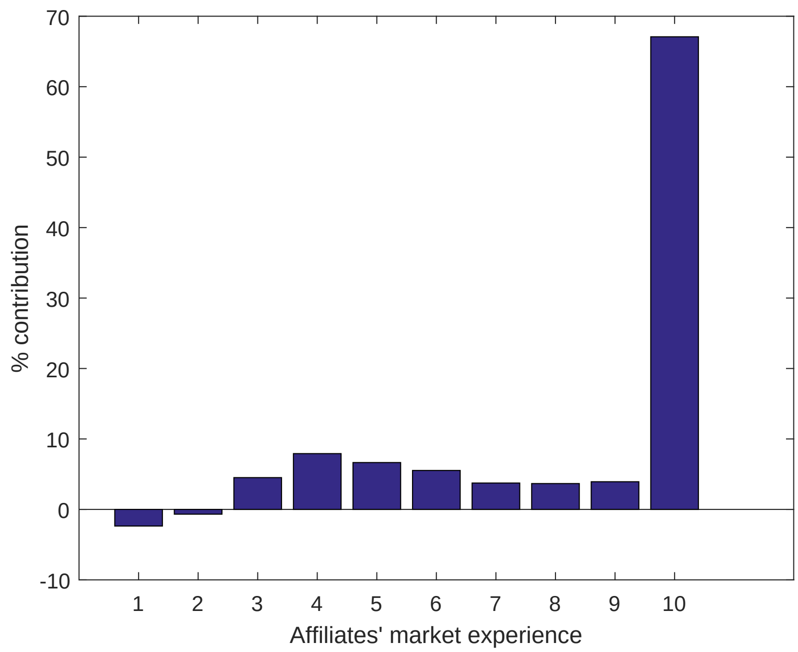
To further understand what drives the different responses to trade liberalization under different values of σ_ϵ, we consider an exact decomposition of the MP sales based on market experience. Consider σ_ϵ and τ that may take different values from the sets $\{\sigma_{\epsilon i}, i = 1, 2, \ldots\}$ and $\{\tau_j, j = 1, 2, \ldots\}$. Denote the total sales by affiliates with n years of market experience as R_{nij}, if $\sigma_\epsilon = \sigma_{\epsilon i}$ and $\tau = \tau_j$, we can decompose the difference in responses as

$$\left(\frac{R_{i'j'}}{R_{i'j}} - 1\right) - \left(\frac{R_{ij'}}{R_{ij}} - 1\right) = \sum_n \left(\frac{R_{ni'j'}}{R_{i'j}} - \frac{R_{nij'}}{R_{ij}}\right).$$

For two sets of parameter values, $\sigma_{\epsilon i'} = 1.55$, $\sigma_{\epsilon i} = 1.05$, $\tau_j = 1.3$, $\tau_{j'} = 1.2$, we calculate the contribution by age n affiliates $R_{ni'j'}/R_{i'j} - R_{nij'}/R_{ij}$, and divide it with the sum of these contributions. The shares of contribution by affilaites of different ages add up to one by construction.

We plot the shares of contribution by affiliates with different ages in Figure 10. It is clear that relatively old firms contribute the most to the differential responses after trade liberalization, while young firms actually contribute negatively to the aggregate outcome. This is because, when learning is more effective, there is a stronger dynamic complementarity between trade and MP. Exporting experience early on helps to generate relatively more entries into MP compared to the case with less effective learning. The additional transitions into MP make the affiliates' sales, especially those from relatively old affiliates, decline less. Therefore, old affiliates contribute the most to the differential response of MP sales to trade liberalization under high and low values of σ_ϵ.

Figure 10: Decompose the differential response under high and low σ_ϵ



Note: The formulas we use to calculate the contribution by affiliates with different market experience is described in the paper.

In sum, even though learning about uncertain demand generates a dynamic complementarity between trade and MP, when calibrating our model to the data, we find that this force is not enough to generate a positive correlation between trade costs and MP sales. When learning is less effective, this force becomes weaker and exports and MP sales are more responsive to changes in trade costs.

5 Conclusion

In this paper, we use a unique dataset on Japanese multinational firms to document the uncertainty they face when operating in foreign markets. We find that multinational affiliates become better at forecasting their sales as they become older. Affiliates whose parent firms have previous export experience in the destination regions also start with lower initial uncertainty. We view these facts as direct evidence of firm learning about their underlying demand, both through affiliate sales and previous exports.

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. (2013)) to an international setting. The calibrated model can replicate the new facts about affiliates' forecast errors, as well as other salient features of the data, such as the growth of average exporter size and the decline of exit rates over the exporters' life cycles. We conduct counterfactual analysis regarding demand uncertainty and trade liberalizations. We find that changing the uncertainty about the time-invariant demand and the temporary demand shocks produces qualitatively different impact on trade and MP patterns. Therefore it is crucial to distinguish between these two sources of uncertainty. Under trade liberalization, we find that MP sales unambiguously decrease while exports increase. Therefore, quantitatively, the model does not produce a negative correlation between trade costs and MP sales, as proposed by Conconi et al. (2016). Other mechanisms are needed to rationalize the negative correlation between distance and FDI as is observed in the data.

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