Export by Cohort

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Highlights

- We find a "cohort effect" among new exporters in the same destination market: firms entering in later cohorts sell more and are more likely to survive at the same age.
- Dissecting the cohort effect requires understanding the drivers of post-entry exporter growth. Two theories lead the discussion in the literature: demand learning and customer base accumulation.
- We show that predictions of demand learning theories on cross-cohort lifecycles are inconsistent with the data.
- We build a tractable customer base accumulation model and show that it can fit the same data both qualitatively and quantitatively.
- The model estimates suggest that cohort effect is a combination of productivity effect and reputation effect: exporters entering one cohort later on average gain 0.2% in measured productivity and start with a 7% larger customer base.

Motivation

- Export pioneers have long been assumed to generate positive spillovers to the rest producers in their home countries, which is the basis of export promotion policies favoring export pioneers. (Hausman and Rodrik, 2003)
- Supported by cases studies in *Export Pioneers in Latin America, IADB*
  - e.g. blueberry in Argentina, fresh cut-flowers in Colombia, soybeans in Brazil
- However, surprisingly little empirical work has been done to verify the existence of such pioneering effect and investigate how it works.

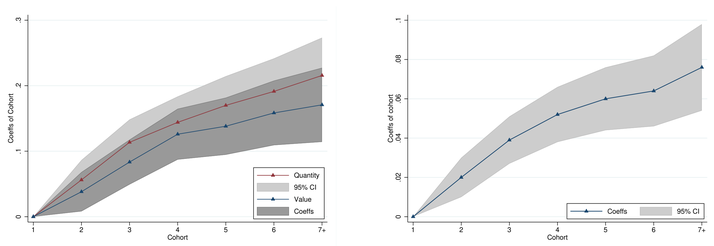
Cohort Effect

We use the Chinese custom data (2000 - 2011) to conduct the following age-year-cohort decomposition on exporters' performance in each product-destination pair (market)

$$w_{ijdt} = \beta_c' \mathbf{c}_{ijdt} + \beta_a' \mathbf{a}_{ijdt} + \mathbf{x}_{jdt} + \eta_{ijt} + \varepsilon_{ijdt}, \tag{1}$$

- i firm, j HS6 product, d destination country and t year
- w_{ijdt}: firm i's log sales, quantity and survival rate on market jd at year t
- $\mathbf{c}_{ijdt}$ is a vector of cohort dummies (cohort effect) and $\mathbf{a}_{ijdt}$ is a vector of age dummies (age effect).
- $\mathbf{x}_{jdt}$ is a set of controls of the year effect: log import value at market jd, HS4-product-destination-year fixed effect and effective applied tariff rates.
- η_{ijt} is the firm-product-year fixed effect.
- Cohort is product-destination specific and defined inductively: an exporter is in the n-th cohort if $n-1$ cohorts of domestic firms had exported to that market before the first year of its current export spell.
- Identification on β_c and β_a: variations across markets within a firm-product-year triplet

Main Findings: later cohorts on average sell more and are more likely to survive at the same age.



(a) Log Value & Quantity (b) Survival Rate

Figure 1: Cohort effect

Dissecting Cohort Effect

- We want to figure out why later cohorts have advantages in doing oversea business.
- Challenge: cohort effect is identified from market level variations. There is no direct data on firm's input use by market and idiosyncratic demand.
- Our solution: a structural approach to back out changes in unobserved firm characteristics from observed firm dynamics
- Pick the right structural model: a line of attack
  - Step 1: Reviewed the literature and found demand learning and customer accumulation are the two predominant theories on post-entry exporter dynamics.[a]
  - Step 2: Derived theoretical predictions and checked if the qualitative predictions are consistent with the data.This step ruled out commonly used demand learning models.
  - Step 3: Parametrized and estimated the structural models and checked the resulting model fit. This step confirmed the use of a customer accumulation model.

Demand Learning: Prediction and Testing

- The major class of demand learning models in the export dynamics literature is à la Jovanovic (1982), in which firms gradually update their beliefs on idiosyncratic profit shifters with signals from realized sales.
- **A major prediction**: firms' growth rates decline on their sizes.
  - Larger firm sizes implies firms have obtained more signals and are closer the the truth. Hence, there will be less belief updating and changes in size.
- **Claim**: *Since later cohorts are larger at entry, they should grow less if demand learning dominates.*
  - In the paper, we show this claim precisely and analytically within a commonly used parametrized version (e.g. Arkolakis et al. 2018) of exporter demand learning models.
- **Testing**: we plot firms' cross-cohort lifecycles on quantities by adding interaction terms between age and cohort to (1)

$$y_{ijdt} = \beta_c' \mathbf{c}_{ijdt} + \beta_a' \mathbf{a}_{ijdt} + \beta_i' \mathbf{c}_{ijdt} \otimes \mathbf{a}_{ijdt} + \mathbf{x}_{jdt} + \eta_{ijt} + \varepsilon_{ijdt}, \tag{2}$$

- From the claim, $\beta_i^{c,1} < 0$ is expected for all cohorts c at age $a = 1$.
- However, $\beta_i^{c,1} > 0$. The signs are insignificant: parallel lifecycles across cohorts.

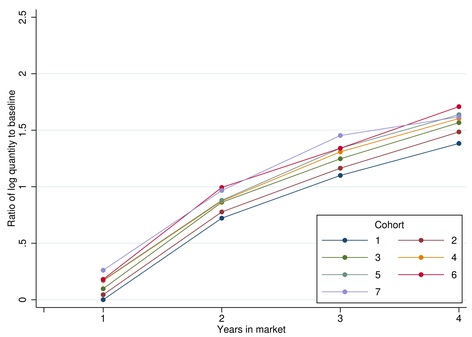


Figure 2: Log Quantity: first four years

Customer Base Accumulation with Multiple Cohorts

- A representative firm receives random opportunity to export. Its static profit π is determined by its measured productivity A and customer base D.
- If an opportunity realizes, this firm will receive cohort-specific productivity A_c and start with an initial customer base D_0^c.
- Fixed cost shocks F are i.i.d over time. This firm then decides whether to continue exporting or withdraw from the foreign market. If continue, it receives the static profit, pays the fixed cost and increases its customer base through advertising. Once exit, its customer base will fully depreciate.
- The following Bellman equation summarizes the decision problem of a cohort c firm:

$$V(A_c, D, F) = \max\Big\{ \max_{D' \geq (1-\delta)D} \pi(A_c, D) - c(D, D') - F + \beta\, \mathbb{E}[V(A_c, D', F')], \\ \beta\, \mathbb{E}[V(A_c, D_0^c, F')] \Big\}$$

  in which $c(D, D')$ is the cost of adjusting customer base from D to D'.
- **Property**: can generate all relationships between size and growth rate
  - Intuitions: higher productivity induces more investment while larger customer base reduces it. Then, increases in both components make larger sales but are ambiguous on growth rate.

Structural Estimation

- Parametrization: profit and cost functions

$$\pi(A, D) = AD^{\alpha}, \quad c(D, D') = D' - (1-\delta)D + \phi \frac{(D' - (1-\delta)D)^2}{D}.$$

- Fixed cost distribution

$$F \begin{cases} \sim G(F), & \text{w.p.} \quad \gamma, \\ = +\infty, & \text{w.p.} \quad 1-\gamma, \end{cases}$$

  in which G is a type II Pareto distribution (Lomax(κ, θ)).
- Structural parameters (17): $\Omega = \{\beta, \alpha, \phi, \delta, \kappa, \theta, \gamma, \{A_c\}, \{D_c^0\}\}$
- Moments: conditional growth rates in sales by age and cohort (6×5), conditional survival rates by age and cohort (6×5), relative initial sales (5).[b]
- Classical minimum distance estimator: $\min_{\Omega}(\hat{m} - m(\Omega))'(\hat{m} - m(\Omega))$
- Results: increasing $\{A_c\}$ (productivity effect) and $\{D_0^c\}$ (reputation effect)
- Model Fit.[c]

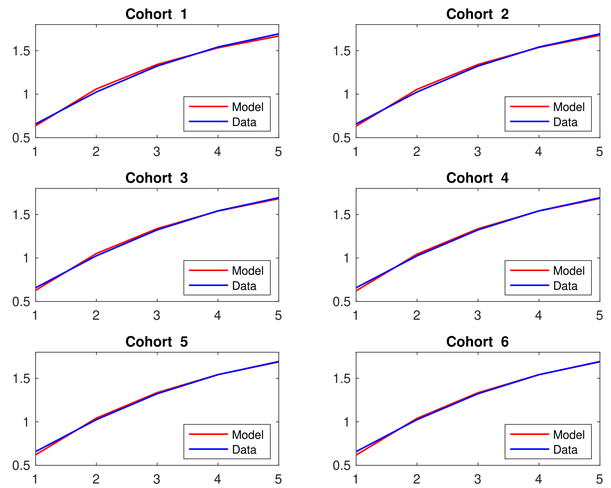


Figure 3: Model fit: growth rate relative to first year sales

Conclusions

- Using the Chinese data, we find evidence that supports the long lasting conviction of a pioneering effect, which works through reputation and productivity effects.
- Cross-cohort lifecycles of exporters present new evidence that sheds light on the ongoing debate over the drivers of post-entry exporter dynamics.

[a] If interested, readers are welcomed to email authors for the detailed discussion on the literature review.

[b] In the paper, we discuss extensively on the identification. Moreover, we also discuss identification challenges in estimating a model with both customer accumulation and demand learning. That is a primary reason why we do not estimate two mechanisms jointly.

[c] Model fits for survival rates and relative initial size are available upon request.