Product Market Competition and Entrepreneurial Activity: Evidence from U.S. Households[1]

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Abstract

Motivated by the accelerated decline in U.S. entrepreneurship in the past two decades, and using a unique panel dataset of U.S. households, we theoretically and empirically analyze the effects of increased product market competition through growth of low-cost imports on household entrepreneurial activity. We find strong empirical support (during 1993-2006) for the theoretical predictions that higher penetration of low-cost imports reduces entry by domestic entrepreneurs in the tradable sector, especially for less wealthy individuals, but has positive spillover effects on entrepreneurial activity in the non-tradable sector. The results are robust to the alternative hypotheses of latent shocks to U.S. industries and local regions; collateralization effects of the housing boom; and feedback effects between imports and business activity. Our analysis highlights the significant and diverse economy-wide effects of increased product market competition (in a given industry) on household entrepreneurial activity.

Keywords Entrepreneurship; Household finance; Product market competition; U.S. Census SIPP data; Entry-exit

1 Introduction

Entrepreneurial activity by households is a major component of new business formation and employment generation (Decker et al., 2014). Furthermore, a long-standing literature emphasizes the positive relation of entrepreneurship and technological innovation (Schumpeter, 1942; Aghion and Howitt, 1992), which is a central driver of long run economic and productivity growth (Solow, 1956; Romer, 1990). However, there is a growing recognition of a decline in entrepreneurship — or the rate of new business formation — in the last few decades in the U.S., which has accelerated since the early 2000s (Decker et al., 2014; Haltiwanger, 2015). This decline appears not to be geographically concentrated but applies across most states and metropolitan regions of the country (Hathaway and Litan, 2014). There is, therefore, an emerging debate on the causes and consequences of this slowdown — for example, for employment and productivity growth — in entrepreneurial activity (Decker et al., 2016, 2017). Meanwhile, there has been a rapid increase since the early 1990s in the growth of imports from low-wage countries into U.S. sectors such as manufacturing, especially since China's accession to the World Trade Organization (WTO) in the early 2000s (Autor, Dorn, and Hanson, 2013; Acemoglu et al., 2016). Utilizing a unique panel dataset of U.S. households, we analyze the effects of increased product market competition — through the rapid growth of low-cost of imports — on household entrepreneurial activity.

Identifying the causative effects of product market competition on entrepreneurial activity is challenging because changes in the competitive environment — due to technological or sectorial demand shocks, for example — may be correlated with factors that influence business entry (or exit) decisions by households, such as variations in real and financial wealth or the opportunity costs of wage income.[1] But, as mentioned above, a clear and persistent "shock" to the U.S. economy since the 1990s has been the growth in imports from low-wage countries. Indeed, our analysis shows that imports from China grew by over 950% between 1993 and 2006, and this growth accelerated in the early 2000s. Focusing on this competitive shock is of substantial interest since it facilitates identification of the effects of product market competition on entrepreneurial activity. Because the most important drivers are likely to be export supply shocks in China rather than latent demand shocks in the U.S. and, furthermore, one can use instrumentation (through Chinese import growth

[1] For example, Decker et al. (2017) point out that during the 1980s and early 1990s the decline in business dynamism was concentrated in the retail trade and services sector and reflected relatively benign factors related to changing business models in the industry. However, since the early 2000s the decline in new business formation has implied lower employment growth.

in other high income countries) to isolate the import component driven by Chinese cost comparative advantage (Autor, Dorn, and Hanson, 2013).

Our theoretical motivation and refutable predictions are derived from an entry model of entrepreneurship in local (or metropolitan) markets that builds on the empirical industrial organization literature (Bresnahan and Reiss, 1991). The theoretical framework predicts negative effects of import penetration from low-wage countries on entrepreneurial activity in the tradable sector, controlling for individual financial wealth and human capital endowments. While this prediction is intuitive, it does not fully encompass the effects of increased product market competition on business entry by households because the model also predicts economy-wide reallocation effects of import penetration on entrepreneurial activity: Infra-marginal entrepreneurial agents who would otherwise have started a business in the tradable sector shift to entrepreneurship in the non-tradable sector. These implications of changes in competition on entrepreneurial activity in *non-exposed* sectors are unexplored in the literature, but are clearly important. As seen in Figure 1, the declining rates of business start-up growth in tradable industries (during 1993-2006) was accompanied by rising rates of business startups in non-tradable industries.

Of course, Figure 1 does not establish a causal relation of increased low-cost competition and entrepreneurial activity. For our formal empirical tests, we utilize the micro-level longitudinal Survey of Income and Program Participation (SIPP) data, a rotating panel that tracks individuals (about 60,000 to 80,000 individuals) for up to four years. The panel structure of the SIPP data allows for observations of transitions from employment to entrepreneurship and vice versa and uses individual fixed effects, which control for time invariant individual unobservables such as entrepreneurial preferences or ability. A notable beneficial aspect of this database is thus that we can cleanly identify new *firm* creation (at the household level) as opposed to confounding this with new *establishments* set up by existing firms, which is an important distinction from the viewpoint of entrepreneurial activity (Decker et al., 2014). We pool the 1993, 1996, 2001 and 2004 SIPP panels, resulting in a final entry sample of 317,496 observations during 1993-2006. Consistent with the literature, we take the tradable sector to comprise of manufacturing, agriculture, and mining; and we identify the "local markets" in our theoretical framework with Metropolitan Statistical Areas (MSA).

Using this unique panel dataset of U.S. households, we empirically test the predictions of our conceptual framework. We examine the impact of import penetration from China on the business entry decisions (that is, the extensive margin) of entrepreneurs at the level of households in both trade-exposed and non-exposed sectors. We also investigate the effects of import penetration on entrepreneurial outcomes (intensive margin) — such as business profits and the exit decision — because they directly impact the incentives for business formation. In particular, this database allows us to control for the effects of total wealth — that is, financial and real assets — and human capital of individuals at the household level that are conceptually important for the business entry decision.

Our tests employ (1) calibration and simulation and (2) formal estimation that pays particular attention to identification. Calibrating the parameters of the model with the sample moments of our data — relating to profits of existing entrepreneurs, education, and total wealth — and simulating the entry of low cost foreign firms, we confirm a negative relation of optimal domestic new business formation and foreign entrants. In addition, household entrepreneurial activity (in response to higher import competition) is positively related to its total wealth. And, while the theoretical effects of human capital on entrepreneurial activity are ambiguous — because higher human capital raises both the expected profits from and opportunity costs of entry — the calibration exercise shows that higher education dilutes the negative effects of import competition on business entry.

The estimation test results also provide strong support for the low-cost import exposure channel for a decline in entrepreneurship in tradable sector: Business creation during 1993–2006 by households is significantly lower across time in regions with large increases in Chinese import penetration, while controlling for time, local (MSA-level), and individual fixed effects. And this effect is economically sizeable: Other things held fixed, a one-standard-deviation increase in this import penetration results in about a 24% decline in the likelihood of creating a business. The dampening effect of import competition on entrepreneurship is concentrated in the manufacturing sector. Thus, we find a significant negative relation of low-cost product market competition and household entrepreneurial activity, while controlling for the underlying time, local, and individual trends.

As we mentioned above, in our context empirical identification may be confounded if imports are positively correlated with unobserved domestic shocks to industries and geographic areas that determine import demand. For instance, some U.S. industries may be declining, or some geographic areas may have scarce investment opportunities, irrespective of changing import penetration. We use Chinese imports to other high-income countries as an instrumental variable (IV) for Chinese comparative advantage that does not depend on U.S.-specific product demand or technology shocks. We continue to find a strong and significant negative impact of import penetration on business creation. As an additional robustness test, we control for dynamic feedback effects between import exposure and the entrepreneur's entry decision by using the dynamic panel GMM approach developed by Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991). We also account for possible nonlinearity in the data by using the control function construction of Petrin and Train (2005, 2006). Our results remain robust to all these identification and robustness tests.

To the extent that local firms may be more sensitive to changes in demand, the impact of falling demand would show up foremost for business creation in the regional non-tradable sector, since this sector depends primarily on local demand, while the tradable sector is more diversified in terms of geographic origins of demand. However, we find the opposite. Consistent with our theoretical prediction, import penetration *increases* new business creation in non-tradable sectors, even when we control for regional heterogeneity in sectors through MSA$\times$sector fixed effects and *time-varying* MSA (MSA$\times$year) and sectorial effects (sector$\times$year). A one-standard deviation increase in import exposure produces a higher likelihood of business creation in non-tradable sectors by 8%. To our knowledge, the positive spillover effect of increasing product competition in one sector on entrepreneurial activity in a non-exposed sector is not highlighted in the literature.

Our conceptual framework implies that import penetration will ceteris paribus more adversely impact the entrepreneurial activity of individuals that either have a lower ability to start a business *or* higher opportunity costs of doing so. For example, the effect of higher educational attainment on entry is theoretically ambiguous because education is positively related to both expected profits from entry and wages in the employment sector. We find that high educational attainment (college or more) ceteris paribus has a strong and significant positive impact on the propensity to start a business. However, import competition significantly reduces the likelihood of highly educated individuals starting a business in the trade-exposed sector (relative to less educated individuals), which is consistent with our entry model. In a related vein, higher pre-entrepreneurial occupational mobility that ceteris paribus reduces both skill formation and wages is negatively related to entrepreneurship, indicating that the positive skill development effect of lower occupational mobility on starting a business dominates the negative opportunity cost effect. Moreover, both financial and non-financial wealth help ameliorate the negative effects of intensified competition on entrepreneurial activity.

Our sample period coincides with the boom in U.S. housing prices. Therefore, another concern is that changes in housing prices could impact entrepreneurial activity through the collateral channel (Adelino, Schoar, and Severino, 2015; Schmalz, Sraer, and Thesmar, 2017). For example, MSAs with a more elastic housing supply would experience a relatively smaller increase in home prices in response to an economy-wide housing demand shock, resulting in lower growth in collateral values — and hence — business creation, compared with business regions with a less elastic housing supply. We devise a number of remedies to control for the impact of the housing market on our results. First, we include individual, state, and year fixed effects, the growth in MSA-level housing price index (HPI), and other proxies for local economic conditions — such as changes in the unemployment rate, changes in income, changes in mortgage debt, and other local controls (see Panel B of Table 2) — in our tests.

However, even after the inclusion of local economic controls and several fixed effects, these estimates do not establish causality, since there may exist an unobserved factor that simultaneously drives both house prices and entrepreneurial activity. As a second remedy, we employ a version of the identification strategy suggested by Schmalz, Sraer, and Thesmar (2017) and compare U.S. homeowners and renters in areas in with higher rates of house price appreciation. In this setup, in order to control for possible endogenity in house prices, we also instrument for the growth in local house prices using the housing supply elasticity $\times$ nation-wide mortgage rates (Chaney, Sraer, and Thesmar, 2012).

An advantage of the SIPP data is that — unlike Schmalz, Sraer, and Thesmar (2017) — we observe the *actual* housing equity that homeowners have in their property, as well as the year when the house was purchased. Therefore, we can estimate the effect of a change in home equity on entrepreneurial activity *within the sample of homeowners* in the same MSA and at the same time. Thus, our third approach for an identification strategy is to isolate the exogenous variation in home equity and property values by using the differences in house prices and housing supply elasticities across housing markets as instruments (Chetty, Sándor, and Szeidl, 2017). More specifically, *for each homeowner* in the sample, we instrument property values and home equity with variations in the current and the time-of-purchase house price index, respectively, at the *national* level interacted with local housing supply elasticity. The key advantage of this source of variation in house prices and home equity is that it avoids the potential for omitted variable bias due to local economic conditions because the variation is driven purely by national demand shocks.

Fourth, we exclude the most obvious sectors that might directly be hurt by (or benefit from) lower (higher) house prices — namely, sectors linked to construction, and firms in the finance, insurance, real estate, rental, and leasing sectors. Fifth, we repeat our analysis only on the subsample of individuals who live in the MSAs with the most elastic housing supply, since, in those areas, the propensity to start a business is less likely to be correlated with the local price response to economy-wide changes in housing demand. Finally, we use joint MSA$\times$year fixed effects — in cross sectional tests — to identify variations across households residing in the same MSA at the same point in time.

Our dataset allows us to examine economic performance and exit decisions of entrepreneurs over time. The results on the effects of increased import penetration on business profits and exit rates are consistent with the hypothesis of increased low-cost competition adversely affecting the competitive environment for entrepreneurs. Increasing import penetration by one-standard deviation on average (across time and regions) decreases business profits in the tradable sector by 4% and raises the likelihood of ending a business (in this sector) by 22%, after controlling for business conditions, individual entrepreneur characteristics, MSA-level controls, and several fixed effects. These results are economically significant because they directly speak to the effects of low-cost import penetration on the economic incentives to start a business in the tradable sector.

Overall, our analysis indicates that increasing product market competition has significant effects on household entrepreneurial activity, while controlling for wealth, human capital, and other characteristics. There is a growing literature that documents the negative impact of low cost imports on labor market outcomes (Krugman, 2008; Autor et al. 2013; Acemoglu et al., 2016). However, to our knowledge, this is the first study to document their effects on household entrepreneurial activity using individual-level data. Our study is also unique in the literature to highlight the contrasting effects of increased low-cost import penetration on household entrepreneurial activity in exposed versus non-exposed sectors.

We organize the paper as follows. Section 2 presents the theoretical model. Section 3 describes the data, sample construction, and empirical measures. Section 4 considers causality and identification, and presents the empirical results on the extensive margin of entrepreneurship. Section 5 analyzes profitability and the exit decision of existing businesses. Section 6 extends the analysis to the non-tradable sector. Section 7 analyzes the impact of entrepreneurial activity in terms of individual characteristics, and Section 8 concludes.

2 Theoretical Motivation

We develop a stylized model to generate refutable predictions on the effects of increased product market competition through imports from a low-cost producer (e.g., China) on the rate of start-up formation and exit (from existing business ownership) by households. The model is set in localized geographic markets (or "localities") denoted by M. In the basic model, we assume that there is a single tradable goods sector T with a large number of monopolistically competitive firms — *including* foreign firms — that produces different product varieties. Subsequently, we will extend the model to introduce a non-tradable sector.

We assume a 'gravity structure' (Anderson and van Wincoop, 2003) so that import quantities — in particular, import penetration (Arkolis, Costinot and Rodriguez-Clare, 2012) — drive the effects of trade on entrepreneurship. Entrepreneurship activity is measured through the likelihood of business start-ups and exit from business ownership by individuals. We allow agents to be heterogeneous in terms of wealth and human capital and in terms of household financial characteristics.

To derive the refutable predictions in the simplest possible way, we consider a discrete time overlapping generation model with risk-neutral agents. Individuals in each locality M live for two periods. Without loss of generality, we fix the population size of each cohort in M to be I_M, with individuals being denoted by i. At "birth," individuals in locality M are endowed with financial capital V_{iM} and human capital H_{iM}. All individuals are also endowed with one unit of labor that they supply inelastically. It is notationally convenient to take the distribution of capital to be time-invariant.

Taking these endowments as given, individuals in the first period of their lives choose to either be an entrepreneur by entering as a business owner or to be a worker at an exogenously given wage. Entry is costly, however, and requires a minimum endowment of financial and human capital, as we will specify shortly. In the second and final period of their lives, individuals take their earnings from the previous period — profits for entrepreneurs and wages for workers — and consume.

We use a simplified form of the entry game modeled in the empirical industrial organization literature (Bresnahan and Reiss, 1991). In this framework, firms are homogenous in each local market, and the (per period) expected profits from entrepreneurship depend negatively on the number of active firms, N_M. Furthermore, controlling for the number of active firms, expected profits are also negatively related to the import penetration of firms from low-wage countries, consistent with the 'imports-as-market-discipline' hypothesis (Helpman and Krugman, 1989; Levinsohn, 1993). Import penetration may differ across localities and is denoted by λ_M. Finally, higher human capital is beneficial to managing a business. Thus, the per period expected profits are given by a time-invariant but locality-specific function $\pi_M(N_M, \lambda_M, H_{iM})$, which is strictly decreasing in the first two arguments but is increasing in the third argument.

Each young generation takes the number of incumbents (from its own generation) and import penetration as given and chooses to either enter or work at an exogenously given per-period wage that is increasing in human capital:

$$w_M(H_{iM}) = w_{0M} + w_{1M} H_{iM}, \tag{1}$$

$w_{1M} > 0$. Meanwhile, business entry is costly, with location specific entry costs denoted by C_M. We assume that entry costs can be financed by full collateralization, which is a reasonable assumption for start-ups by individuals (Adelino, Schoar, and Severino, 2015). Entry costs should arguably depend on the level of low cost product market competition. For example, greater import penetration from low-cost countries ceteris paribus forces domestic entrants to invest in lower cost technologies and supply chains. In addition, financing costs should increase with profit risk, other things held fixed. We thus assume that C_M is an increasing function of λ_M. Individuals' collaterizable wealth is a positive function of their financial and real assets (V_{iM}) and their human capital (H_{iM}). It will be convenient to denote the total wealth index relevant for business ownership as $Q_{iM} \equiv V_{iM} + \phi_M H_{iM}$ (where ϕ_M is a locality-specific factor that converts human capital to wealth units).

Thus, for the set of feasible entrants in each young generation is $\bar{E}_M = \{i \,|\, Q_{iM} \geq C_M(\lambda_M)\}$. Then, at any time t, and conditional on λ_{Mt}, let the equilibrium entry set be $E_{Mt} \subseteq \bar{E}_M$ with the cardinality N_{Mt}. By convention, N_{Mt} is also the equilibrium number of active firms. And because individuals choose their occupations to maximize their end-of-period wealth, E_{Mt} is determined as follows: For every $i \in E_{Mt}$,

$$\pi_M(N_{Mt}, \lambda_{Mt}, H_{iM}) - C_M(\lambda_{Mt}) \geq w_{0M} + w_{1M} H_{iM} \tag{2}$$

And for every $i \in \bar{E}_M - E_{Mt}$,

$$\pi_M(N_{Mt} + 1, \lambda_{Mt}, H_{iM}) - C_M(\lambda_{Mt}) < w_{0M} + w_{1M} H_{iM}. \tag{3}$$

That is, in equilibrium, the net profits from entry for any potential entrant are non-positive, while they are negative for the agents who have chosen entry. It is then straightforward to show that for any locality M:

Proposition 1 *The equilibrium likelihood that individuals will choose entry in the tradable sector is decreasing in the import penetration λ_{Mt}, but is non-decreasing in their wealth V_{iM}. The effect of human capital on the entry likelihood is generally ambiguous, but it is positive if w_{1M} is sufficiently low.*

Figure 2 graphically depicts the impact of individual wealth on the optimal response of domestic business entrants to foreign competition. Here we use the Cournot equilibrium with a linear demand curve (see, e.g., Pindyck, 2009).[2] The demand curve parameters are calibrated to match the observed average profits prior to foreign entry and ex post. The low, medium, and high wealth levels are also calibrated from the data at \$45,000, \$66,000 and \$90,000, respectively.[3] We recall that in our model, wealth only relaxes the financing constraints for entry costs, but does not influence the profitability rates per se. We exhibit the optimal number of domestic entrants (as a function of foreign entrants) when there are no wealth constraints. As expected, there is a negative relation of optimal domestic new business formation and foreign entrants. But we also indicate where wealth constraints bind for low, medium, and high wealth level individuals. In particular, for the calibration used in Figure 2, the optimal entry response for high wealth individuals is equal to the unconstrained entry response, and we see that entry optimally stops after 93 foreign entrants. However, for medium wealth individuals, entry costs can not be financed as the number of foreign entrants exceeds 80, while for low wealth individuals, entry can not be financed once the number of foreign entrants exceeds 50.

Figure 3 graphically depicts the effect of education (human capital) on the optimal response

[2] Specifically, with a linear industry demand curve $P = a - bQ$ (where Q is the industry output) and constant marginal cost κ, the symmetric Cournot profit with N firms is $\frac{(a-\kappa)^2}{b(N+1)^2}$. For this simulation, we calibrate $\frac{(a-\kappa)^2}{b}$ prior to foreign entry using average profits of \$30,000 (calibrated from the average profitability of entrepreneurs in the tradable and non-tradable sectors in our sample), and assuming 25 firms in the industry. We calibrate the entry cost function as $C = \$7500 + 0.1N$, and solve for the number of existing firms that just sets the net profits from entry less than or equal to the labor income of \$24,000 (the average labor income of individuals with no more than high school education, the most numerous educational group in our sample).

[3] Table 1 below shows that in our sample the mean total wealth for households who started a business, and those that did not, is \$114,871 and \$61,920, respectively. These figures guide the calibration of low and medium wealth levels. For our demand and entry cost parameterization in Figure 2, the wealth constraint on starting a business becomes non-binding at \$90,000.

of domestic entry to foreign entrants.[4] Because human capital positively affects the profitability rate in our model, the optimal domestic entry response function (to foreign entry) differs in slope as well as the vertical intercept for individuals with different education levels. We display the optimal entry responses for individuals with only high school education, some College education, and College degrees. At every level of foreign competition, the profit maximizing number of new domestic entrepreneurs is negatively related to the education level.

We now turn to empirical tests of the refutable predictions in Proposition 1. We describe first our data and the empirical test design. We then present the empirical results.

3 Empirical Implementation

3.1 Import Penetration

Our model emphasizes the role of product market competition through higher import exposure, financial resources, and human capital resources in the entry decision. We present here definitions of salient empirical measures used in our tests. Consistent with our theoretical framework, our measure of import penetration attempts to capture the changes in local (at the MSA-level) exposure in the tradable sector to imports from low-cost countries. In our paper, for the reasons mentioned in the Introduction, we will focus on imports from China. We take Agriculture, Manufacturing, and Mining industries to comprise the tradable sector T. We construct a time-varying regional exposure to Chinese imports — that corresponds to our theoretical construct λ_{Mt} — as follows:

$$dIMP_{M,t}=\sum_{j\in J}\frac{N_{Mj,1993}}{N_{j,1993}}d^{US}Import_{j,1993\to t}. \tag{4}$$

Here, we calculate each region's exposure to trade as the cumulative import growth weighted by the share of region M in U.S. business establishments in industry j. More specifically, for each region M and industry j (based on four-digit NAICS codes) we have $\frac{N_{Mj,1993}}{N_{j,1993}}$ as weights, where $N_{Mj,1993}$ is the total number of establishments in (MSA) M and industry j in 1993, and $N_{j,1993}$ is the number of establishments in industry j across all MSAs in 1993. $d^{US}Import_{j,1993\to t}$ is the cumulative

[4] In our data, the principal education categories are "High School or less," "Some College", and "College." The corresponding profit margins (calibrated to the data from the tradable sector) are taken to be \$30,000, \$37,5000, and \$57,000, respectively. The corresponding labor incomes (calibrated from the data) are taken to be \$24,000, \$34,000, and \$56,000 respectively. To focus on the human capital effects, the total wealth is taken to exceed \$112,000, which ensures that the wealth constraints on the entry costs are non-binding for all education groups.

growth in U.S. imports from China in industry j between 1993 and year t. We use the distribution of establishments across regions and industries in 1993 to address the endogeneity concern that variations in Chinese imports and the number of local business establishments may be correlated with latent regional and sectorial shocks. This approach is similar to that adopted by the literature on the effects of import shocks from low-wage countries on local labor markets (Autor et al., 2013; Acemoglu et al., 2016; Ebenstein et al., 2014). However, fixing the MSA shares in 1993 may lead to a loss of information because the regional allocation of economic activity in the U.S. economy is not static and will change for reasons that are exogenous to import competition (such as demographic and technological changes). Therefore, we also utilize an alternative measure (in Section 4.2.), which considers the potential feedback effects between import exposure and entrepreneurial activity.

One concern about (4) as a measure of import exposure is that observed changes in the import penetration may in part reflect domestic shocks to U.S. industries and MSAs that determine U.S. import demand. Even if the key factors behind China's export growth are internal supply shocks in China, U.S. import demand shocks may still taint bilateral trade flows. To capture this supply-driven component in U.S. imports from China, we instrument (4) using the growth of Chinese imports in other high-income major trading partners of China (Acemoglu et al., 2016, Autor et al., 2013; Bloom et al., 2015):

$$dIMPO_{M,t}=\sum_{j\in J}\frac{N_{Mj,1993}}{N_{j,1993}}d^{O}Import_{j,1993\to t} \tag{5}$$

where $d^{O}Import_{j,1993\to t}$ is the cumulative growth in imports from China in industry j during the period 1993 to t or some subperiod thereof in other high-income countries excluding the United States.[5]

Our identification strategy implicitly assumes that the surge in Chinese exports to high-income countries between 1993 and 2006 was due to shocks that originated from China rather than due to underlying demand trends in the countries themselves. This IV approach is thus in the spirit of the Hausman (1996) instrument that is frequently used in the industrial organization literature (where prices in one market are instrumented by the prices of the same product by the same firm in other markets). Furthermore, in defense of our identification assumptions, evidence suggests that China's

[5] Note that including *time-varying* regional and sectoral fixed effects in our regressions — as in sections 4.3 and 5 — additionally addresses the concern that the import exposure may, in part, be correlated with an underlying overall *trend* in U.S. industries and local demand rather than heterogeneous regional exposure to rising Chinese competition.

annual aggregate productivity growth was about 2% between 1988 and 1998 and soared to about 5% between 1998 and 2007 (Zhu, 2012) — with productivity growth in manufacturing reaching as high as 8% per year (Brandt et al., 2012). Moreover, if product demand shocks are correlated across high-income countries, then both our OLS and IV estimates will be biased downward, implying that the true effects are even *larger* than the ones we estimate.[6]

Figure 4 shows the highly correlated growth rates of imports from China for the U.S. and other high-income countries (such as Germany, France, Italy, Spain, Netherlands, Belgium, Austria, Finland, Japan, United Kingdom, Canada, Australia, Switzerland, Sweden, Norway, Denmark, New Zealand). The high correlation between the growth of Chinese imports to U.S. and other high income countries facilitates identification by allowing us to instrument the former with the latter in our empirical tests. Moreover, Figure 5 displays the correlation between $dIMP_{M,t}$ and $dIMPO_{M,t}$ for all MSAs in our sample between 1993-2006 after controlling for time-varying MSA macro and demographic factors (as listed in Panel B of Table 3), MSA and year fixed effects. The coefficient is 0.95, and the t-statistic and R-squared are 8.6 and 0.73, respectively, indicating the strong predictive power of import growth in other high-income countries for U.S. import growth from China.

3.2 Data

To analyze the effect of variation in import penetration on the decision to start a new business, we use several large datasets obtained from the Census Bureau: longitudinal data from the Survey of Income and Program Participation (SIPP) from 1993 to 2006; product-level trade data from the U.S. Trade Online (USTO) Database; and County Business Patterns (CBP). Moreover, we use data from the Bureau of Labor Statistics, Bureau of Economic Analysis, Dealscan, Federal Housing Finance Agency, and Equifax at the MSA-level.

3.2.1 SIPP panel data

Our sample of households is drawn from the 1993, 1996, 2001, 2004 panels of the micro-level longitudinal Survey of Income and Program Participation (SIPP) data. Each SIPP panel tracks 60,000 to 80,000 individuals over a period of up to four years. The SIPP survey is built around a core set of questions on demographic attributes, employment and income, business ownership, profit/loss

[6] See Autor, Dorn, and Hanson (2013) for further discussion of identification using this instrumentation approach.

from business, and business size (number of employees).[7] But each wave also includes topical modules that include detailed questions on assets and liabilities — such as the ownership and market value of different types of assets, including real estate, vehicles, and financial assets (including IAs and 401Ks), which are reported annually. Our analysis is conducted at the individual level and includes only respondents who are 18 or older.[8] Since we are interested in the transition into entrepreneurship, for our entry sample we drop respondents who were already self-employed/owned a business in the previous year. This leaves us with an "entry" sample of 317,496 observations.

The SIPP identifies owners of home, other real estate, business, and vehicles owned on the date of the interview. We exploit this to compute $Total\ wealth$ for each respondent in our sample, which includes financial assets as well as non-financial assets such as all real estate (including second homes), vehicles, and private business equity. In addition, we extract information on *Labor income* from gross monthly earnings (before deductions) or (for those paid on hourly basis) from the regular hourly pay-rate and the number of hours worked. The data also allow us to identify if the respondent's current status is unemployed ($Unemployed$).

For human capital wealth, we identify various levels of formal education ($High\ school\ or\ less$, *Some college*, and *College or more*). In our stylized model, we use common notation for an individual's human capital resources (H_i) that are relevant for starting a business or his/her wage rate. In practice, of course, human capital is multi-dimensional; in particular, certain job-related attributes pertain especially to the wage rate, while others are particularly relevant to business-related human capital. The former category of variables includes job tenure, which is positively correlated with firm- or skill-specific human capital; we measure $Job\ tenure$ from the start date of the job. On the other hand, greater occupational mobility indicates lower commitment to employment and less formation of skill-specific human capital. The data identify a worker's employer, the employer's 3-digit Census Industry Classification (CIC), and the Integrated Public Use Microdata Series (IPUMS)

[7]Each SIPP panel is a multi-stage stratified sample of U.S. civilian, non-institutionalized population. The longitudinal design of SIPP dictates that all persons 15 years old and over present as household members at the time of the first interview be part of the survey throughout the entire panel period. To meet this goal, the survey collects information useful in locating persons who move. In addition, field procedures were established that allow for the transfer of sample cases between regional offices. Persons moving within a 100-mile radius of an original sampling area (a county or group of counties) are followed and continue with the normal personal interviews at 4-month intervals. Those moving to a new residence that falls outside the 100-mile radius of any SIPP sampling area are interviewed by telephone. The geographic areas defined by these rules contain more than 95 percent of the U.S. population.

[8]There are no mandated upper age limits on business ownership. Corporate laws vary by state, but all states require the principals of a company that incorporates to be 18 years or older. (see, https://www.sba.gov/blogs/6-things-you-need-know-about-starting-business-minor). For robusteness, we also exclude those aged below 20 or above 64, leading to similar results.

code for the worker's occupation. We measure the *Occupational mobility rate* as the number of individuals employed in successive time periods who change occupations divided by the number of individuals employed in both periods.[9] Finally, to measure financial literacy, we use a binary variable equal to one for individuals in a finance related occupation (*Financial experience*). There also additional individual characteristics that may impact the propensity for entrepreneurship — such as age, marital status, race and gender. For instance, the literature highlights the negative relation of age and entrepreneurship for older age groups (Parker, 2009). We use $Log(Age)$, the natural log of the individual's age.

Table 1 presents a univariate analysis of the differences in salient personal characteristics — including demographics, wealth and human capital related variables — between business "starter" and "non-starter" subsamples.[10] A significantly higher number of business starters are male, white, and married; these demographic differences are consistent with other studies of entrepreneurship that use the SIPP data (Corradin and Popov, 2015).

Turning to characteristics that are directly related to our theoretical framework, the mean wealth related variables are significantly greater for the business starter group compared with the non-entrepreneur group. The average total wealth of the former is more than twice that of the latter, while liquid wealth — which is the sum of safe assets such as government securities, munis, corporate bonds, money market deposit accounts, checking accounts, savings accounts, and stockholdings — and home equity are 39% and 67% higher, respectively. Notably, the labor income of the business starters is also significantly higher than that of the non-entrepreneurs.[11] In sum, there is a positive correlation between total wealth and the propensity to start a business.

In terms of human capital related variables, the business starter group is clearly more educated compared with the non-starter group. The mean proportion of individuals with an educational attainment of high school or less is significantly higher in the non-starter group, while the mean proportion of individuals with a college degree or more is significantly greater in the starter group.

[9] Occupational mobility can occur with or without job mobility. An example of occupational mobility without job mobility would be if a carpenter who works for a general building contractor changes occupations by being promoted into a management position for the same contractor. An example of occupational mobility with job mobility would be if the carpenter changed employers to work outside the construction field, such as working at the local fire department as a firefighter. Occupational mobility has not occurred if the carpenter leaves one contractor for another while continuing to work as a carpenter.

[10] The former subsample is comprised of respondents who did not own a business in year t but owned a business in year $t+1$, while the latter involves those who did not own a business in year t and still did not own a business in year $t+1$.

[11] Many recent entrepreneurs in our sample still maintain their jobs in the year that they start the business.

Moreover, the business starters have significantly higher experience in business and financial related fields. Thus, human capital endowment is positively related to starting a business. But as we mentioned above, the relation of occupational mobility, unemployment, and job tenure to the propensity to start a business is ambiguous ex ante. We find that there is no significant difference between starters and non-starters in terms of being unemployed. But business starters exhibit significantly lower occupational mobility and job tenure compared with non-starters in our sample. Finally, there is a negative correlation between age and entrepreneurship: the proportion of business starters in 18-55 age groups is significantly greater than non-starters, but the reverse is true for the 55+ age group.

3.2.2 Trade data

Our main source of data on imports is the USTO Database of the Census Bureau at the six-digit Harmonized System (HS) product level. While the HS six-digit classification allows comparisons across countries in a given year, it has undergone changes over time. The World Customs Organization (WCO) revises the HS classification on the basis of the value of trade realized for each product during the previous period. Three major revisions took place in years 1996, 2002 and 2007. The modifications introduced in each of these revisions have taken two forms: (i) two different codes with low trade volume were converted into a single code, and (ii) an existing code with an increasing trade volume was split into various codes. In order to address these inconsistencies, and calculate industry level imports (for Agriculture, Mining and Manufacturing), we transform six-digit HS codes to four-digit NAICS codes using the HS-NAICS bridge developed by Pierce and Schott (2012). The bridge file is updated through 2009. As industry level price indices for imports and exports are not available in the U.S., following Acemoglu et al. (2016), we adjust imports from China to the U.S., along with total U.S. imports and exports with the Personal Consumption Expenditure (PCE) index.[12]

Panel A of Table 2 shows the dominance of Chinese import growth into the U.S. starting in the early 1990s, as has been pointed out in the literature. In particular, during 1993-2006, the growth of imports from China into the U.S. far outpaced import growth from other low- income countries.

[12] The Personal Consumption Expenditures (PCE) price index is produced by the U.S. Bureau of Economic Analysis (BEA). Despite differences in scope, weight, and methodology, the CPI and the PCE price index both measure inflation from the perspective of the consumer. PCE indices can be downloaded from FRED Economic Data of the St. Louis Fed: https://fred.stlouisfed.org/series/PCEPI#0.

As we mentioned already, imports from China during this period rose by over 950%, which is more than 4.5 times the corresponding growth of imports from other low- income countries. These figures support our focus on import growth from China as a major competitive shock in tradable industries for U.S. entrepreneurship. For the sake of comparison, Table 2 also provides the growth rates from the same exporters to a group of high-income countries. While lower than the corresponding import growth to the U.S., Chinese imports during 1993-2006 into other high-income countries grew by 773%, substantially exceeding the import growth from other low-income countries that are mostly located in Africa and Asia.

3.2.3 Regional data

Finally, we use data from CBP on U.S. employment and number of establishments. These data are tabulated by geographic area, industry, and employment and receipt size of the enterprise. We identify the "local markets" in our theoretical framework with Metropolitan Statistical Areas (MSA) and obtain MSA-level demographic and macro data from the Bureau of Labor Statistics (*Labor force participation rate, Unemployment rate*), Bureau of Economic Analysis (*GDP growth rate*), the Census Bureau (*College educated population)*, Dealscan (*% Change in industrial/commercial loans*), Federal Housing Finance Agency (*Housing price index*), and Equifax (*Delinquency rate on mortgage loans*). Panel B of Table 2 provides descriptive statistics for MSA-level control variables. There is a significant dispersion of the weighted import growth measure $dIMP$ across MSAs, with the standard deviation being 1.2 times the mean. We see substantial dispersion across MSAs in the housing price appreciation index and the growth of industrial/commercial credit. But there is relatively small dispersion for macroeconomic variables such as the unemployment rate, GDP growth, and the labor force participation rate.

3.3 Specification

Our entry sample consists of repeated cross sections of unique non-business owners who may transition into self-employment from year t to year $t+1$. We take advantage of the individual-level panel data structure of the SIPP and use individual fixed effects to control for latent individual heterogeneity in the propensity to start a new business (Bertrand, 2004). Specifically, let t be the year in which the individual is surveyed, i be a non-business owner in year t, and M be a region.

Our estimating equation is:

$$\begin{aligned} Entry_{iM,t+1} &= \mathbf{Z}'_{iM,t}\boldsymbol{\beta} + \gamma_1 dIMP_{M,t} + e_t + \\ & f_M + g_i + \varepsilon_{iM,t} \end{aligned} \tag{6}$$

$Entry_{iM,t+1}$ is a dummy variable equal to one if individual i living in region M and surveyed in year t becomes self-employed at date $t+1$; $dIMP_{M,t}$ is the cumulative import penetration in region M (as defined in specification (4)).

Meanwhile, $\boldsymbol{\beta}$ is a vector of unknown parameters; e_t are year fixed effects; f_M are MSA-level fixed effects; g_i are individual fixed effects; and $\varepsilon_{iM,t}$ is an error term. These fixed effects capture aggregate and time-invariant unobservable local shocks to economic activity as well as unobserved individual characteristics. Additionally, the vector $\mathbf{Z}_{iM,t}$ includes a rich set of time-varying observable individual- and MSA-level covariates relating to wealth, human capital, and propensity to start a business — specifically personal wealth, labor income, employment status, age, occupational mobility, job tenure, education level as well as respondent's marital status, household wealth, and household size, race, gender, and financial experience where the last three controls and all other unobserved time-invariant individual characteristics are subsumed by the individual fixed effects.

Based on Proposition 1, we expect γ_1 to be negative. Furthermore, the coefficients for covariates related to wealth should be positive. But the model indicates that the sign of coefficients for human capital covariates related to formal education should be ambiguous: Greater education can provide human capital skills for running a successful business but also raise the opportunity cost of entrepreneurship by increasing the wage rate. For analogous reasons, the effect of being unemployed is ambiguous since unemployment both reduces wealth and the opportunity cost of starting a business. Similarly, the impact of *Job tenure* and *Occupational mobility* are ambiguous. For example, greater tenure increases both the opportunity cost of entrepreneurship and the development of skills useful for running a business, while greater occupational mobility indicates both lower opportunity costs and skill development.

4 Results

4.1 Decision to start a business

The results of OLS and IV estimation of equation (6) are presented in Table 3. The standard errors are clustered at the MSA level. Columns (1) and (3) utilize only the import penetration measures as the covariate (that is, $\mathbf{Z} = \mathbf{0}$ in (6)) with fixed effects and local controls, while columns (2) and (4) present the results of estimating the full specification of (6). The coefficient of -0.031 in column 1 indicates that a one-standard deviation increase in an MSA's import exposure is predicted to reduce the likelihood of starting a new business — that is, the entrepreneurship propensity — by 24%, significant at the 1% level. The point estimate of exposure drops slightly to about -0.028 when we control for a full set of individual characteristics as well as household wealth, household size. And columns (3) and (4) indicate that the depressing effect of import penetration is robust in terms of statistical significance, with a marginal decline in economic significance when we use the IV. That the estimated coefficient is similar in magnitude in both time periods and all four models underscores the stability of the statistical and economic relationships.

The bottom panel of Table 3 displays first-stage estimates for 2SLS (columns 3 and 4), which also includes all control variables (as 'included' instruments) that are used in the second stage estimations. The estimated coefficients are about 0.9, and the values for t-statistic and R-squared are 10 and 0.75, respectively, indicating the strong predictive power of import growth in other high-income countries for U.S. import growth from China. Finally, we report the results of the F-test of the joint significance of the excluded instruments in the first-stage regression. If the explanatory power in the first stage is weak, then this is a cause for concern (Staiger and Stock, 1997; Baum, Schaffer, and Stillman, 2003). Staiger and Stock (1997) suggest a simple rule of thumb that in the presence of a single endogenous regressor, the instrument is deemed to be weak if the first-stage F-statistic is less than 10. For our regressions, the value of the F-statistics is about 129.

Table 3 also shows that wealth has a significant positive effect on the propensity to start a business, other things held fixed. And controlling for wealth, we do not find any significant impact of labor income. These results hold for both the OLS and 2SLS estimates, and in fact the wealth effect on entrepreneurship is stronger when we use the IV. Thus, we find support for a main individual-level prediction of the theoretical entry model. Turning to the effects of human capital endowment, high educational attainment (college or more) ceteris paribus has a strong and significant positive impact on the propensity to start a business. Other things being equal, the OLS estimates indicate that sample respondents with high education have a greater likelihood of starting a business compared with respondents that have high school or less. In light of the equilibrium entry model, this implies that the positive benefits of high levels of educational attainment on starting and operating a business dominate the positive relation of education and wages.[13] Relatively lower levels of educational attainment ("some college"), however, have no significant incremental impact on entrepreneurship propensity. These results thus provide an empirical clarification on the theoretically ambiguous effects of higher education on entrepreneurship.

As we mentioned above, the effects of unemployment and occupational mobility are theoretically ambiguous. We find that unemployment has no significant effect on entrepreneurship. However, occupational mobility is significantly and negatively related to entrepreneurship, indicating that the positive skill development effect of lower occupational mobility on starting a business dominates the negative opportunity cost effect. Finally, we confirm that age is significantly negatively related to entrepreneurship, other things held fixed.

In sum, the analysis in Table 3 supports the theoretical prediction (cf. Proposition 1) that low-cost import competition will have a significant negative effect on business formation or entrepreneurship. In addition, the findings support the theoretical entry model in terms of the positive role of wealth. The results also empirically resolve the ambiguous prediction regarding the effects of human capital — in the form of higher educational attainment — on entrepreneurial activity.

4.2 Additional Identification Tests

The results in Table 3 show significant negative impact of import penetration from low-wage countries on entrepreneurial activity. Even if the dominant factors driving China's export growth are internal supply shocks in China, U.S. industry and MSA import demand shocks may still contaminate bilateral trade flows. To capture this supply-driven component in U.S. imports from China, in our tests we have utilized multiple fixed effects and an IV approach. Nevertheless, there remain additional endogeneity concerns that can confound identification. In this section, we describe these concerns and our identification strategies to address them. The results for the various tests are presented in Table 4.

[13] Given the focus of our study, and for reasons of space, we do not conduct a formal examination of labor income and education in our sample. But the empirical evidence on the positive effects of higher education in the literature is overwhelming (see, e.g., Psacharopoulos and Patrinos, 2004).

4.2.1 Role of the Housing Market

As we noted in the Introduction, our sample period overlaps with that of the housing boom, leading to the endogeneity concern that regions which experienced larger changes in import exposure also had smaller increases in housing prices. In that case omitting any variables that drive housing prices would lead to a biased estimate of the elasticity of entrepreneurial activity to trade exposure. So far, we have controlled for MSA fixed effects, time-varying appreciation in MSA-level housing price index (HPI), and other proxies for local economic conditions (such as changes in the unemployment rate, changes in income, changes in mortgage debt, and others given in Panel B of Table 2) in our regressions. However, even after the inclusion of local economic controls and MSA fixed effects, these estimates do not establish causality, since there might be an unobserved third factor that could simultaneously move both house prices and entrepreneurial activity. We probe the robustness of our results by additional tests to ensure that the housing effect does not mask our findings, and we can alleviate concerns that our results are driven by local demand booms.

Identification strategy 1: Our first methodology follows Schmalz, Sraer, and Thesmar (2017), who compare French homeowners and renters and find that homeowners are more likely to start a business in areas in which house prices appreciated more. Our estimation equation now becomes:

$$\begin{aligned} Entry_{iM,t+1} \quad = \quad & \mathbf{Z}'_{iM,t}\boldsymbol{\beta} \ + \ \gamma_1 dIMP_{M,t} \\ & +\delta_1 Owner_{iM,t} \times GHPI_M^{1993\to t} + \delta_2 Owner_{iM,t} + \delta_3 GHPI_M^{1993\to t} \\ & + e_t \ + f_M \ + \ g_i \ + \ \varepsilon_{iM,t} \end{aligned} \tag{7}$$

where $Owner_{iM,t}$ is a dummy equal to one if the individual is a home owner in year t, $GHPI_M^{1993\to t}$ is the cumulative house-price appreciation in MSA M between year 1993 and t, and the vector of other controls $\mathbf{Z}$ are as defined in equation (6). We continue to instrument $dIMP_{M,t}$, as in preceding tests, with $dIMPO_{M,t}$. In this setup, to control for the possible endogenity in house prices, we also instrument for the growth in local house prices $\left(GHPI_M^{1993\to t}\right)$ using the housing supply elasticity $\times$ nation-wide mortgage rates (Chaney, Sraer, and Thesmar, 2012). The intuition for this instrument is that for a fixed housing demand shock during the (housing) boom, house prices should rise more in areas where housing supply is less elastic. The key advantage of this source of variation in house prices is that it avoids the potential for omitted variable bias due to local economic conditions because the variation is driven purely by *national* demand shocks. We use two measures of housing supply elasticity as instruments for home prices: the geography-based measure of Saiz (2010), and the regulation-based measure from the Wharton Regulation Index (Gyourko, Saiz, and Summer, 2008).[14]

The exclusion restriction requires that housing supply elasticity affects entrepreneurial decision only through its impact on house prices. To provide some evidence for the validity of the Saiz (2010) instrument, Mian and Sufi (2011, 2014) show that wage growth did not accelerate differentially in elastic and inelastic areas between 2002 and 2006. They also show that the instrument is uncorrelated with the 2006 employment share and employment growth in construction during 2002–2005, and population growth in the same period. Consistent with this, we find no relationship between housing supply elasticity and income growth in our sample: during the housing boom, income growth has a correlation of 0.061 with the Saiz (2010) instrument and -0.012 with the Wharton Regulation Index (see also Davidoff, 2013, for a discussion of the exclusion restriction).[15]

The results are shown in the first column of Table 4. For the sake of brevity, we only report the results for the Saiz supply elasticity $\times$ nation-wide mortgage rates. We continue to find a highly statistically significant negative effect of import exposure ($dIMP_{M,t}$) on business entry, and the economic significance is commensurate with the results in Table 3.

Identification strategy 2: In our data — unlike Schmalz, Sraer, and Thesmar (2017) — we observe the actual housing equity that homeowners have in their property, as well as the year when the house was purchased. Therefore, we can estimate the effect of a change in home equity on entrepreneurial activity *within the sample of homeowners* in the same MSA M and time t. Thus, our second approach to addressing the possible omitted variable bias is to employ a version of the identification strategy suggested by Chetty, Sándor, and Szeidl (2017), who isolate the exogenous variation in home equity and property values by using differences in house prices and housing supply elasticities across housing markets as instruments.

We begin the implementation of this approach by disaggregating total wealth as home equity

[14] Saiz (2010) constructs predicted elasticities using measures of local physical and regulatory constraints. The measure assigns a high elasticity to areas with a flat topology without many water bodies, such as lakes and oceans. Gyourko, Saiz, and Summer (2008) conduct a nationwide survey to construct a measure of local regulatory environments (Wharton Regulation Index) pertaining to land use or housing. Their index aggregates information on who can approve or veto zoning requests, and particulars of local land use regulation, such as the review time for project changes. In areas with a tighter regulatory environment, the housing supply can be expanded less easily in response to a demand shock, and prices should therefore rise by more.

[15] Both instruments are highly predictive of housing price changes, with low-elasticity MSAs experiencing larger house price and equity gains during the housing boom. The first-stage F-stats of the Saiz (2010) and Gyourko, Saiz, and Summer (2008) instruments are 52.8 and 45.34, respectively.

and non-housing wealth (which denotes the total wealth of the household net of the amount of home equity) and then estimating the following specification:

$$\begin{aligned} Entry_{iM,t+1} \;\; = \;\; & \mathbf{Z}'_{iM,t}\boldsymbol{\beta} \; + \; \gamma_1 dIMP_{M,t} \\ & + \delta_1 Property\ value_{iM,t} + \delta_2 Home\ equity_{iM,t} \\ & + \; e_t \; + f_M \; + \; g_i \; + \; \varepsilon_{iM,t} \end{aligned} \tag{8}$$

where *Property value* is the property value in the current year (for individual i in MSA M), *Home equity* is the home equity (difference between the value and outstanding mortgage debt owed against the primary residence) in the current year (for individual i in MSA M). We continue to control for aggregate shocks and cross-sectional differences across housing markets by including state and year fixed effects, and thereby exploit only differential within-state variation for identification. Following Chetty, Sándor, and Szeidl (2017), we instrument for the property value and home equity using variations in the current and the time-of-purchase house price index, respectively, at the *national* level interacted with MSA-level housing supply elasticity. As before, we continue to instrument $dIMP_{M,t}$ with $dIMPO_{M,t}$. We show the estimation in the second column of Table 4 and find results similar to that from applying the first identification strategy.

Identification strategy 3: The next refinement to our identification strategy is to run (7) and (8) after (i) we exclude households living MSAs with a very inelastic housing supply and (ii) drop businesses which are driven by the housing boom — such as construction, finance, insurance, real estate, rental, and leasing. Column 3 of Table 4 indicates that both with Schmalz, Sraer, and Thesmar (2017) — *SST estimation* — and Chetty, Sándor, and Szeidl (2017) — *CSS estimation* — identification approaches, the sensitivity of business formation to import exposure similar to our earlier findings.

Finally, we use joint MSA-year fixed effects to identify variations across households residing in the same MSA at the same point in time. This cross-sectional exercise is undertaken in Section 4.3 below.

4.2.2 Feedback Effects

Following Autor et al. (2013), our measure of import penetration adapts weights at the start of 1993 (as in (4)), which is the beginning of our sample period. However, fixing the MSA shares in 1993 may lead to a loss of information because the regional allocation of economic activity in the

U.S. economy is not static and will change for reasons that are exogenous to import competition (such as demographic and technological changes). We therefore utilize the following measure as an alternative:

$$dIMP^*_{M,t} = \sum_{j \in J} \frac{N_{Mj,t-1}}{N_{j,t-1}} d^{US} Import_{j,1993 \to t}.$$

Here, the shares of industry establishments in MSAs are determined by weights computed from the prior year, generating possible feedback effects from a dynamic decision of local business activity to future import penetration. If such feedback effects exist, then the identification approaches and estimation techniques that are useful with strictly exogenous variables may no longer be valid. Fortunately, this particular form of weight definition can easily be accounted for by using well-known panel data techniques where the $dIMP^*_{M,t}$ is said to be *predetermined* (see Chapter 8 in Arellano, 2003; Wooldridge, 2010).[16]

The panel GMM estimator discussed in Arellano and Bond (1991) is probably the most popular approach for estimating dynamic panels with unobserved heterogeneity and predetermined regressors and is well-suited with small T (time-series dimension), large N (cross-sectional dimension) panels. More precisely, the GMM estimator in our case follows a two-step procedure: In the first stage, variables in (6) are differenced to remove individual fixed effects while still controlling for common time-varying and regional shocks to the entrepreneurial decision through a full set of year dummies and MSA dummies. In the second stage, as pointed out by Arellano and Bond (1991), all of the lags of the predetermined variable are valid instruments, as are the additional independent explanatory variables. Including these variables as instruments improves efficiency, as long as they are correlated with the regressor they are instrumenting for. Therefore, we use three lags as instruments for $dIMP^*_{M,t}$. In addition, we use the entire time series of all the exogenous regressors ($\mathbf{Z}_{iM,t}$ in entry decision). Overall, this procedure avoids dynamic panel bias (Nickell, 1981) and addresses potential bias caused by the feedback effects between import penetration and entrepreneurship over time.

The results are presented in Column 5 of Table 4. We continue to find significant negative effects of import penetration on the decision to start a business. The estimated coefficients are somewhat lower but are still commensurate with the point estimates in the corresponding columns in Table 3.

[16] Predetermined regressors are also labeled as sequentially exogenous in the literature (Wooldridge, 2010).

4.2.3 Non-Linear Effects

We have so far reported estimates of linear probability models that allow us to use a large number of fixed effects while also dealing with potential endogeneity in $dIMP_{M,t}$. To account for possible non-linearities in the data we also estimate a logit model. Unfortunately, fixed effects cannot be easily included in logit models because of an incidental parameter problem, and allowing endogenous explanatory variables in logit models is notoriously difficult. But Petrin and Train (2005, 2006) illustrate how a control function can be used to test for and correct the omitted variables (endogeneity) problem. To accommodate fixed effects in our binary model, we follow Mundlak (1978) and Chamberlain (1980).

The method proceeds in two steps. The first step is a linear regression of $dIMP_{M,t}$ on an excluded instrument ($dIMPO_{M,t}$), included instruments (exogenous variables), and fixed effects. We use this regression to construct the *expected* $dIMP_{M,t}$ for each MSA in each year. The residual from the first-stage regression (difference between $dIMP_{M,t}$ and expected $dIMP_{M,t}$) is then used to estimate the control function. In the second step, a conditional logistic choice model with fixed effects is estimated with the control function entering as an extra variable.[17]

Because the second step uses estimated residuals from the first step, as opposed to the true residuals, the asymptotic sampling variance of the second-step estimator needs to take this extra source of variation into account. Either the bootstrap can be implemented, or the standard formulas for two-step estimators can be used (Murphy and Topel, 1985; Newey and McFadden, 1994). Karaca-Mandic and Train (2003) derive the specific form of these formulas that is applicable to the control function approach.[18] As they note, the bootstrap and asymptotic formulas provide similar standard errors for the application that we describe in our empirical results.[19] We create

[17] Note that one can include nonlinear forms of the control function and other explanatory variables, including quadratics and interactions for more flexibility.

[18] To formalize the approach, consider a model —where fixed effects are suppressed for notational ease— $D = G(\mathbf{X}, \boldsymbol{\beta}, \varepsilon)$, where $\mathbf{X}$ is a vector of covariates, $\boldsymbol{\beta}$ a vector of parameters, and ε is the error. We assume there are functions G, h, and well-behaved error u such that $X^e = G(W, e)$, $\varepsilon = h(e, u)$, and $u \perp (\mathbf{X}, e)$. We first estimate $G(.)$, the endogenous regressor as a function of instrument W and other exogenous variables as our included instruments and derive fitted values of the errors e. Then we have $D = G(\mathbf{X}, \boldsymbol{\beta}, h(e, u)) = \tilde{G}(\mathbf{X}, \boldsymbol{\beta}, e, u)$ where error term of the model $\tilde{G}$ is u, which is suitably independent of $(\mathbf{X}, e)$. This model no longer has an endogeneity problem and can be estimated via straightforward methods. Given $D = I(X^e\beta_e + \mathbf{X}^0\boldsymbol{\beta}_0 + \varepsilon \geq 0)$, $X^e = W\alpha + \mathbf{X}^0\boldsymbol{\beta}_0 + e$ with (ε, e) jointly normal, we can first linearly regress X^e —which is the ΔIMP— on W —which is the $\Delta^O IMP$— and other exogenous variables (included instruments) with residuals being estimates of e. This yields the ordinary binary choice model $D = I(X^e\beta_e + X^0\beta_0 + \lambda e + u \geq 0)$.

[19] Early applications of a control function were performed by Smith and Blundell (1986) in a tobit model and Rivers and Vuong (1988) in a probit model. More recent applications include Liu, Lovely, and Ondrich (2011), Ricker-Gilbert, Jayne, and Chirwa (2011).

a pseudo random sample by drawing observations from the base sample with replacement. Thus in every replication some of the observations appear more than once, and some do not appear at all. With 500 such replications, we generate an empirical distribution of estimated coefficients in the conditional Logit model. The standard deviations of these estimates are then used to obtain bootstrapped p-values for our estimation. This methodology does not rely on any structural form for the estimation of a variance-covariance matrix and has the advantage of benchmarking base estimates against their empirical distributions. The results are shown in Column 6 of Table 4 and again indicate statistically and economically significant negative impact of import competition on the propensity to start a business. For example, the point estimate in column 2 indicates that a one-standard deviation increase in import penetration leads to a 20% decrease in the odds of entry.

5 Import Competition and Economic Performance of Firms

The results presented above support the hypothesis that increased low-cost competition reduces the incentives to start a business, other things held fixed. This hypothesis (see Section 2) is based on the assumption that the profit function $\pi_M(\cdot, \lambda_M, \cdot)$ is strictly decreasing in the level of import penetration λ_M (in each local region M). Our data allow us to examine the empirical validity of this assumption directly, however, because we have information on the profits/loss of existing businesses. More generally, controlling for the profit/loss, the impact of higher import penetration on business formation will depend on the ability of *existing* entrepreneurs to sustain their businesses. This is because the expected profits from entry are negatively related to the likelihood of exiting the business. In this section, we provide evidence on the effects of import penetration on the profits/loss and exit rates of existing businesses.

We estimate the impact of import penetration on profits/loss of existing businesses through the equation:

$$\begin{aligned} Profit/Loss_{iM,t+1} \quad &= \quad \mathbf{X}'_{iM,t}\boldsymbol{\beta} + \theta_1 dIMP_{M,t} + \theta_2 dIMP_{M,t} \times \textit{Tradable sector} + \\ & \quad\quad e_t + f_M + \ g_i \ + \ \varepsilon_{iM,t} \end{aligned} \tag{9}$$

Here, $Profit/Loss$ is measured as the difference between gross receipts and expenses. $\mathbf{X}_{iM,t}$ is a vector of individual (such as business owners' wealth, age, occupational mobility, education, marital status), household (such as household size and household wealth), and MSA-level covariates as in

(6) and includes $Business\ size$ — measured as the number of employees — to control for the effect of firm size on profits. Furthermore, e_t are year fixed effects; f_M are MSA-level fixed effects; g_i are individual fixed effects; and $\varepsilon_{iM,t}$ is an error term. As before, we continue to instrument $dIMP_{M,t}$, as in preceding tests, with $dIMPO_{M,t}$ using 2SLS. We expect θ_1 and θ_2 to be negative under the theoretical assumption of Section 2. Our sample includes only business owners at time $t+1$ with non-missing information on their business profit and size at time t.

For parsimony, column 1 of Table 5 reports the estimates for import penetration, business size, and interaction term in Eq. (9) with individual, MSA and year fixed effects, whereas column 2 uses individual and MSA×year fixed effects, subsuming θ_1 in our estimations. Import penetration has a significantly negative effect on business profit, especially in the tradable sector, controlling for firm size and other individual and MSA level controls. The adverse impact of import penetration on business profits in the tradable sector is also economically sizeable: Column 1 indicates that one-standard deviation increase in $dIMP_{M,t}$ on average reduces profits by 4% in the tradable sector, other things held fixed. A concern with this specification is that we only observe outcomes ex post for those firms that do not exit the sample. The possibility of exit may generate a survivorship bias because businesses started in regions that experienced large import penetration growth from 1993 to 2006 are more likely to exit (see below). However, had they remained, these businesses would have been less profitable; hence, their attrition creates a *downward* bias on the estimates of θ_1 and θ_2, suggesting that the true effects are even larger than the ones we estimate.

We examine, next, the decision to end a business, controlling for the effects of import penetration on profits. This analysis is informative of the effects of import competition on the expectations of existing business owners regarding future economic performance. Our exit sample excludes respondents who were not self-employed/owned a business in the previous year and consists of repeated cross-sections of unique business at time t. Our final "exit" sample includes 34,481 observations. Specifically, let $Exit_{iM,t+1}$ be a dummy variable equal to one if a business owner i living in region M and surveyed in year t did not own a business at date $t+1$. Then, our estimating equation is:

$$\begin{aligned} Exit_{iM,t+1} \quad &= \quad \mathbf{Y}'_{iM,t}\boldsymbol{\beta} + \theta_1 dIMP_{M,t} + \theta_2 dIMP_{M,t} \times Tradable\ sector\ + \\ &\quad\ \ e_t + f_M + \ g_i \ + \ \varepsilon_{iM,t} \end{aligned} \tag{10}$$

The notation for the fixed effects and the error term is as given in Eq. (9). $\mathbf{Y}_{iM,t}$ is a vector of MSA-level covariates as in (6), individual and household-level controls as in (9), augmented with other relevant factors in the exit decision and available in our data. Models of business exit in the literature highlight the positive relation of exit to negative profits (losses) and a negative relation to firm size (Klepper, 1996). In addition, the likelihood of exit is higher ceteris paribus for firms with greater debt since this increases bankruptcy risk (Fan and White, 2003). We therefore control for $Profit/Loss$, *Business size*, and *Business leverage* (defined as the ratio of total debt owed against the business to business equity).

If import penetration adversely affects the ability of existing entrepreneurs to sustain their business, other things held fixed, then we expect the estimates of θ_1 and θ_2 to be positive. Again in column 3 Table 5, we only report the estimates of θ_1, θ_2 and business-specific controls with individual, MSA and year fixed effects. Column 4 replaces MSA and year fixed effects with MSA$\times$year fixed effects, which absorbs coefficient θ_1 in our estimations. Results confirm that impetration has a significant, positive effect on the likelihood of ending an existing business in the tradable sector, even when we control for business, individual, and MSA-level characteristics. This impact is also economically significant. The point estimates in column 3 indicate that a one-standard deviation increase in $dIMP_{M,t}$ on average raises the likelihood of ending a business by 2.9% in the tradable sector. This implies that a one-standard deviation increase in an MSA's import exposure is predicted to increase the likelihood of ending a business by 22%, significant at the 1% level.

6 Extension to Non-Tradable Goods

The basic entry model developed above focuses on the effects of import penetration from low-cost countries on entrepreneurship in the tradable sector — the sector that is most directly impacted by the increased competition from cheaper imports. Realistically, the economy also consists of industries producing non-tradable goods (for example, services) and goods where buyer demand exhibits a low elasticity of substitution for imports from low-cost countries (for example, hi-tech and luxury brand goods). While such industries may not be directly affected by cheap imports, there will be *spillover effects* on the entrepreneurship in these industries from cheaper imports in tradable sectors, for the reasons mentioned in the Introduction.

To develop refutable predictions on these effects, we extend the basic model of the previous section in a stylized fashion. Each locality M has two sectors: A sector T that produces tradable goods and a sector of non-tradables S. For expositional ease, we will refer to these as tradable and non-tradable sectors, respectively. Agents can now choose to open a business in either the tradable or non-tradable sector or work for wages.

Formally, the entry cost is sector-specific and given by $C_M^T(\lambda_M^T)$ and C_M^S. The wage function will also be allowed to be sector specific, viz., $w_M^k(H_{iM}) = w_{0M}^k + w_{1M}^k H_{iM}, k \in \{T, S\}$. In a similar vein, the per period expected profit function for the tradable and non-tradable sectors are denoted by the functions $\pi_M^T(N_M^T, \lambda_M^T, H_{iM})$ and $\pi_M^S(N_M^S, H_{iM})$, where N_M^k is the number of active firms in sector k; these functions are strictly decreasing in N_M^k and λ_M^T but are increasing in H_{iM}. Since the tradable and non-tradable sectors include a diversity of industries, we are agnostic about the relative magnitude of the wage and entry function parameters across the two sectors. We thus derive (intersecting) sets of potential entrants in the two sectors, $\bar{E}_M^k$ in the manner specified in Section 2. Namely, denoting the total wealth index relevant for business ownership for individual i in sector k as $Q_{iM}^k \equiv V_{iM}^k + \phi_M^k H_{iM}$, the feasible set of (potential) entrants in that sector is $\bar{E}_M^k = \{i \,|\, Q_{iM}^k \geq C_M^k\}$.

Then, for any t, in equilibrium the number of entrants $(N_{Mt}^{T*}, N_{Mt}^{S*})$ and entrant sets E_{Mt}^{k*}, $k \in \{T, S\}$ are characterized in the following fashion. Given any pair (N_{Mt}^T, N_{Mt}^S) and conditional on the import penetration in the tradable sectorλ_{Mt}^T, put $\Lambda_{Mt}^T(y, \lambda_{Mt}^T, H_{iM}) \equiv \pi_M^T(y, \lambda_{Mt}^T, H_{iM}) - C_M^T(\lambda_{Mt}^T)$, and analogously define $\Lambda_{Mt}^S(y) \equiv \pi_M^S(y, H_{iM}) - C_M^S$. Then, for every $i \in E_{Mt}^{T*}$,

$$\Lambda_{Mt}^T(N_{Mt}^{T*}, \lambda_{Mt}^T, H_{iM}) \geq \max(\Lambda_{it}^S(N_{Mt}^{S*} + 1, H_{iM}), w_M^T(H_{iM}), w_M^S(H_{iM})) \tag{11}$$

and $i \in E_{Mt}^{S*}$,

$$\Lambda_{Mt}^S(N_{Mt}^{S*}, H_{iM}) \geq \max(\Lambda_{it}^T(N_{Mt}^{T*} + 1, \lambda_{Mt}^T, H_{iM}), w_M^T(H_{iM}), w_M^S(H_{iM})) \tag{12}$$

while for each $i \in \bar{E}_M^T - E_{Mt}^{T*}$,

$$\Lambda_{Mt}^T(N_{Mt}^{T*} + 1, \lambda_{Mt}^T, H_{iM}) < \max(\Lambda_{it}^S(N_{Mt}^{S*} + 1, H_{iM}), w_M^T(H_{iM}), w_M^S(H_{iM})), \tag{13}$$

and $i \in \bar{E}_M^S - E_{Mt}^{S*}$,

$$\Lambda_{Mt}^S(N_{Mt}^{S*} + 1, H_{iM}) < \max(\Lambda_{Mt}^T(N_{Mt}^{T*} + 1, \lambda_{Mt}^T, H_{iM}), w_M^T(H_{iM}), w_M^S(H_{iM})). \tag{14}$$

Based on these equilibrium conditions, we can derive the following refutable predictions on the determinants of the entry likelihood in the two sectors.

Proposition 2 *In equilibrium, the likelihood that individuals will choose to start a new business in the tradable sector is decreasing in the import penetration λ_{Mt}, but the entry likelihood is increasing in λ_{Mt} in the non-tradable sector, other things held fixed. The equilibrium entry likelihood is non-decreasing in wealth V_{iM} in both sectors, other things held fixed. The effect of human capital on the entry likelihood is generally ambiguous, but it is positive if w^k_{1M}, $k \in \{T, S\}$, are sufficiently low.*

The notable aspect of Proposition 2 is the prediction of a positive spillover effect of increased import exposure on entrepreneurship in the non-tradable sector. The intuition here is that as the rising import penetration from low-cost countries worsens the expected profits from entering the tradable sector, *infra-marginal* agents who would otherwise have started a business in this (tradable) sector shift to starting a business in the non-tradable sector. Thus, there is a positive inter-sectorial entrepreneurial allocation effect of higher import penetration from the tradable to the non-tradable sector.

To test this spillover effect of increased import penetration, we first divide the tradable sectors into highly exposed (manufacturing) and low-exposed (agriculture and mining segments). The other sectors, such as services and finance (see Figure 6 for the full list) comprise the non-tradable sector. For this analysis, we enhance the baseline (6) as follows. Let $Entry_{iM,t+1}$ be a dummy variable equal to one if individual i living in region M and surveyed in year t becomes self-employed at date $t+1$ in sector k. We then use the specification:

$$\begin{aligned} Entry_{iMk,t+1} \quad = \quad & \mathbf{Z}'_{iMK,t}\boldsymbol{\beta} \; + \; \gamma_1 dIMP_{M,t} \times \mathbf{1}\left\{\text{High-exposed tradable}_k\right\} \\ & +\gamma_2 dIMP_{M,t} \times \mathbf{1}\left\{\text{Low-exposed tradable}_k\right\} \\ & +\gamma_3 dIMP_{M,t} \times (\mathbf{1} - \mathbf{1}\left\{\text{High-exposed tradable}_k\right\} \\ & -\mathbf{1}\left\{\text{Low-exposed tradable}_k\right\}) + r_{kt} + v_{Mk} + f_{Mt} + \varepsilon_{iMk,t} \end{aligned} \tag{15}$$

Because we are now differentiating the effects of import amongst different types of sectors, the concern is that the estimated effects could reflect latent time-varying shocks at the MSA *and* sector level. For that reason, we include the joint fixed effects r_{kt} (Sector× year), f_{Mt} (MSA×year), as well as v_{Mk} (MSA×sector), which controls for regional variations in sector trends and meant to capture region-sector-specific investment opportunities.

Table 6 presents the results of estimating (15) using the 2SLS with the IV, $dIMPO_{M,t}$, (see (5)).

For parsimony, we report only the estimates of the coefficients γ_1, γ_2, γ_3. To help understand the effects of different types of latent shocks or trends, columns (1)-(3) utilize different combinations of fixed effects, while column (4) presents the results of estimating (15) with a full set of fixed effects.

It is evident that the negative impact of import penetration on entrepreneurship strongly resides in manufacturing — the sector most exposed to trade. This is consistent with intuition and — more formally with the theoretical framework developed above — we expect higher import penetration of cheap imports to have the maximal impact on business formation in industries most exposed to foreign trade.

Table 6 also shows that import penetration from low-cost countries has a significantly *positive* impact on entrepreneurship in the non-tradable sector when we control for latent time-varying regional and sector trends (columns (3) and (4)), latent time-varying and regional heterogeneity in sector trends (columns (1) and (4)), or latent time-varying and sectorial heterogeneity in regional trends (columns (2) and (4)). In sum, consistent with the conceptual discussion preceding Proposition 2, there is some evidence in Table 6 of substitution of entrepreneurial activity from the high-exposed tradable sector to non-tradable sectors in the face of increasing import penetration. However, these reallocation effects are much weaker than the significant dampening effects of import penetration on entrepreneurial activity in tradable sectors.

7 Competition, Entrepreneurship, and Individual Characteristics

The unique nature of our dataset allows additional insight on the relative impact of product market competition through higher import exposure on individual and business-related characteristics. This analysis is of independent interest and helps validate further the entry models of Sections 2 and 6. We undertake this analysis through the inclusion of interaction terms in the basic business formation specification (6). In such a set-up, we cannot estimate the direct effect of import exposure on an entry decision of individuals, but incorporating the interaction terms is potentially important because they ensure that our effects are not simply driven by individuals reacting differently to time-varying local investment opportunities/demand shocks — that is, we can difference out unobserved time-varying local shocks through MSA$\times$year fixed effects. The results are presented in Table 7, where we control for household-level covariates in column 2.

We find that import penetration has highly significant negative effects on the business start-up decisions of subgroups characterized by high educational attainment, higher occupational mobility, greater age, or higher labor income. On the other hand, the negative effect of import penetration on entrepreneurial activity is relatively mild (or diluted) for wealthier agents. We argue that these results are consistent with our generalized theoretical entry model in Section 6 and the previous empirical results.

Our theoretical model of entry indicates that import penetration will have relatively greater negative impact on the entrepreneurial activity of subgroups that have *either* lower ability to start a business in the trade-exposed sectors *or* higher opportunity costs of doing so. Consistent with the former hypothesis, our previous results indicate that ceteris paribus individuals that are older, or are less wealthy, or have higher occupational mobility are less likely to start a business. Meanwhile, subgroups with greater labor income or higher educational attainment (college or more) have higher opportunity costs of starting a business — either by joining the workforce or by starting a business in the non-tradable sectors. Therefore, the results in Table 7 are consistent with the view that the adverse competitive environment for business formation following import penetration also reduces the incentives of such subgroups for starting a business in the trade-exposed sectors.

8 Summary and Conclusions

Entrepreneurial activity is important for innovation and employment generation, and has implications for wealth generation and income inequality. Therefore, an apparent decline in U.S. entrepreneurial activity in the last couple of decades attracts increasing attention. We theoretically develop and empirically test the hypothesis that increased product market competition from the explosive growth in imports from low-cost countries has contributed to reduced entrepreneurship activity in sectors most exposed to such competition. We develop a theoretical framework of endogenous entry to show that entrepreneurial activity will ceteris paribus be negatively related to low-cost imports, especially for less wealthy individuals. The more subtle results are that the effects of human capital on entry are ambiguous, and that there may be positive spillover effects of cheap imports on entrepreneurial activity in non-tradable sectors.

Our empirical tests utilize a unique panel dataset on individuals across the U.S. during 1993-2006, which allows observations of transitions from employment to entrepreneurship and vice versa, along with a host of personal characteristics. We find strong support for increased low-cost product market competition as a channel contributing to lower entrepreneurial activity in the tradable sector, especially for less wealthy and less educated households. We also find reliable evidence of a positive spillover effect of low-cost import penetration on entrepreneurship in non-exposed sectors. These results indicate the importance of gauging the economy-wide effects of changes in product market competition in a given industry/sector on entrepreneurial activity.

Appendix: Proofs

Proof of Proposition 1: Consider two different levels of import penetration, $\lambda'_{Mt} > \lambda_{Mt}$, and let N'^{*}_{Mt} and N^{*}_{Mt} be the corresponding equilibrium number of entrants, respectively. Since $\pi_M(\cdot, \lambda_{Mt}, \cdot)$ is strictly decreasing it follows that if

$$\pi_M(N^*_{Mt}, \lambda_{Mt}, H_{iM}) - C_M(\lambda_{Mt}) = w_{0M} + w_{1M} H_{iM} \tag{16}$$

for some i, then

$$\pi_M(N^*_{Mt}, \lambda'_{Mt}, H_{iM}) - C_M(\lambda_{Mt}) < w_{0M} + w_{1M} H_{iM} \tag{17}$$

Hence, $N'^{*}_{Mt} < N^{*}_{Mt}$ because $\pi_M(N_{Mt}, \cdot, \cdot)$ is also strictly decreasing. Thus, the equilibrium number of entrants is negatively related to λ_{Mt}.

Next, consider a situation where $V'_{iM} > V_{iM}$ for every i, and again let N'^{*}_{Mt} and N^{*}_{Mt} be the corresponding equilibrium number of entrants, respectively. Clearly, for each i, and holding fixed H_{iM},

$$Q'_{iM} \equiv V'_{iM} + \phi_M H_{iM} > V_{iM} + \phi_M H_{iM} \equiv Q_{iM} \tag{18}$$

Hence,

$$\bar{E}'_M \equiv \{i \big| Q'_{iM} \geq C_M C_M(\lambda_{Mt})\} \supset \bar{E}_M \equiv \{i \big| Q_{iM} \geq C_M(\lambda_{Mt})\} \tag{19}$$

It follows from Eq. (19) that $N'^{*}_{Mt} \geq N^{*}_{Mt}$, so that the equilibrium number of entrants is non-negatively related to total wealth. Finally, consider a situation where $H'_{iM} > H_{iM}$ for every i. Clearly, for each i

$$\begin{aligned} \pi_M(N_{Mt}, \lambda_{Mt}, H'_{iM}) &> \pi_M(N_{Mt}, \lambda_{Mt}, H_{iM}) \qquad (20) \\ w_{0M} + w_{1M} H'_{iM} &> w_{0M} + w_{1M} H_{iM} \qquad (21) \end{aligned}$$

and it follows from Eqs. (2)-(3) that the relation of H_{iM} to N^{*}_{Mt} is ambiguous, but if w_{1M} is sufficiently high, then $N'^{*}_{Mt} < N^{*}_{Mt}$. Q.E.D.

Proof of Proposition 2: The arguments for the relation of N^{T*}_{Mt} to λ_{Mt}, V_{iM}, and H_{iM} is analogous to that given in the proof of Proposition 1. Turn, then, to the relation of N_{Mt}^{S*} to λ_{Mt}. Again, consider two different levels of import penetration, $\lambda'_{Mt} > \lambda_{Mt}$, and let $N_{Mt}^{\prime S*}$ and N_{Mt}^{S*} be the corresponding equilibrium number of entrants to the non-tradable sector, respectively. Focus first on the case where the import penetration is λ_{Mt}, and the equilibrium number of entrants in the tradable sector is N_{Mt}^{T*}. Without loss of generality, let us order $i \in E_{Mt}^{T*}$ in decreasing magnitude of $\pi_M(N_{Mt}^{T*}, \lambda_{Mt}, H_{iM})$. Suppose now that λ_{Mt} increases exogenously to λ'_{Mt}. Then, $\pi_M(N_{Mt}^{T*}, \lambda'_{Mt}, H_{iM}) < \pi_M(N_{Mt}^{T*}, \lambda_{Mt}, H_{iM})$, for each $i \in E_{Mt}^{T*}$. Therefore, there may exist $j = 1, ..., n$, $j \in E_{Mt}^{T*}$, such that

$$\Lambda_{jt}^{S}(N_{Mt}^{S*} + 1, H_{jM}) > \max(\pi_M(N_{Mt}^{T*}, \lambda'_{Mt}, H_{jM}), w_M^T(H_{iM}), w_M^S(H_{iM})) \tag{22}$$

Hence, these agent types will enter sector S with import penetration λ'_{Mt}. Q.E.D

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Appendix

This appendix includes the description of the main variables used in the analysis.

Variable Name	Description
Household variables	
Age	respondent's age.
Business equity	difference between the value of the business and total debt owed against the business.
Business leverage	ratio of total debt owed against the business to business equity.
Business size	a binary variable if the business has fewer than 25 employees.
College or more	a binary variable equal to 1 if the respondent has at least a college degree, and 0 otherwise.
Equity in other real estate	difference between the value and total debt owed against the other real estate (including second homes, vacation homes, underdeveloped lots).
Equity in vehicles	difference between the value and total debt owed against the vehicle.
Entry	a binary variable equal to one if an individual living in an MSA and surveyed in year t becomes an entrepreneur at date t+1.
Exit	a binary variable equal to one if a business owner living in an MSA and surveyed in a given year t did not own a business at date t+1.
Female	a binary variable equal to 1 if the respondent is a female, and 0 otherwise.
Financial experience	a binary variable if the respondent holds a business or finance related occupation.
High school or less	a binary variable equal to 1 if the respondent has finished at most high school, and 0 otherwise.
Home equity	difference between the value and total debt owed against the primary residence.
Household size	number of people in the household.
Household wealth	sum of financial assets, real estates, vehicles, and private business equity aggregated for all individuals in the household excluding the respondent since respondent's personal wealth is already accounted for in the variable "Total wealth".
IRA/Keogh/401K accounts	market value of IRA/Keogh/401K plans in the person's name.
Job tenure	number of months spent in respondent's current job.
Labor income	annual and obtained from gross monthly earnings (before deductions), or, for those paid on hourly basis from the regular hourly pay-rate and the number of hours worked.
Liquid wealth	sum of safe assets -- such as government securities, munis, corporate bonds, money market deposit accounts, checking accounts, savings accounts, and stockholdings.
Married	a binary variable equal to 1 if the respondent is married, and 0 otherwise.
Occupational Mobility	number of individuals employed in successive time periods who change occupations divided by the number of individuals employed in both periods.
Race	a binary variable equal to 1 if the respondent is white, and 0 otherwise.
Profit/Loss	difference between gross receipts and expenses (in log-units).
Some college	a binary variable equal to 1 if the respondent is a college drop-out, and 0 otherwise.
Total wealth	sum of personal financial assets, real estates, vehicles, and private business equity.
Unemployed	an indicator variable equal to 1 if the respondent's labor force status is unemployed.

Appendix (Contd.)

MSA-level variables	
*d*IMP	import exposure defined as the cumulative import growth weighted by the share of region *M* in U.S. business establishments in industry *j*.
% Change in industrial/commercial loans	annual percentage change in industrial and commercial business loans made by all commercial banks in an MSA.
% Change in mortgage debt	MSA-level annual percentage change in mortgage debt.
College educated population	percentage of MSA population with a bachelor degree or higher.
Delinquency rate on mortgage loans	MSA-level delinquency rate on single-family residential mortgage.
Housing price index (HPI)appreciation	percentage change in MSA's housing price index is the weighted index of single-family house prices obtained from Federal Housing Finance Agency.
Labor force participation rate	percentage of MSA population in the labor force.
GDP growth rate	annual growth rate in MSA's GDP.
Unemployment rate	MSA's number of unemployed as a percentage of the labor force.

Table 1. Summary statistics for SIPP Panel Sample

The sample includes respondents who are 18 or older in the SIPP for the 1993-1995, 1996-2000, 2001-2003, 2004-2006 waves. *Business starters* are those who transitioned from being unemployed or a wage worker to a business owner. All statistics are means, and all monetary values are in real 1993 dollars. *Female* and *Married* are binary variables equal to 1 if the respondent is a female and married, respectively. *18 year to 35 year* is a dummy variable equal to 1 if the respondent's age is between 18 and 34 years. *35 year to 45 year* is a binary variable equal to 1 if the respondent's age is between 35 and 44 years. *45 year to 55 year* is a binary variable equal to 1 if the respondent's age is between 45 and 54 years. *55 year to 65 year* is a binary variable equal to 1 if the respondent's age is between 55 and 64 years. *65 years or older* is a binary variable equal to 1 if the respondent's age is at or over 65 years. *High school or less* is a dummy variable equal to 1 if the respondent has finished, at most, high school. *Some college* is a binary variable equal to 1 if the respondent is a college drop-out. *College or more* is a binary variable equal to 1 if the respondent has at least a college degree. *Total wealth* includes personal financial assets as well as all non-financial assets such as real estate (including second homes), vehicles, and private business equity. *Liquid wealth* is defined as the sum of safe assets (such as bonds, checking accounts, and savings accounts) and stockholdings. *Home equity* denotes the difference between the value and total debt owed against the primary residence. *Equity in vehicles*, *Equity in other real estate*, *Business equity* are constructed as the difference between the value and total debt owed against the vehicle, other real estate (other than primary residence such as a second home, a vacation home or undeveloped lot), and business, respectively. *IRA/Keogh/401K accounts* is the market value of IRA/Keogh/401K plans in the person's name. We extract the information on *Job tenure* from the start date of the job and information on *Labor income* from gross earnings (before deductions) received for a given month or from the regular hourly pay rate for those who are paid on an hourly basis and number of hours work at the job. *Race* is 1 for whites and zero for non-whites. *Financial experience* is a binary variable if the respondent holds a business or finance related occupation. *Unemployed* is a binary variable equal to 1 if the respondent's labor force status is unemployed. *Occupational mobility* is the number of individuals employed in two time periods who change occupations divided by the number of individuals employed in both periods calculated at the occupational level.

	Business starters	Non-starters	*p*-value of difference
Female	0.443	0.552	(0.000)
Race	0.869	0.825	(0.000)
Married	0.643	0.572	(0.000)
Household size	3.167	2.980	(0.105)
Age			
18 to 35 years	0.322	0.277	(0.000)
35 to 45 years	0.271	0.202	(0.000)
45 to 55 years	0.222	0.185	(0.000)
55 to 65 years	0.129	0.134	(0.051)
65 and above	0.052	0.201	(0.000)
Education			
High school or less	0.341	0.452	(0.038)
Some college	0.312	0.296	(0.414)
College or more	0.303	0.212	(0.006)
Financial experience	0.012	0.008	(0.007)
Unemployed	0.036	0.031	(0.136)
Occupational mobility	4.282	6.728	(0.000)
Job tenure (months)	42.13	73.61	(0.000)
Labor income	52,472	44,179	(0.086)
Total wealth	114,871	61,920	(0.000)
Liquid wealth	17,140	12,845	(0.000)
Home equity	40,301	27,352	(0.000)
Business equity	33,082	3,228	(0.000)
Equity in other real estate	9,066	6,282	(0.000)
IRA/Keogh/401K accounts	11,190	9,085	(0.000)
Equity in vehicles	4,092	2,828	(0.000)

Table 2 (Panel A). Summary statistics on growth of imports and MSA level controls

Other advanced countries include Germany, France, Italy, Spain, Netherlands, Belgium, Austria, Finland, Japan, United Kingdom, Canada, Australia, Switzerland, Sweden, Norway, Denmark, New Zealand. The set of low-income countries include Afghanistan, Benin, Burkina Faso, Burundi, Central African Rep., Chad, Comoros, Congo, Eritrea, Ethiopia, Gambia, Guinea-Bissau, Haiti, Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Rwanda, Senegal, Sierra Leone, Somalia, South Sudan, Tanzania, Togo, Uganda, Zimbabwe. Column 3 covers imports from Mexico and the Central American and Caribbean countries covered by the CAFTA-DR. Trade imbalance is the difference between imports and exports.

	(1)		(2)	(3)	(4)
	China		Low-income countries	Mexico/ CAFTA	Rest of the world
	Imports	Trade imbalance	Imports	Imports	Imports
United States					
Growth rate 1993-2006	963%	909%	218%	393%	202%
Annual growth rate	18.7%	19.6%	8.40%	11.6%	8.03%
Other advanced countries					
Growth rate 1993-2006	773%	718%	247%	403%	245%
Annual growth rate	16.5%	17.9%	7.76%	10.2%	8.21%

Table 2 (Panel B). Summary statistics on growth of imports and MSA level controls

This table presents summary statistics for MSA-level time-varying controls. *dIMP* is the measure of MSA-level import penetration, defined as the cumulative import growth weighted by the share of region *M* in U.S. business establishments in industry *j*. *College-educated individuals* is the number of people over 25 with a bachelor degree or higher as a proportion of the total population over 25 years old. *Labor participation rate* is the share of the population in the workforce, defined as the total population in the civilian labor force over 16 years old divided by the total population 16 years old or older. *Unemployment rate* is the number of unemployed as a percentage of the labor force. *Change in industrial/commercial loans* is obtained from Dealscan. *Housing price index* is the weighted index of single-family house prices obtained from Federal Housing Finance Agency. *Delinquency rates* and *Mortgage debt* outstanding are obtained from Equifax. Delinquent loans are those past due thirty days or more and still accruing interest as well as those in nonaccrual status. % changes and GDP growth rate are at the annual rate.

	Mean	Median	Standard deviation
*d*IMP	14.05	9.102	16.73
Unemployment rate	0.056	0.058	0.013
Housing price index (HPI) appreciation	0.030	0.035	0.049
GDP growth rate	0.044	0.041	0.011
College educated population	0.273	0.288	0.046
Labor force participation rate	0.656	0.661	0.015
Delinquency rate on mortgage loans	0.022	0.021	0.009
% Change in industrial/commercial loans	0.042	0.083	0.103
% Change in mortgage debt	0.077	0.086	0.038

Table 3. The decision to start business

This table relates the product market competition through lower-cost import penetration, *d*IMP, to the entrepreneurial decision of individuals. The dependent variable is a dichotomous variable that takes value one if individual *i* starts a business and zero otherwise. Individuals who were *already* entrepreneurs are excluded from the entry sample. Sample covers 1993-1995, 1996-2000, 2001-2003, 2004-2006 SIPP waves. *Some college* is a dummy variable equal to 1 if the respondent is a college drop-out. *College or more* is a dummy variable equal to 1 if the respondent has at least a college degree. Respondents who finished at most high school are treated as omitted category. Unreported survey controls include respondent's marital status, household wealth (which excludes the respondent's personal wealth since it is already accounted for in the covariate "Total wealth"), and household size. All survey related controls and MSA level time-varying controls are defined in the Appendix. In columns 3 and 4 import penetration to US by China (*d*IMP) is instrumented by import penetration to other advanced countries by China (*d*IMPO). First stage estimates also include the control variables that are used in the second stage. All regressions include fixed effects as indicated in the table, whose coefficients we do not report. Robust standard errors in parentheses are clustered at the MSA level and reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
*d*IMP	-0.031***	-0.028***	-0.023***	-0.022***
	(.005)	(.006)	(.005)	(.005)
Log(Total wealth)		0.013***		0.019***
		(.005)		(.006)
Log(Labor income)		0.035		0.039
		(.028)		(.032)
Unemployed		0.013		0.023
		(.012)		(.015)
Log(Age)		-0.007**		-0.006***
		(.003)		(.001)
Occupational mobility		-0.040*		-0.026**
		(.021)		(.013)
Job Tenure		-0.005		-0.004
		(.004)		(.003)
Some college		0.002		0.009
		(.000)		(.001)
College or more		0.046***		0.013***
		(.011)		(.005)
MSA f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
Individual f.e.	Y	Y	Y	Y
MSA controls	Y	Y	Y	Y
Household controls	N	Y	N	Y
Observations	317,496	317,496	317,496	317,496
First-stage estimates:				
*d*IMPO			-0.886***	-0.856***
			(.082)	(.099)
R-squared	0.805	0.832	0.704	0.751
First-stage *F*-statistics (*p-value*)			(0.000)	(0.000)

Table 4. Dynamic endogeneity, non-linearity, and housing market effects

This table reports the results from robustness tests on the relationship between import exposure, *d*IMP, and the business entry decision of individuals. The dependent variable is a dichotomous variable that takes value one if individual *i* starts a business and zero otherwise. Individuals who were *already* entrepreneurs are excluded from the entry sample. Columns 1-4 controls for housing market effects in different ways. Column 1 carries out Schmalz, Sraer, Thesmar (**SST**) (2017) estimation, where the MSA-level housing price growth is instrumented with *MSA-level supply elasticity × nation-wide mortgage rates*. Column 2 undertakes Chetty, Sandor, Szeidl (**CSS**) (2017) estimation, where the variation in individual house values is instrumented using variation in *current house prices at the national level × MSA-level supply elasticity*. The home equity is instrumented using the variation in *national house prices in the year of purchase × MSA-level supply elasticity*. In columns 3 and 4 we repeat Chetty, Sandor, Szeidl (2017) estimation on subsamples which exclude (i) housing boom-driven sectors such as construction, finance, insurance, real estate, and rental and leasing, (ii) households living in MSAs with most inelastic housing supply. Column 5 accounts for the feedback effects using dynamic Arellano-Bond (1991) model with lagged import exposure as an instrument. Column 6 estimates a logit model with flexible control function (Petrin and Train, 2010; Imbens and Wooldridge, 2005) with bootstrapped standard errors. In the logit model reported numbers are the standardized odds ratios. Note that in all estimations *d*IMP is also instrumented with *d*IMPO (similar to Table 3 column 4). Robust standard errors in parentheses are clustered at the MSA level and reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	Role of housing market							
	(1) Schmalz, Sraer, Thesmar **(SST)** estimation	(2) Chetty, Sandor, Szeidl **(CSS)** estimation	(3) Excluding housing boom-driven sectors		(4) Excluding MSAs with most inelastic supply elasticity		(5) Feedback effects	(6) Non-linear effects
			SST estimation	**CSS** estimation	**SST** estimation	**CSS** estimation		
*d*IMP	-0.037*** (0.007)	-0.033*** (0.005)	-0.029** (0.010)	-0.020** (0.008)	-0.018** (0.008)	-0.017** (0.008)	-0.024** (0.007)	-0.919*** (0.216)
Fixed effects and other controls	As in Table 3 Column 4	As in Table 3 Column 4	As in Table 3 Column 4		As in Table 3 Column 4		As in Table 3 Column 4	As in Table 3 Column 4
Observations	317,496	317,496	317,496		317,496		317,496	317,496

Table 5. Entrepreneurial outcomes

This table explores the entrepreneurial outcomes for business owners in our sample. In columns 1 and 2 the dependent variable is the net profit or loss, *Profit/Loss,* defined as the difference between gross receipts and expenses (in log-units), and the sample includes all business owners. In columns 3 and 4, the dependent variable is a dichotomous variable that takes the value of one if entrepreneur *i* ends a business and is zero otherwise. Individuals who are not business owners (or entrepreneurs) are excluded from the exit sample. *Business size* is an indicator variable if the business has fewer than 25 employees. *Business leverage* is the ratio of total debt owed against the business to business equity. Estimations are executed through 2SLS as in column 4 of Table 3 and controls include business owners' total wealth (in log-units), age (in log-units), occupational mobility, education, marital status, household size, household wealth (which excludes the respondent's personal wealth since it is already accounted for in the covariate "Total wealth"), and a different combination of fixed effects as indicated in the table, whose coefficients we do not report. Survey related and MSA-level controls are defined in the Appendix. Robust standard errors in parentheses are clustered at the MSA level and reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Profit/Loss	Profit/Loss	Exit	Exit
*d*IMP	-0.016*		0.090*	
	(.009)		(.049)	
*d*IMP $\times$ Tradable sector	-0.040**	-0.065***	0.104***	0.109***
	(.018)	(.022)	(.025)	(.032)
Business size	0.003	-0.005	0.029*	0.027
	(.002)	(.003)	(.016)	(.018)
Business leverage			0.055**	0.011*
			(.024)	(.032)
Profit/Loss			-0.066***	-0.068**
			(.021)	(.029)
MSA f.e.	Y	N	Y	N
Year f.e.	Y	N	Y	N
Individual f.e.	Y	Y	Y	Y
MSA $\times$ year f.e.	N	Y	N	Y
MSA controls	Y	N	Y	N
Individual and household controls	Y	Y	Y	Y
Observations	58,324	58,324	34,481	34,481

Table 6. Differential impact of import exposure on entrepreneurship in different types of sectors

This table reports the impact of import exposure, *d*IMP, on the entry of entrepreneurs in high-exposed (manufacturing), low-exposed (mining and agriculture) and non-exposed sectors (all other sectors). The dependent variable is a dichotomous variable that takes value one if individual *i* starts a business in sector *k* and zero otherwise. Individuals who were *already* entrepreneurs are excluded from the entry sample. Estimations are executed through 2SLS using controls as in column 4 of Table 3. All specifications fixed effects as indicated in the table, whose coefficients we do not report. Robust standard errors in parentheses are double clustered at the MSA level and sector. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
1{High-exposed tradable sector} × *d*IMP	-0.034***	-0.038***	-0.036***	-0.031**
	(.010)	(.009)	(.012)	(.014)
1{Low-exposed tradable sector} × *d*IMP	-0.012*	-0.011	-0.011*	-0.009
	(.007)	(.007)	(.006)	(.006)
1{Non-exposed Non-tradable sector} × *d*IMP	0.011*	0.014*	0.014**	0.011*
	(.0058)	(.008)	(.006)	(.006)
Sector × year f.e.	Y	N	Y	Y
MSA × year f.e.	N	Y	Y	Y
Sector × MSA f.e.	Y	Y	N	Y
Individual f.e., individual & household controls	Y	Y	Y	Y
Observations	317,496	317,496	317,496	317,496

Table 7. Which Individuals are More Affected?

This table explores cross-sectional differences in the effect of import exposure, *d*IMP, on the business entry decision of individuals. The dependent variable is a dichotomous variable that takes value one if individual *i* starts a business and zero otherwise. Individuals who were *already* entrepreneurs are excluded from the entry sample. Estimations are executed through 2SLS as in column 4 of Table 3. Unreported controls include MSA-level time-varying covariates (as defined in the Appendix) and all individual-level controls from column 4 of Table 3. All regressions include fixed effects as indicated in the table, whose coefficients we do not report. Column 2 also includes household level of total wealth (which excludes the respondent's personal wealth since it is already accounted for in the covariate "Total wealth") and household size as additional covariates. Robust standard errors in parentheses are clustered at the MSA level and reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)		(2)	
Female × *d*IMP	-0.005*	(.003)	-0.004	(.005)
Unemployed × *d*IMP	-0.003	(.002)	-0.002	(.004)
Married × *d*IMP	0.001	(.004)	0.001	(.006)
Race × *d*IMP	-0.002	(.005)	-0.003	(.007)
Financial experience × *d*IMP	-0.003	(.002)	-0.002	(.002)
Log(Age) × *d*IMP	-0.006**	(.003)	-0.005*	(.003)
Some college × *d*IMP	0.003	(.002)	0.003	(.002)
College or more × *d*IMP	-0.010***	(.005)	-0.009***	(.007)
Occupational mobility × *d*IMP	-0.008***	(.002)	-0.008**	(.004)
Log(Total wealth) × *d*IMP	0.007**	(.003)	0.006**	(.003)
Log(Labor income) × *d*IMP	-0.008**	(.004)	-0.007*	(.004)
Job tenure × *d*IMP	0.003	(.005)	0.003	(.005)
MSA × year f.e.	Y		Y	
Individual f.e.	Y		Y	
Household controls	N		Y	
Observations	317,496		317,496	

Figure 1. Growth in entrepreneurship relative to 1993

Changes in US tradable (manufacturing, mining, agriculture) and nontradable entreprenurship between 1993–2006. Entrepreneur counts are normalized to unity in 1993.

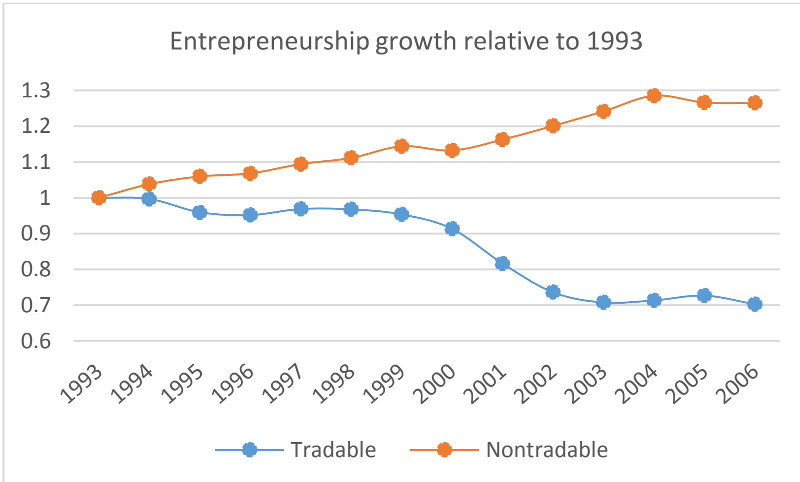


Figure 2. Optimal Response of Domestic Business Entrants Exposed to Foreign Entry: Effects of Wealth

This figure depicts the impact of individual wealth on the optimal response of domestic business entrants to foreign competition. The model is parameterized so that high wealth individuals can finance the fixed costs of entry. Medium and Low wealth individuals cannot finance entry beyond the number of foreign entrants indicated by the arrows.

Figure 3. Optimal Response of Domestic Business Entrants Exposed to Foreign Entry: Effects of Education

This figure depicts the effects of individual education level on the optimal response of domestic business entrants to foreign competition. At every level of foreign competition, the optimal number of domestic entrants is negatively related to individuals' educational attainment.

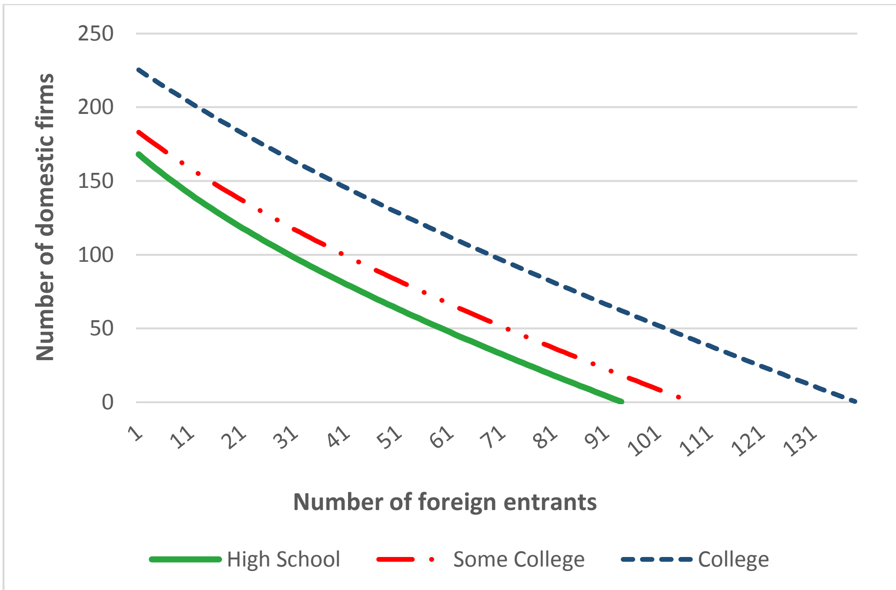
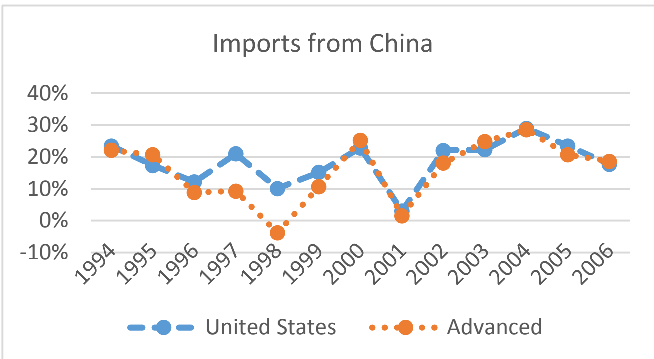
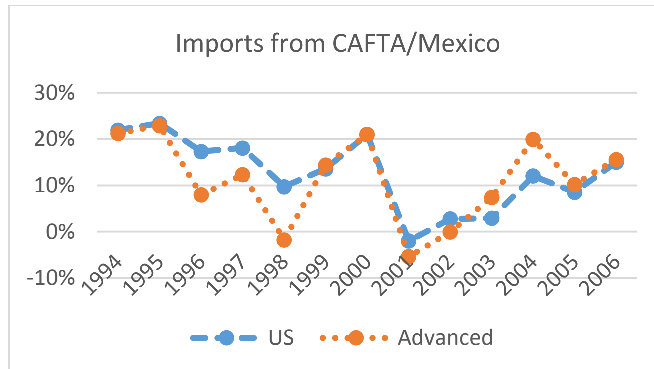
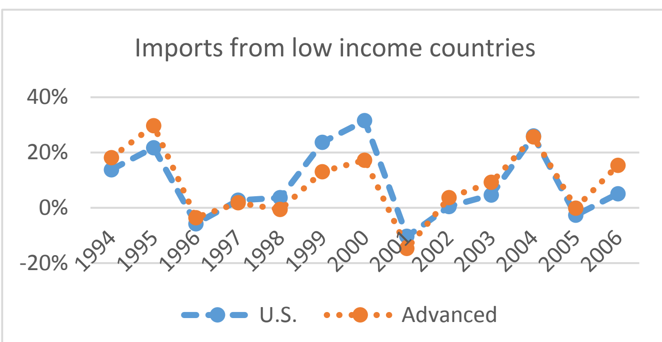


Figure 4. Annual import growth rates for the U.S. and other advanced high-income countries

Other advanced countries include Germany, France, Italy, Spain, Netherlands, Belgium, Austria, Finland, Japan, United Kingdom, Canada, Australia, Switzerland, Sweden, Norway, Denmark, New Zealand. The set of low-income countries include Afghanistan, Benin, Burkina Faso, Burundi, Central African Rep., Chad, Comoros, Congo, Eritrea, Ethiopia, Gambia, Guinea-Bissau, Haiti, Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Rwanda, Senegal, Sierra Leone, Somalia, South Sudan, Tanzania, Togo, Uganda, Zimbabwe.







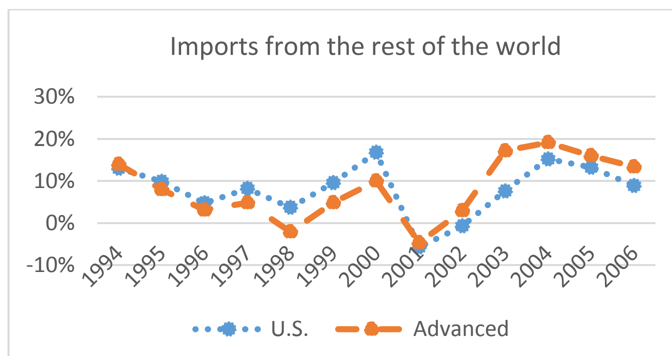


Figure 5. Validity of IV

The correlation between import exposure of US to China, *d*IMP, is instrumented by import exposure of other advanced countries to China, *d*IMPO, at the MSA level. Other controls included are the time-varying MSA-level macro and demographic factors (as listed in Panel A of Table 3), MSA and year fixed effects.

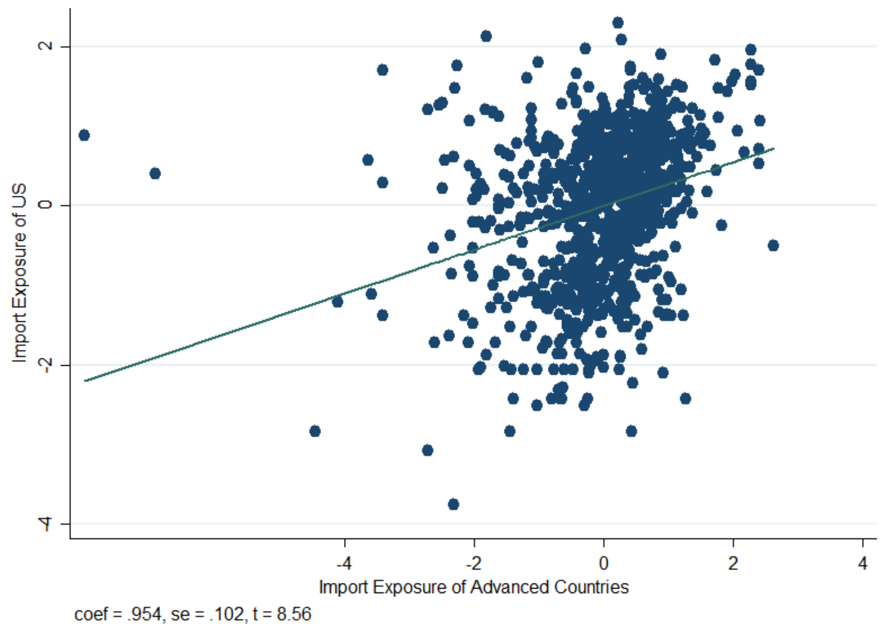


Figure 6. Sectoral distribution of business entry rates

This graph reports sectoral distribution of business entry rates. The sample includes respondents who are 18 or older in the SIPP for the 1993-1995, 1996-2000, 2001-2003, 2004-2006 waves. Respondents who were already entrepreneurs at time *t*-1 are excluded from the entry sample. The sector classification is based on the SIPP data.