Community Networks, Entrepreneurship and the Process of Economic Development*

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Abstract

This research provides a novel characterization of occupational choice (entrepreneurship) during the process of economic development in which community-based networks emerge at each stage to facilitate the occupational mobility of groups of individuals, and pre-existing networks slow down the growth of the networks that follow. The model that we develop to describe this dynamic process is tested with data covering the universe of registered firms over the 1994-2009 period and the universe of exporters over the 2002-2009 period, spanning the initial transition from agriculture to domestic production and the subsequent transition to higher value exporting in China.

Keywords. Business networks. Entrepreneurship. Occupational mobility. Structural transformation.

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1 Introduction

The process of economic development is often characterized by an initial transition from agriculture to domestic production, followed by a second transition to higher value exporting. It is well known that entrepreneurs play a critical role in this process by setting up firms. The conventional individual-specific view of entrepreneurship is that it is determined by talent (Murphy, Shleifer and Vishny, 1991), education (Levine and Rubinstein, 2017) and inherited wealth when credit is constrained (Banerjee and Newman, 1993). These factors have been seen to be relevant in the initial phase of development, as well as in the subsequent shift to exporting (Melitz, 2003; Atkin and Khandelwal, 2020). However, they do not fully explain the variation in entrepreneurship across communities (populations) that we document in China's structural transitions. Extending standard economic models of occupational choice and trade, our analysis identifies the important role played by productivity enhancing community networks in supporting (and dampening) the entry of private firms in China.

Over the past decades, the Chinese economy has grown at an unprecedented rate (Zhu, 2012). Its transition out of agriculture commenced in the early 1980's with the establishment of township-village enterprises (TVE's) and then accelerated with market reforms and the entry of private firms in the 1990's. Starting with almost no private firms in 1990, there were eight million registered private firms in 2009, accounting for nearly 90 percent of all registered firms. A decade after privatization commenced, China entered the WTO and soon became the largest exporter in the world (Brandt et al., 2017). However, homegrown private firms were less dominant in this second transition, in part for reasons provided below, accounting for about half of all exporting firms in 2009.[1]

Chinese entrepreneurship is relatively broad based, with a large fraction of firms set up by rural-born businessmen. The State Administration of Industry and Commerce (SAIC) registration database, which covers the universe of registered firms in China and which we use for much of the analysis in this paper, provides a list of key individuals in each firm with their citizenship ID (which can be used to recover the county of birth). Among these individuals, we designate the firm's principal or legal representative as the "entrepreneur" for the purpose of our analysis. Based on this classification, we find that individuals born in rural counties make up two-thirds of all entrepreneurs in China, with their firms (which are usually established outside the birth county) accounting for a comparable share of private registered capital.[2] There were approximately 2000 rural counties in China when market reforms commenced, accounting for 74 percent of its population, and our initial objective, which addresses a central question in development economics, is to determine which populations were better positioned to supply entrepreneurs in the first transition into domestic production, as well as in the second transition to exporting.

[1] Homegrown private firms are not just large in numbers, they also accounted for a substantial share of total registered capital (75 percent) and export revenues (38 percent) in 2009, the end point of our analysis on account of the financial crisis.

[2] Among the county-born entrepreneurs, 41% established their firm in their birth county, 15% in their birth prefecture but outside the birth county, 15% in their birth province but outside the birth prefecture, and 29% outside their birth province.

Based on the conventional view, entry into business following the market reforms of the 1990's would have been determined by agricultural productivity, which, in turn, is associated with pre-industrial economic development. For example, households in counties with higher agricultural productivity would have accumulated greater wealth that could be subsequently channelled into business. The population in these counties might also have had higher levels of education and exposure to non-agricultural occupations. We assess the empirical validity of the conventional view by constructing county-level measures of entrepreneurial and export propensity, and agricultural productivity. The propensities are measured by the total number of firms and the number of exporting firms, drawn from a given birth county in a given year, divided by the number of potential entrepreneurs from that county. Agricultural productivity is measured by county-level population density in 1982, when the Chinese economy, after decades of stalled industrialization, was still largely agrarian. The implicit assumption here is that greater agricultural productivity would have supported a larger population density in the pre-industrial period and at early stages of economic development (Diamond, 1997; Acemoglu, Johnson and Robinson, 2002; Ashraf and Galor, 2011).

We find in Section 2.1 that there is a positive and significant association between both propensities and birth county population density, which is retained when we instrument for population density with exogenous measures of agricultural productivity. Agricultural productivity does not determine the propensity to set up a firm directly and, hence, we proceed to add mediating (intervening) variables associated with the entrepreneurial traits listed above, such as education and occupational experience among potential entrepreneurs, as additional covariates in the estimating equations. Conditional on these covariates, birth county population density continues to have a *positive* and statistically significant effect on entry into domestic production [Fact 1], but it now has a *negative* and marginally significant effect on entry into exporting [Fact 2]. Our primary objective in this paper is to make sense of these divergent facts, which we will see are more broadly informative about occupational mobility in developing economies. While there are possibly many mediating mechanisms that remain to be accounted for, we focus on a particular network-based mechanism that can explain both facts. Once this mechanism is isolated, it will be shown to have a precisely estimated positive effect on the entrepreneurial propensity and a precisely estimated negative effect on the export propensity.

The mechanism that we propose to explain Facts 1 and 2 is based on the idea that networks of firms organized around the hometown (birth county) are active in China and that firms from birth counties with higher population densities have access to better functioning networks that increase the productivity of their members, both in domestic production and exporting. This productivity boost, with its accompanying increase in revenues, brings more firms from denser counties into domestic production to explain Fact 1. At the same time, incumbent (more successful) domestic networks drawn from denser counties create a disincentive to subsequently enter exporting, as elucidated in the model described below, to generate Fact 2. Previous research has documented that networks can support occupational mobility (Munshi, 2011) and discourage such mobility (Munshi and Rosenzweig, 2006), but in disconnected settings. Our research breaks new ground by documenting the positive and negative role played by the *same* networks at different stages of economic development. While our quantitative analysis (described below) indicates that the hometown networks contributed substantially to the entry of firms in the first transition from agriculture to domestic production, it also tells us that they had an important dampening effect on the number of exporters in the second transition to exporting (international trade).

The analysis in this paper, fleshing out the mechanism described above, proceeds in the following steps: We first document that birth county networks are active and that networks drawn from denser counties are more effective, after providing micro-foundations for this heterogeneity across communities. Next, we develop a model that builds on these results to deliver Facts 1 and 2. We complete the analysis by testing the model and showing empirically that it can indeed generate both facts. We describe each of these steps below.

The idea that business networks are active in China and that these networks are organized around the birth county is not new. Previous research has argued that informal arrangements, providing mutual help to their members, must have been at work in China to allow millions of rural-born entrepreneurs to establish and grow their businesses in an environment characterized by weak market institutions and property rights (Peng, 2004; Allen, Qian and Qian, 2005; Greif and Tabellini, 2017). There is also good reason to believe that these informal arrangements, based on reputation and trust, are organized around the birth county, in light of a well established sociological literature that takes the position that ethnicity in China is defined by the native place (Honig, 1992, 1996; Goodman, 1995). The additional assumption that we need for our analysis is that networks drawn from denser counties function more effectively, regardless of where they are established.

Our explanation for the preceding assumption is based on the idea that population density in rural areas is positively associated with local social interactions, which, in turn, gives rise to more inter-connected social networks that can support higher levels of enforceable trust among neighbors (but not strangers). Firms from denser birth counties leverage these high levels of trust in their origin populations, clustering together in a limited number of locations where they can provide mutual help to each other. We provide descriptive evidence supporting the preceding argument in Section 2.2, utilizing nationally representative data from the China Family Panel Survey and the SAIC registration database. While these micro-foundations are important, they do not formally establish that birth county networks are active or that networks drawn from denser counties function more effectively. The mutual help that members of a network provide to each other cannot be observed, by its very nature. Our strategy to identify network effects in this paper is based on the idea that if networks are active, they must improve the *outcomes* of their members. If mutual help is complementary, then firms will benefit from a larger network and if networks drawn from denser counties function more effectively, then these size effects will be increasing in birth county population density. The network effects that we estimate are synonymous with agglomeration effects, as they are commonly specified (Akcigit and Nicholas, 2019; Rosenthal and Strange, 2020) except that the productivity enhancing interactions are restricted to firms from the same origin.

We implement the test of network effects described above in Section 3. For this component of the analysis, we utilize the SAIC inspection database, which provides revenues and assets for a subset of registered firms over time and the Customs database, which provides export revenues for all exporting firms over time. These databases can be linked to the SAIC registration database, which, as noted, provides the entrepreneur's birth county. The productivity enhancing mutual help that members of a network provide to each other, such as information and connections, is inherently local (as documented in the agglomeration literature). We thus specify the domain of the network as the birth county-destination prefecture; there are 350 prefectures in China and firms from a given birth county will typically locate in multiple destinations. The domestic network is defined by the (lagged) stock of all firms from the birth county operating in that prefecture and the export network is defined by the corresponding stock of export firms, as in Fernandes and Tang (2014). The equations that we estimate in Section 3 to identify network effects include firm fixed effects, which subsume entrepreneurial ability, network size as specified above, and its interaction with birth county population density. Firm outcomes – revenue and productivity – are measured relative to other firms in the same sector-prefecture-time period to account for local business opportunities. While this adjustment takes care of conventional agglomeration effects, government infrastructure, labor supply and any factor that affects all firms equally, regardless of their origin, it does not control for unobserved birth county-destination prefecture shocks. For example, if entrepreneurs from a birth county have unexpected access to government connections in a particular prefecture, then this will give their revenues (relative to their competitors) a boost and *pull* firms into that prefecture, with an accompanying increase in network size. The estimated network size effects will be evidently biased, and we address this possibility by constructing a shift-share instrument for network size that is based on agricultural shocks in the birth county that *push* individuals into business.

Our estimates indicate that firm revenues and productivity are increasing in network size, with the estimated network size effect increasing in birth county population density. These estimates provide direct evidence that birth county networks are active and that networks drawn from denser counties are more effective. They are obtained for both domestic production and exporting and are robust to the tests that we implement to validate each component of the shift-share instrument. While our analysis focuses on business networks, it complements a well established literature that documents the positive effect of migrant labor networks on the outcomes of their members. One line of research shows that job referrals increase wages, controlling for unobserved heterogeneity with fixed effects; e.g. Dustmann et al. (2016); Heath (2018); Barwick et al. (2023). An alternative approach, which is similar to the current paper, has been to estimate the effect of exogenous changes in network size on labor market outcomes; e.g. Munshi (2003); Beaman (2012). While there is an extant literature on ethnic (migrant) business networks in economics, this literature has largely focussed on providing descriptive evidence that these networks are active; e.g. Fafchamps (2000); Rauch (2001); Munshi (2011); Kerr and Mandorff (2023). Our analysis is the first to provide causal evidence that networks of firms can improve the outcomes of their members. The additional virtue of our analysis is that it covers both domestic production and exporting, and is based on the universe of (registered) firms in a major developing economy.

Having established that birth county networks are active, we next proceed to show theoretically that these networks can generate Facts 1 and 2. The dynamic model of occupational choice that we develop in Section 4 adds a network component and a trade component to the Roy (1951) model. In our model, successive cohorts of agents choose between a traditional occupation and becoming an entrepreneur (serving the domestic market, the export market, or both markets). Placing standard restrictions on the production technology, the returns to ability increase more steeply in business (domestic production) than the traditional occupation (agriculture, wage labor). This implies that there is an ability threshold above which individuals select into domestic production. In the Melitz (2003) model, there is a higher threshold above which individuals select into exporting. Our model departs from the Melitz model in a number of ways, the most important of which is a scope diseconomy (a fixed cost of setting up a domestic plant and an export plant) that results in the presence of "pure" exporters who specialize in that activity and who are needed to generate Fact 2.[3] It follows that there are three ability thresholds in our model: a lower threshold above which individuals select into domestic production, an intermediate threshold above which individuals select into pure exporting, and a higher threshold above which individuals select into "mixed" exporting (operating export and domestic plants).

We saw above that firm revenues are increasing in domestic network size and its interaction with birth county population density. This shifts down the lower threshold and increases the fraction of individuals from denser birth counties who select into business to explain Fact 1. The fraction of individuals who select into exporting, which is determined by the intermediate threshold, is increasing in the size of the export network (and its interaction with birth county population density) and decreasing in the size of the domestic network (and its interaction with birth county population density). These interaction effects arise because networks drawn from denser counties function more effectively, both in domestic production and exporting, as described above. The first interaction effect encourages potential pure exporters to enter that activity, whereas the second effect works in the opposite direction. If the latter effect is sufficiently strong and dominates the first effect, then the export propensity (pinned down by the marginal pure exporter's ability) could be declining in population density to explain Fact 2.

We estimate the firm entry equations implied by the model in Section 5.1. We find that the propensity to become an entrepreneur is increasing in domestic network size and in its interaction with birth county population density, net of birth county-destination prefecture effects and prefecture-time effects, to explain Fact 1. Conditional on the same covariates, the propensity to become an exporter is *increasing* in export network size interacted with birth county population density and *decreasing* in domestic network size interacted with population density.[4] While these opposing effects highlight the tension between networks that is a novel feature of our dynamic model, we noted that the domestic "overhang" must be sufficiently large for the net network effect

[3]The presence of such exporters has recently been documented in many developing countries (de Astarloa et al., 2015; Blum et al., 2020) and we show that they also exist in China.

[4]We cannot use agricultural income shocks in the birth county as instruments for network size, as we did when estimating the revenue equations because they will now directly determine the dependent variable (entrepreneurial or export propensity). For this component of the analysis, we thus construct an instrument for network size that is based on the initial level of entry in each birth county-destination prefecture network interacted with its duration, separately for domestic production and exporting. This instrument is validated in different ways in Section 5.1.

to be decreasing in population density (to explain Fact 2). Completing the empirical analysis, we verify in Section 5.2 that this is indeed the case. Based on our estimates, the number of domestic producers would have declined by 39% and the number of exporters would have increased by 16% in 2009 had the domestic networks been absent.

A voluminous literature, going back to Galor and Zeira (1993) and Banerjee and Newman (1993) has studied how market imperfections constrain occupational mobility during the process of economic development. Our analysis examines the community networks that emerge in response to these imperfections, allowing *groups* of individuals to move into new activities. While these networks played an important facilitating role in the initial transition to domestic production, the pre-existing domestic networks slowed the growth of newly emerging export networks and delayed the transition to the next stage of economic development. Entrepreneurs do not internalize their contribution to the networks and, hence, there is a role for entry and export subsidies. While export subsidies are unambiguously efficiency enhancing, the entry subsidies must be attentive to their negative effect on export profits, due to the domestic network overhang, highlighting the complexity of industrial policy in economies where (overlapping) networks are active. The networks that we describe in this paper are not specific to China or to business. As discussed in the concluding section, their importance in other developing economies will, however, depend on their social structure, and this will vary across regions of the world.

2 Descriptive Evidence

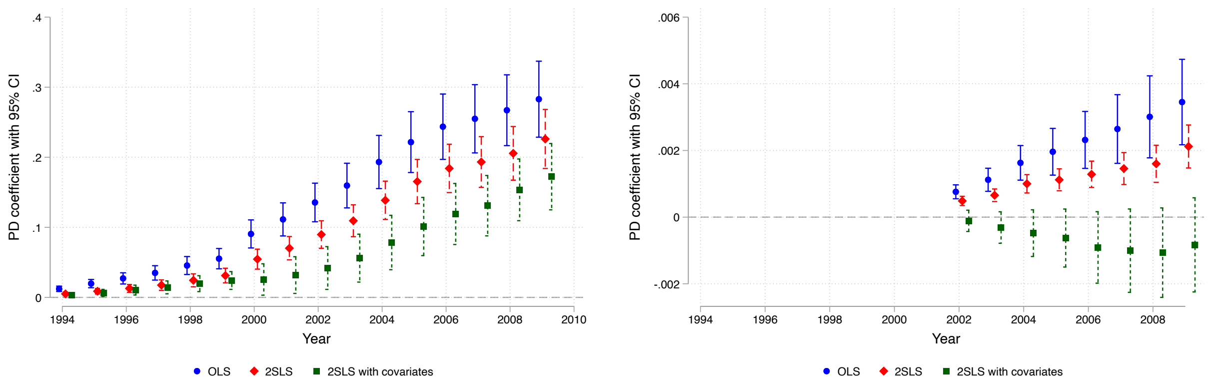
2.1 Entrepreneurship in China

Which rural populations were better positioned to supply entrepreneurs in China, following the market reforms of the early 1990's? As discussed in the previous section, the conventional view is that agricultural productivity is positively associated with entrepreneurship at early stages of economic development. We measure agricultural productivity by county-level population density in 1982, prior to the emergence of private firms, when the Chinese economy was still largely agrarian. Entrepreneurial propensity is measured by the number of registered private firms from a given birth county, who are engaged in domestic production, exporting, or both activities, divided by the number of potential entrepreneurs. The latter statistic is specified as the number of men aged 25-55 born in that county, obtained from the population census.[5]

Our analysis of entrepreneurship runs from 1994, when company registration was made mandatory, up until 2009 and the financial crisis. We thus proceed to estimate the association between

[5]The SAIC registration database provides the gender and age for a subset of principals (legal representatives). Among those principals who report their gender, 79 percent are men. Among those that report their age, 89 percent are aged 25-55. The number of 25-55 year old men born in a county is derived in each year using a one percent sample from the most recent population census: the 1990 census for the 1994-1999 period and the 2000 census for the 2000-2009 period. Large-scale internal migration only commenced in China in the 1990's and, hence, the age distribution of county residents in the 1990 census can be used, without modification, to derive the number of 25-55 year olds born in that county in each subsequent year. However, the age distribution obtained from the 2000 census, and used for the years that follow, is adjusted to account for in-migration and out-migration over the preceding five years.

entrepreneurial propensity and 1982 birth county population density, separately in each year over this period. The population density (PD) coefficients are reported in Figure 1a – the blue circles are the point estimates and the blue vertical lines demarcate the 95 percent confidence intervals – and, as can be seen, these coefficients are positive and significant in each year.[6] In line with the conventional view, individuals born in counties with greater agricultural productivity are more likely to become entrepreneurs and this advantage persists over time.



(a) Entry into Business

(b) Entry into Exporting

Figure 1: Entrepreneurial Propensity, Export Propensity, and Population Density

Source: Registration database, Customs database and Population Census 1982, 1990, 2000
2SLS estimates use potential crop yields as instruments for population density in 1982.
Covariates measure education distribution, occupational structure and industry structure in the birth county in each year.

Agriculture was the dominant activity in our counties as recently as the 1982 population census, with 68 percent of the workforce employed in this sector (this statistic declines to 37 percent in the 2010 census). While it thus seems reasonable to associate population density in these counties with agricultural productivity, this variable could also have been determined (in part) by conflict, famines and other historical events. Agricultural productivity is determined by crop suitability, which, in turn, is determined by geo-climatic conditions (Acemoglu, Johnson and Robinson, 2002; Galor and Özak, 2016). We thus proceed to identify the agricultural productivity channel by using *potential* crop yields, obtained from the Food and Agricultural Organization Global Agro-Ecological Zones (FAO-GAEZ) database, as instruments for population density.[7] The estimated 2SLS population density coefficients, reported as red diamonds in Figure 1a, are qualitatively similar, albeit smaller in magnitude, than the corresponding benchmark coefficient estimates in blue.

Although agricultural productivity may have a causal effect on the entrepreneurial propensity, there are many mediating (intervening) channels through which it could determine entry into

[6]Counties with less than 20 people per square km. are dropped from the analysis. This excludes sparsely populated regions such as Western China, Inner Mongolia, and Tibet. The analysis in this paper is based on the remaining 1648 counties.

[7]We use potential yields for the following 11 crops, which account for 96% of cultivated area in China to predict population density: wheat, maize, rice, sorghum, potato, millet, cotton, groundnut, rapeseed, soybean, and sugarbeet. The FAO-GAEZ database provides potential crop yields for different levels of technology and irrigation. Following Galor and Özak (2016) we use low technology-rainfed agriculture to measure the yields so that population density is predicted by geo-climatic conditions alone.

business. We thus proceed to estimate the following equation:

$$\frac{n_{jt}}{P_{jt}} = \beta_t p_j + M_{jt}\gamma + \epsilon_{jt} \tag{1}$$

where n_{jt} is the stock of firms from birth county j that were active in period t, P_{jt} is the number of potential entrepreneurs, p_j is the population density, M_{jt} is a vector of mediating variables, and ϵ_{jt} is a mean-zero disturbance term. The results reported above were based on a specification of the estimating equation without M_{jt}, where we were instrumenting for p_j with potential crop yields. When we add M_{jt}, which includes conventional determinants of entrepreneurship such as the education distribution, occupational structure and industry structure in the birth county, we see that the β_t coefficient, marked by green squares in Figure 1a, declines even further.[8] This implies that agricultural productivity (measured by the instrumented p_j) is positively correlated with mediating variables that, in turn, have a positive effect on the entrepreneurial propensity. While this result is in line with the conventional view, the population density coefficient remains positive and significant, which tells us that other mediating variables remain to be accounted for [Fact 1].

While private firms emerged in China in the early 1990's, the second structural transition – into higher value exporting – started a decade later, with China's entry into the WTO in 2002. As documented above, counties with greater agricultural productivity were better positioned to support private enterprise in the first structural transition. The analysis that follows examines whether these counties were similarly advantaged in the second transition into exporting, from 2002 up until 2009, the end point of our analysis.

There are two types of exports in China: production exports and processing exports. The latter activity is restricted to the assembly of imported inputs for resale abroad. Based on their productivity and skill intensity, production exporters are superior to domestic producers who, in turn, are superior to processing exporters (Dai, Maitra and Yu, 2016). Given our interest in the transition from domestic production to higher value exporting, the analysis in this paper thus restricts attention to production exports. Production exports can be further divided into direct exports and indirect exports through intermediaries. Indirect exporters are less productive than direct exporters in China (Ahn, Khandelwal and Wei, 2011). In fact, the capital intensity of production, a common proxy for productivity, is even lower for indirect exporters than for domestic producers (see Appendix A). For the purpose of our analysis, we thus define an exporter as a firm who manufactures goods that are shipped directly to foreign buyers. Using this definition, and linking the SAIC registration database with the Customs database, 57% of domestically owned

[8] As with the number of potential entrepreneurs, we use the one percent sample from the 1990 and 2000 censuses to construct the mediating variables in each year. The education distribution is measured by the share of 25-55 year old men in each of the following categories: illiterate, primary, secondary, high school, university. The occupational structure is measured by the share of these men who are managers, science professionals, liberal arts professionals, clerical workers, commercial service staff, primary sector workers, operators of production and transportation equipment, and unemployed. The industry structure is measured by the corresponding shares in primary, secondary and tertiary sectors. We do not measure wealth (another conventional determinant of entrepreneurship) directly, but it will be correlated with these variables.

export firms were set up by entrepreneurs born in rural counties.

How does the propensity to export, measured by the number of active exporters from a given birth county divided by the number of potential entrepreneurs, vary across counties? The export propensity is regressed on 1982 birth county population density over the 2002-2009 period, with the estimated population density coefficients reported in each year in Figure 1b. As in Figure 1a: (i) The blue circles and vertical lines represent the benchmark estimates. (ii) The red diamonds and lines represent the 2SLS estimates, using only that part of the variation in population density that can be explained by potential crop yields. (iii) The green squares and lines are estimates derived from a specification that includes the additional mediating variables. The export propensity is increasing in population density, with the benchmark and 2SLS specifications, and the population density coefficient declines when the additional mediating variables are included in the estimating equations.[9] These findings match what we reported in Figure 1a and can be interpreted using the same argument as above. The key difference between the two figures is that the population density coefficient turns negative (and marginally significant) in Figure 1b when the mediating variables are included [Fact 2]. The analysis that follows will focus on a particular network-based mechanism, from among the mediating variables that remain to be accounted for, and we will see that this mechanism can generate both Fact 1 and Fact 2.

We complete the analysis in this section by examining the robustness of the facts we have uncovered: (i) The economic census, conducted in 2004 and 2008 by the National Bureau of Statistics, is our most reliable source of data. The economic census was restricted to manufacturing firms in 2004, but included all firms in 2008. To be consistent across rounds, all analyses using economic census data in this paper are based on manufacturing firms alone. The number of (manufacturing) firms reported to be active in the SAIC registration database is compared with the number of firms in the 2004 and 2008 economic censuses, by county, in Appendix Figure B1. Although the registration database reports more firms, the discrepancy does not vary with population density and thus cannot explain the results that we obtain. (ii) We verify that Facts 1 and 2 are obtained with economic census data in Appendix Figure B2. (iii) Some of the analysis that follows will restrict attention to firms located outside their birth county to rule out the possibility that the results are being driven by unobserved hometown amenities. Appendix Figure B3 verifies that the facts documented above are qualitatively unchanged with this reduced sample of firms.

2.2 Business Networks and Birth County Population Density

What role do business networks play in a developing economy? Possibly their most important role is to provide various forms of mutual support to their members that increase their productivity (Nee and Opper, 2012). For example, a longstanding literature describes how firms respond to the difficulty in enforcing formal contracts in developing economies by establishing relational contracts

[9] We observe that the same set of mediating variables weakens the association between birth county population density and the propensity to become an entrepreneur and an exporter. This indicates that the conventional individual-specific determinants of entrepreneurship (domestic production) also apply to exporting in developing countries.

(McMillan and Woodruff, 1999; Macchiavello and Morjaria, 2015, 2021). Community networks can expand the scope of such bilateral arrangements; a firm in a long-term relationship with a buyer or supplier can provide a (credible) referral for another firm from its network who only requires that connection temporarily. Members of a network can also provide information about new technologies and business opportunities to each other. This type of informal support is difficult to sustain through the market mechanism due to the inherent problem of verifying help sought and received, coupled with a weak legal environment. Cooperation in community networks is based, instead, on social enforcement, backed by pre-existing ties among the entrepreneurs in each network (as described by Nee and Opper for China). We noted in the introductory section that ethnicity in China is defined by the native place, and it is well documented that *laoxiang* or "native-place fellows" help each other in different ways (Ma and Xiang, 1998; Zhang and Xie, 2013).[10] Chambers of commerce that bring entrepreneurs from the same origin together (*yidi shanghui*) are also commonly found in Chinese cities. While it thus seems reasonable to assume that business networks are organized around the birth county, we will need the additional assumption that networks drawn from denser counties function more effectively to explain Facts 1 and 2.

Why might business networks drawn from denser counties function more effectively? To answer this question, we take a step back and examine the level of enforceable cooperation or trust that can be sustained in the populations from which the entrepreneurs hail. We posit that social interactions with neighbors are increasing in population density (spatial proximity) in relatively sparsely populated rural counties. This, in turn, gives rise to more inter-connected social networks that can sustain higher levels of mutual cooperation, supported by the threat of social sanctions, as argued in early papers on social norms and community enforcement (Coleman, 1988; Greif, 1993, 1994; Kandori, 1992; Ellison, 1994). To make the preceding argument more precise, consider a random graph model in which the probability that an individual is connected to any other individual in a local population, γ, is rising in population density. A higher γ directly raises the degree of the social network (the number of links per capita) and indirectly also network inter-connectedness; for example, the probability that the two nodes in any link have mutual connections (triadic closure). More generally, we expect γ to be positively associated with the number of mutual links "supporting" any given link in the social network, which results, in turn, in higher levels of cooperation or trust (Jackson, Rodriguez-Barraquer and Tan, 2012).

We provide empirical support for the preceding argument with nationally representative data from the China Family Panel Survey (CFPS). The CFPS is a longitudinal, general social survey conducted at the individual, household, and community level that was launched in 2010, with subsequent rounds in 2012 and 2014. The adult individual module of the 2010 CFPS asks who the respondent interacts (chats) with most. We construct three binary variables that indicate whether the respondent lists neighbors, relatives, or friends (including classmates and colleagues) as their most frequent partners. We expect spatial proximity to be most relevant for the frequency

[10]In Chinese cities, migrant enclaves are often named after a sending province, but as Ma and Xiang (1998) note, this nomenclature is misleading because the enclave typically consists of individuals from a single county or two neighboring counties. In this paper, we use the terms hometown and birth county interchangeably.

of social interactions with neighbors and this is indeed what we observe in Table 1. Residents of rural counties with higher population densities are more likely to list neighbors as their most frequent interaction partners in Column 1. This must be offset by less frequent interactions in another category, which turns out to be relatives in Column 2. Notice that the population density coefficient is small in magnitude and statistically insignificant for urban residents in Columns 4-6. This is once again what we would expect, since spatial proximity is not a constraint to social interactions in cities.

Table 1: Social Interactions and Population Density

Repondent's location:	county			city		
Most frequent interactions:	neighbor	relatives	friends/ colleagues	neighbor	relatives	friends/ colleagues
	(1)	(2)	(3)	(4)	(5)	(6)
Population density	1.267***	-0.974*	0.165	0.010	-0.077	0.072
	(0.421)	(0.510)	(0.247)	(0.129)	(0.171)	(0.080)
Mean of dependent variable	0.198	0.547	0.198	0.122	0.601	0.247
Observations	20,652	20,652	20,652	7,555	7,555	7,555

Note: Social interactions, household income and individual education are obtained from China Family Panel Survey (2010). Population density is obtained from the 1982 Population Census.
Household income and individual education are included as covariates in the estimating equation.
Standard errors clustered at the birth county (urban district) level are reported in parentheses.* significant at 10%, ** at 5%, *** at 1%.

The next step in the analysis is to map the variation in social interactions across counties that we have documented into variation in enforceable trust or cooperation. The 2012 CFPS included questions on (i) trust in neighbors, which we interpret as measuring localized enforceable trust, and (ii) trust in strangers, who cannot be sanctioned by the community. We see in Table 2, Column 1 that there is a positive and significant association between trust in neighbors and population density among rural residents. This is not because they are intrinsically more trusting. The estimating equations include characteristics such as household income and individual education that have been associated with trust and, moreover, there is no association between trust in strangers and population density in Column 2. As with the analysis of social interactions, there is also no association between either measure of trust and population density in the urban sample in Columns 3-4. We infer from these results that increased social interactions among neighbors in denser counties, as documented in Table 1, give rise to the higher levels of trust (among neighbors) that we document in Table 2.[11]

Turning to the business networks that are drawn from rural populations, the help provided

[11]The trust-population density association is not China-specific and we find that the same patterns are obtained across countries with different population densities, using data from the most recent (sixth) round of the World Values Survey in Appendix B.2.

Table 2: Trust and Population Density

Respondent's location:	county		city	
Dependent variable:	trust in neighbors	trust in strangers	trust in neighbors	trust in strangers
	(1)	(2)	(3)	(4)
Population density	5.425***	-1.113	-0.384	-0.045
	(1.971)	(2.774)	(0.533)	(0.543)
Mean of dependent variable	6.429	2.194	6.282	2.177
Observations	20,047	20,047	6,674	6,674

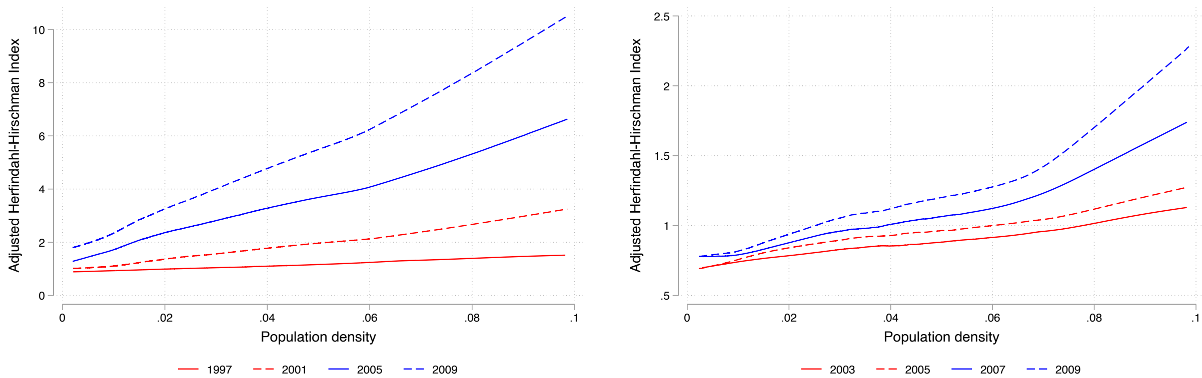
Note: Trust, household income and individual education are obtained from the China Family Panel Survey (2012). Population density is obtained from the 1982 Population Census.
Trust is measured as an ordinal variable that takes values from 0 to 10.
Household income and individual education are included as covariates in the estimating equation.
Standard errors clustered at the birth county (urban district) level are reported in parentheses.* significant at 10%, ** at 5%, *** at 1%.

by firms to each other, such as connections and information, is inherently local. We thus define the scope of the network by the birth county-destination prefecture.[12] We posit that county-born entrepreneurs remain connected to their rural origins, despite the fact that most of their firms are established elsewhere, and that business links between firms from the same birth county operating in a given prefecture can thus be supported by the origin social network. Although we do not observe these hometown connections, we note that 49% of listed (key) personnel in our registered firms were born in the same county as the entrepreneur (legal representative). This statistic is based on firms located outside the entrepreneur's birth county who were active in 2009, and is 50 times larger than what would be obtained if listed individuals were randomly assigned across firms in each prefecture.

Given our trust results, we expect that informal links between firms from denser birth counties will sustain higher levels of cooperation. To provide preliminary support for this assumption, we exploit the fact that firms will tend to cluster in particular locations (where they can provide mutual support to each other) when networks are active. Building on this observation, we construct a measure of spatial concentration across prefectures that is based on the Herfindahl Hirschman Index (HHI), adjusted for the fact that the measured concentration could vary with the number of firms and the number of locations, even with random assignment (the derivation is in Appendix B.3). As observed in Figure 2, this measure of concentration is larger than what would be obtained by random assignment (in which case the adjusted HHI would be equal to one). Moreover, the

[12]Each prefecture consists of an urban center and eight counties on average, and there are approximately 350 prefectures in China. Many government infrastructure and investment initiatives are organized at this administrative level and buyer and sellers will also locate in prefecture-level cities, so the birth county-destination prefecture would appear to be the appropriate domain for the networks that we study. We could, instead, have measured the network at the narrower birth county-destination prefecture-sector level, but, as discussed below, many forms of support will cross sectoral lines.

adjusted HHI is increasing in birth county population density, in each year, for all firms and for exporting firms. While these results are consistent with the hypothesis that birth county networks are active and that networks drawn from denser counties are more effective; i.e. can sustain higher levels of cooperation, the variation in concentration could also be generated by unobserved heterogeneity; for example, if entrepreneurs from those counties had preferred access to prefectures that were growing faster for exogenous reasons. The causal analysis that follows will address this possibility.



(a) Spatial Concentration of All Firms

(b) Spatial Concentration of Exporters

Figure 2: Spatial Concentration and Population Density

Source: Registration database, Customs database and Population Census 1982.

3 Identifying Network Effects

If mutual help is complementary, then firms will benefit from a larger network. It follows that if networks are active, then a firm's *performance* – revenue or productivity – will be increasing in the *number* of firms from its birth county that are established in the same prefecture. If networks drawn from denser counties function more effectively, then the additional implication is that the network size effect will be increasing in birth county population density. The key to this empirical test is to identify an exogenous source of variation in network size.

While the SAIC registration database provides the location and sector of each firm, it does not include information on its performance. To examine the effect of the network on the performance of domestic producers, we thus turn to the SAIC inspection database, which provides revenues and assets (which can be used to construct productivity, as shown in Appendix C.1) for a subset of registered firms over time.[13] An immediate concern with the inspection data is that selection into the sample varies with birth county population density. Since these data are self-reported, their accuracy is an additional concern. We address these concerns in Appendix C.2 by using the economic census (our most accurate source of information) as the benchmark to verify that

[13]The inspection database has reasonable coverage for 23 (out of 31) provinces from 1998 onwards and, hence, the sample that we use for the analysis spans the 1998-2009 period.

both the accuracy and the representativeness of the inspection data do not vary by birth county population density. Neither of these concerns arises with export revenues, which are recorded, by shipment, for each direct exporter in the Customs database. However, firm assets specific to exporting activity are unavailable, since most exporters are also engaged in domestic production, and thus measures of export productivity cannot be constructed. A firm's revenue is an affine transform of its productivity (see Appendix D.1) and, hence, this limitation may not be significant in practice.

Based on the preceding discussion, we estimate the following equation to identify network effects:

$$\log y_{ijkt} = (\theta_0 + \theta_p p_j) \log n_{jk,t-1} + f_i + u_{jkt}, \tag{2}$$

where y_{ijkt} measures the revenue or productivity of firm i from birth county j located in prefecture k in period t, p_j is birth county population density, firm fixed effects f_i capture entrepreneurial ability and u_{jkt} measures unobserved shocks to firm outcomes. The network variable $n_{jk,t-1}$ measures the stock of firms from county j located in prefecture k in period $t-1$; i.e. prior to period t. For the analysis of domestic production, we use the SAIC inspection data to construct firm outcomes, while the network variable is measured by the (lagged) stock of all firms, obtained from the SAIC registration database.[14] For the analysis of exporting, revenues and network size are obtained from the Customs database, with network size $n_{jk,t-1}$ restricted to the stock of exporting firms. The implicit assumption, as in Fernandes and Tang (2014), is that the information and connections needed for exporting are specific to that activity.

Notice that our definition of the network does not distinguish between sectors. Firms from a given birth county were located in eight prefectures on average in 2009, consistent with the high degree of spatial concentration that we documented in Figure 2. Within a prefecture, 62% of these firms were established in two, most popular, 2-digit industries. However, an additional 22% were set up in upstream-downstream and complementary industries.[15] In addition, many forms of mutual help, such as government connections, will cross sectoral lines and, hence, our more expansive definition of the network's scope seems reasonable. Notice also that other birth county networks do not affect the firm's revenue in equation (2). The implicit assumption is that networks do not have the market power to compete or collude strategically. Based on the SAIC registration data, firms from a given birth county account for 6.3% of firms in the prefectures where they locate, on average (within 2-digit sectors). This statistic is based on all entrepreneurs, including those who locate their firms in their county of birth. The corresponding statistic for the capital share is 5.9%.

If birth county networks are active, then $\theta(p) \equiv \theta_0 + \theta_p p_j > 0$. If networks drawn from denser

[14] Although the inspection database includes exporters, these firms account for a tiny fraction of all firms. In addition, most exporting firms also produce for the domestic market, as seen below. While we thus retain exporters in the sample for completeness, we could exclude them without changing the results.

[15] We use the 2007 input-output table from the Chinese National Bureau of Statistics to determine whether any two industries are upstream-downstream or complementary. An industry is defined as being upstream or downstream of another industry if its input or output share (derived from the input-output table) exceeds 0.05. Two industries are defined as being complements if the average correlation coefficient of their input-output shares, across upstream-downstream industries, exceeds 0.2. This methodology is based on Fan and Lang (2000).

counties function more effectively, then $\theta'(p) \equiv \theta_p > 0$. However, the latter result could also be generated if firms from denser birth counties have preferred access (are more proximate) to sectors or production centers that were growing relatively fast. To establish that networks drawn from these counties do indeed function more effectively, we thus measure firm performance relative to all other firms (from rural and urban origins) in the same sector-prefecture by constructing a Z-score: $\frac{\log y_{ijkt} - \overline{y}_t}{\sigma_t}$, where $\overline{y}_t$ is average (log) performance across all firms in the sector-prefecture in period t and σ_t is the corresponding standard deviation. The more stringent network test that we now implement is that firms will perform better *relative* to their competitors when there is an increase in the number of firms from their birth county in the prefecture, with this size effect increasing in birth county population density.

Table 3: Revenue, TFP, and Network Effects

Model:	OLS			IV		
Dependent variable:	log revenue	log TFP	log (exporting revenue)	log revenue	log TFP	log (exporting revenue)
	(1)	(2)	(3)	(4)	(5)	(6)
$\log n_{jk,t-1}$	0.235***	0.149***	0.278***	0.096***	-0.014	0.231***
	(0.007)	(0.006)	(0.022)	(0.024)	(0.026)	(0.068)
$p_j \times \log n_{jk,t-1}$	1.812***	1.184***	1.473***	4.461***	3.677***	2.196*
	(0.188)	(0.181)	(0.382)	(0.623)	(0.750)	(1.139)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	26.73	26.73	11.50
Observations	2,251,473	2,251,473	79,307	2,251,473	2,251,473	79,307

Note: Revenue and TFP are derived from the Inspection database, covering the 1998-2009 period. Export revenue is obtained from the Customs database, covering the 2002-2009 period. Network size is constructed with SAIC registration data and Customs data.
log revenue, log TFP, and log exporting revenue are measured as a Z-score within the one-digit industry-prefecture-time period.
p_j denotes population density in 1982 for birth county j and $n_{jk,t-1}$ is the stock of firms from county j established in prefecture k by the end of the preceding period $t-1$. When the dependent variable is export revenue, $n_{jk,t-1}$ is measured by the stock of export firms.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

As seen in Table 3, Columns 1-2, firm revenues and productivity are increasing significantly in network size and in its interaction with birth county population density. This is also true for export revenues in Column 3. By constructing the dependent variable as a Z-score, we are effectively controlling for any source of unobserved variation at the sector-prefecture-time period level, such as infrastructure, labor supply or agglomeration effects. The threat to identification, given that firm fixed effects are also included in the estimating equation is that unobserved birth county-destination prefecture shocks, u_{jkt}, could be correlated with network size, giving rise to a spurious network effect. For example, suppose that potential entrepreneurs from a given birth county unexpectedly have preferred access to government resources in a particular destination prefecture (perhaps because a newly appointed official hails from the same county). Business outcomes will improve for those entrepreneurs, with an accompanying increase in the number of firms established in that prefecture. Basing the network effect on lagged size, as in equation (2), does not solve the problem when shocks are serially correlated, in which case a spurious network effect could be obtained. One strategy to address this identification problem is to construct an instrument for network size. For example, Munshi (2003) uses income shocks at Mexican origins to construct an instrument for the size of migrant networks operating in U.S. labor markets. Since mobility in our application is occupational rather than spatial, the analogous strategy would be to use income shocks to non-business activities in the birth county; i.e. the outside option for potential entrepreneurs, as instruments for the size of the business networks that emerge from those counties (and are established in different prefectures).

We construct the instrument for network size in the following steps: (i) Using time series variation in world crop prices, and assuming that these prices follow an AR1 process, we construct a price shock in each year for the 11 crops that we used above to predict 1982 population density. (ii) For a given birth county, we weight each crop's price shock by a fixed factor that reflects its contribution to local agricultural production (by value) to construct a composite agricultural income shock in each year. (iii) We assume that the decision to establish a firm and, hence, firm entry in a given year is based on the average of the income shocks over the past five years. Since the stock of firms is just the sum of past entry flows, it is then possible to construct a predictor of the stock in each year that is based on the history of past income shocks (aggregated in a particular way, as shown in Appendix C.3). (iv) To predict the stock of firms from a given birth county in a particular destination prefecture, $\log n_{jk,t-1}$, we multiply the predictor derived above by a factor, estimated from a gravity equation, that is decreasing in the distance between the two locations. Finally, when we construct the corresponding instrument for $p_j \times \log n_{jk,t-1}$, we interact the potential yield for each of the 11 crops with the instrument for $\log n_{jk,t-1}$.

Details of instrumental variable construction are provided in Appendix C.3, where we see in Appendix Table C3 that the instrument has a statistically significant effect on the network variables, for all firms and for export firms. These first-stage estimates indicate that a negative agricultural income shock *pushes* individuals into business, as implied by the model that follows in Section 4. The instrumental variable estimates of the network effects are reported in Table 3, Columns 4-6. Network size effects continue to be positive and significant (with one exception) and to be increasing in birth county population density. The latter effect, in particular, is consistent with the descriptive evidence in Section 2.2 indicating that firms remain connected to their home towns and that denser rural counties can sustain higher levels of cooperation in their populations.

The instrument that we construct can be compared and contrasted with the instrument used by Imbert et al. (2022) in their analysis of labor migration and firm productivity in China. We follow Imbert et al. in steps (i) and (ii), except that the income shocks are constructed in the birth county rather than the origin prefecture. Where we depart from their approach is in the steps that follow: we aggregate up the history of income shocks in (iii) since we need to predict firm stocks rather than flows, and we use a pre-estimated distance multiplier to allocate the predicted stock of firms across destination prefectures, instead of the initial entry level, in (iv). Both our instruments have a shift-share structure, but the structure is interpreted differently. Imbert et al. think of the income shock as the shift, implicitly assuming that the crop shares are exogenous, while allowing the initial migration shares to be endogenous. We think of the crop price shocks as the shifts, with the crop shares and the distance multiplier together constituting the shares. We treat all components of our instrument as exogenous, with the discussion that follows assessing the validity of the exclusion restriction for each of them.

We begin with the price shocks. One way in which agricultural price shocks could directly impact business outcomes is if they affect the local economy more broadly and firms are located in the birth county itself. We allow for this possibility by restricting the sample to firms located outside their birth county in Appendix Table C4. As can be seen, the estimates are very similar to what we obtain with the full sample in Table 3. A second way in which agricultural price shocks could affect a firm's payoffs is if it is operating in that sector. We address this concern by dropping firms that are engaged in activities associated with agriculture, such as food processing. Once again, the estimates reported in Appendix Table C5 are very similar to what we obtain with the full sample. Finally, a third way in which agricultural price shocks could directly affect business is through the wealth channel. If own (family) wealth is used to finance business, as in Song, Storesletten and Zilibotti (2011), then a negative price shock will curtail the operations of entrepreneurs from agricultural families. This is true regardless of the location in which they are active and will result in a decline in their revenues. We account for this in Appendix Table C6 by verifying that the results are robust to including the uninteracted agricultural income shock in the birth county as a covariate in the estimating equation. The income shock has a positive and significant direct effect on firm revenues and productivity, whereas our first-stage estimates in Appendix Table C3 indicate that it has a negative effect on firm entry and, with it, network size. These effects work in opposite directions and, hence, by ignoring a potential wealth effect in the benchmark specification, we are (if anything) reporting conservative estimates of the network size effect.

Next we turn to the crop shares, which map crop-specific price shocks into the income shock for a given county. The shares are fixed characteristics and, hence, their direct effect on the level of the outcome is subsumed in the firm fixed effect. However, Goldsmith-Pinkham, Sorkin and Swift (2020) note that the interaction of the shares with time must also be considered when examining the validity of any shift-share instrument. For example, suppose that (historical) cultivation of a particular crop is associated with an entrepreneurial culture or a greater willingness to bear risk in the local population. If these traits have a differential effect on firm outcomes over time with economic development, then our instrument would violate the exclusion restriction. Alternatively, if counties growing particular crops industrialize relatively fast due to the nature of the agricultural production technology, then entrepreneurs born in those counties will have preferred access to capital (to the extent that firms are self-financing). This would undermine the validity of the instrument once again.

To address the preceding concerns, we take advantage of the fact that if the crop shares are exogenous, then the shift-share instrument that we construct is "equivalent" to using the shares associated with each crop, interacted with time effects, as independent instruments for network size (Goldsmith-Pinkham, Sorkin and Swift, 2020). It follows that if the share for any crop violates the exclusion restriction, then the instrumental variable estimates obtained with that crop would differ from the estimates obtained with other crops. Table 4 reports results with firm revenue as the dependent variable, using the share for each crop interacted with time effects (and the distance multiplier) as instruments for network size. We report estimates with all 6 of the 11 crops that have a positive Rotemberg weight, a statistic derived by Goldsmith-Pinkham, Sorkin and Swift that measures the contribution of a given crop to the shift-share instrument. Among these crops, maize, rapeseed, soybean, and potato have the largest weights, together accounting for 93.7% of the variation in the instrument and 69.8% of the harvesting acreage. The network effects estimated separately with each of these crops are positive, significant, and similar in magnitude to each other and to the benchmark estimates with the shift-share instrument in Table 3, Column 4. This indicates that no crop has a separate and independent effect on firm performance, validating the exogeneity of the corresponding shares.

Table 4: Testing the Exogeneity of the Crop Shares

Dependent variable:	log revenue					
Crop used to construct IV:	maize	repeseed	soybean	potato	sorghum	wheat
	(1)	(2)	(3)	(4)	(5)	(6)
$\log n_{jk,t-1}$	0.202***	0.181***	0.176***	0.240***	0.169***	0.259***
	(0.014)	(0.019)	(0.017)	(0.023)	(0.018)	(0.021)
$p_j \times \log n_{jk,t-1}$	3.219***	3.488***	4.252***	2.954***	4.370***	2.102***
	(0.437)	(0.562)	(0.589)	(0.707)	(0.570)	(0.651)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	16.55	12.02	12.21	46.92	26.98	6.465
Observations	2,251,473	2,251,473	2,251,473	2,251,473	2,251,473	2,251,473

Note: Revenue is derived from the Inspection database, covering the 1998-2009 period. Network size is constructed with SAIC registration data.
log revenue is measured as a Z-score within the one-digit industry-prefecture-time period.
p_j denotes population density in 1982 for birth county j and $n_{jk,t-1}$ is the stock of firms from county j established in prefecture k by the end of the preceding period $t-1$.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Finally, we examine the exogeneity of the distance multiplier. Suppose that firms located at a greater distance from their rural origin are established in faster-growing cities or production clusters. Distance interacted with time will then determine firm performance, but this does not undermine our identification strategy because all firm outcomes are measured as Z-scores relative to other firms in the same sector-prefecture-time period. The threat to identification with this component of the shift-share instrument is that particular types of individuals may choose to move far away and the outcomes of those types may vary differentially with experience or at different stages of economic development. The firm fixed effects that we include in the estimating equation will not account for such variation. To address the preceding concern, we include (log) distance interacted with time effects in the estimating equation. As observed in Appendix Table C7, the results are robust to the inclusion of these additional variables.

We complete the instrumental variable analysis with a comment on the interpretation of the estimates. Negative agricultural income shocks in the birth county will also increase labor migration, as documented by Imbert et al. (2022). While their results indicate that an exogenous increase in labor supply at a destination city reduces firm productivity, this effect is accounted for in our analysis because the dependent variable is measured as a Z-score at the sector-prefecture-time period level. However, if birth county-destination prefecture labor networks also emerge, then our estimates cannot distinguish between these networks and the business networks of interest. To isolate business network effects, an instrument that is specific to these networks is required, and we will construct such an instrument in Section 5 when we test the model. That model, which follows, will build on the preceding results, showing that both Fact 1 and Fact 2 can be generated when networks are active and networks drawn from denser counties are more effective.

4 The Model

4.1 Population and Technology

A given birth county with population density $p \in [\underline{p}, \overline{p}]$ has successive cohorts of agents indexed by $t' = 1, \ldots, T$. All agents continue to live until the terminal date T. The aggregate measure of agents in each cohort is $s(p)$, which is increasing in p. The model is designed to explain Facts 1 and 2, which are derived conditional on a set of covariates associated with entrepreneurial ability. We thus assume that the (conditional) ability distribution is homogeneous across counties, although we will reintroduce the heterogeneity later in Section 5 when we estimate the model. In particular, the ability ω of each agent is drawn from an i.i.d. log normal distribution: $\log \omega$ is uniformly distributed on $[A-1, A]$.

Cohort t' agents who enter the workforce in period t' choose occupations at each date $t \geq t'$. There are two possible occupations: a traditional occupation and entrepreneurship. An agent of ability ω earns a stationary payoff ω^σ in the traditional occupation at each date, where $\sigma \in (0, 1)$. If he chooses to become an entrepreneur, he can produce either for the domestic (d) market or the export (e) market, or both. Serving a market $i \in \{d, e\}$ requires investing in a plant specific to that market, with capital size K_{it} at date t. Investments in either type of plant are irreversible: capital already invested cannot be disinvested, while it is possible to invest more at later dates. Hence, an entrepreneur is committed to a market i once he invests in it. The capital irreversibility constraint is $K_{it} \geq K_{i,t-1}$ for all t.

A plant of size K_{it} owned by an entrepreneur of ability ω generates revenues at t:

$$R_{dt} = C_{dt}\omega^{1-\alpha}K_{dt}^{\alpha}, R_{et} = C_{et}\omega^{\delta(1-\alpha)}K_{et}^{\alpha}, \tag{3}$$

where $\alpha \in (0,1)$ reflects diminishing returns to size and $\delta > 1$ represents an ability premium on the export market. TFP (or revenue productivity, to be more precise) depends on the entrepreneur's individual ability ω and a productivity multiplier term C_{it}, which we describe in greater detail below.

Capital costs for domestic and export plants are as follows:

$$E_{dt} = rK_{dt}, E_{et} = r(1+I)K_{et} \tag{4}$$

where r includes interest and material costs of equipment, and $I > 0$ is the incremental cost of operating an export plant, arising from the need to vertically integrate production or to conform to international quality standards.[16] An important additional feature of the model is the presence of diseconomies of scope, incurred by *mixed exporters* who produce for both the domestic and the export market. This diseconomy of scope, which could be reformulated as a managerial technology with diminishing returns to "span of control," as in Lucas (1978), is represented by a fixed cost β in addition to plant costs (4). Hence, the total cost of a mixed exporter equals $E_{dt} + E_{et} + \beta$. This will allow us to explain the presence of *pure exporters*, who specialize in that activity and who are needed to generate Fact 2 below.

We now turn to the productivity multiplier term, C_{it}, which is comprised of an exogenous market-time effect, Q_{it}, and the endogenously determined birth county-destination prefecture network, which we introduced in the previous section:

$$C_{dt} = Q_{dt} \cdot [n_{t-1}]^{\theta_d(p)}, C_{et} = Q_{et} \cdot [n_{e,t-1}]^{\theta_e(p)}$$

In the analysis that follows, it will be convenient to take logs and, hence, we denote $q_{it} \equiv \log Q_{it}$.

The market-time effect incorporates agglomeration effects and other exogenous business opportunities associated with product demand, government support and infrastructure that apply equally to all firms in a market regardless of their origin. This term is increasing over time: $q_{it} \geq q_{i,t-1}$ for each $i = d, e$ and t, which is plausible in the context of the growing Chinese economy. The assumption in the analytical model that we develop in this section is that firms from all origins are operating in a single market or location, since our interest is in the occupational dynamics for a given origin. We will, however, allow for multiple locations when we estimate the model.

The network component of the productivity multiplier is specified to be consistent with the revenue and productivity equations that we estimated in Section 3. A firm's profit, in domestic production or exporting, can be obtained from (3) and (4). Taking logs, substituting the value of the profit maximizing capital investment, and unpacking C_{dt}, C_{et}, we derive revenue and productivity equations, for domestic production and exporting, in Appendix D.1. Comparing the specification of these structural equations with the equations that we estimated in Section 3, the estimated

[16]We assume a common interest rate r for all agents, irrespective of their birth county. This is without loss of generality, as the model can be reformulated to one where (community-wide or individual) differences in capital costs are reflected instead in the ability parameter ω. We could similarly introduce a labor input in the production function, without changing the results that follow, as long as all firms face a common wage.

coefficients on (log) network size can be interpreted as $\theta_i(p)$, $i \in \{d, e\}$ if this function is assumed to be linear in p: $\theta_i(p) \equiv \theta_{i0} + \theta_{ip} \cdot p$. It follows from those estimates, reported in Table 3, that $\theta_i(p)$ and $\theta_i'(p) \equiv \theta_{ip}$ are positive.[17] These parametric restrictions will be key to generating Facts 1 and 2 below and will also discipline the tests of the model that follow.

The number of firms in the network will evolve endogenously over time. To initiate the dynamics, we set the number of initial entrants to be independent of p. Given the irreversibility of market entry decisions, network sizes cannot shrink: $n_t \geq n_{t-1}$, $n_{et} \geq n_{e,t-1}$. We will see that although network sizes may not vary systematically with p to begin with, there will be divergence over time because $\theta_d'(p) > 0$, $\theta_e'(p) > 0$.

4.2 Occupational Choice in Equilibrium

To simplify the exposition, we assume that agents are myopic and that network sizes at past dates are observable by all agents. As shown in Appendix D.3, the results that follow extend to the case where agents are forward looking but discount future profits at a high enough rate. Consider date t with given productivity multiplier $C_{it}, i \in \{d, e\}$. An entrepreneur of ability ω who was active in previous periods inherits plant sizes $K_{i,t-1}$ and selects current plant sizes $K_{it}, i \in \{d, e\}$ to maximize

$$[C_{dt}\omega^{1-\alpha}K_{dt}^{\alpha} - rK_{dt}] + [C_{et}\omega^{\delta(1-\alpha)}K_{et}^{\alpha} - r(1+I)K_{et}] - \beta\mathbb{I}(K_{dt}K_{et}) \quad (5)$$

subject to the irreversibility constraints

$$K_{it} \geq K_{i,t-1}, i \in \{d, e\} \quad (6)$$

where $\mathbb{I}(x)$ denotes an indicator function which takes the value 1 if $x > 0$ and 0 otherwise, and past plant size is set equal to zero for any entrepreneur that has not entered the corresponding market previously.

Recall that market-time effects, Q_{it}, are assumed to be increasing over time and that network sizes are non-decreasing. This implies that the productivity multiplier $C_{it}, i \in \{d, e\}$, is increasing over time and, hence, that optimal plant sizes must increase over time for incumbents. It follows that the irreversibility constraint can be ignored on the intensive margin. Maximizing profit with respect to capital in each market and then substituting back in the profit function, the equilibrium profit (conditional on entry) for an entrepreneur with ability ω in period t can then be derived for each occupation $W \in \{O, D, E, M\}$, where O refers to the traditional (other) occupation, D is domestic production, E is pure exporting, and M is mixed exporting:

[17] As in Section 3, the domestic network is specified to include the (lagged) stock of all firms, n_{t-1}, whereas the export network is restricted to exporting firms, $n_{e,t-1}$. We could also consider an alternative version of the model where this asymmetry is absent, and the size of both networks is defined by the incumbents in the respective markets. In other words, where pure exporters do not belong to the domestic network in the same way that domestic producers do not belong to the export network. This version of the model is more difficult to solve analytically. In the Chinese context, exporters constitute a miniscule fraction of firms, below 2%, and pure exporters, an even smaller fraction of firms. Hence, this assumption is unlikely to be empirically relevant.

$$\begin{aligned}
\Pi_{Ot}(\omega) &= \omega^{\sigma} \\
\Pi_{Dt}(\omega) &= \omega[\frac{1}{\zeta}]C_{dt}^{\frac{1}{1-\alpha}} \\
\Pi_{Et}(\omega) &= \omega^{\delta}[\frac{1}{\zeta\gamma}]C_{et}^{\frac{1}{1-\alpha}} \\
\Pi_{Mt}(\omega) &= \Pi_{Dt}(\omega) + \Pi_{Et}(\omega) - \beta
\end{aligned} \tag{7}$$

where $\zeta \equiv \frac{r^{\frac{\alpha}{1-\alpha}}}{\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}}}$ and $\gamma \equiv (1+I)^{\frac{\alpha}{1-\alpha}}$.

The above profits are generated by optimal choices on the intensive margin, for a given occupational choice W on the extensive margin. We now turn to equilibrium (extensive form) occupational choices. Observe from (7) that the return to ability is increasing as we progress from the traditional occupation (Π_{Ot}) to domestic production (Π_{Dt}) to exporting (Π_{Et}, Π_{Mt}). At the same time, the entrepreneur must face increasing costs as he moves up the occupational ladder: he must bear a cost of capital, r, if he selects domestic production, there is an incremental cost, I, if he opens an export plant, and then there are the diseconomies of scope that accompany mixed exporting. It follows that there will be positive selection on ability in equilibrium, moving up the occupational ladder, as specified below:

Proposition 1 *Parametric restrictions specified in Appendix D.2 ensure that for any cohort t' at date $t \geq t'$, each between 1 and T, and for any $p \in [\underline{p}, \bar{p}]$, there are three ability thresholds:*

$$A - 1 < \log \omega^*_{dt} < \log \omega^*_{et'} < \log \omega^*_{mt} < A \tag{8}$$

and a unique Nash equilibrium involving the following strategies:

(a) those with ability below ω^*_{dt} stay in the traditional occupation (O)

(b) those between ω^*_{dt} and $\omega^*_{et'}$ specialize in domestic production (D)

(c) those between $\omega^*_{et'}$ and ω^*_{mt} specialize in exports (E)

(d) those above ω^*_{mt} serve both markets (M).

The proof of the proposition is in Appendix D.2. The condition $\log \omega^*_{et'} < \log \omega^*_{mt}$ for all t in (8) maintains the ordering of the three ability thresholds for any cohort t' at each point in time.[18] This ensures that some pure exporters in cohort t' stay that way, which implies that domestic producers from that cohort, who have ability less than $\omega^*_{et'}$, never transition to (mixed) exporting. As a result, the export propensity (fraction of potential entrepreneurs that export) of any given cohort does not change over time. However the export propensity may vary across different cohorts, depending on the evolution of market-time effects and network sizes in the domestic and export

[18] We impose a strong version of this condition for analytical convenience. Weaker versions would allow the inequality to be reversed in later time periods for some cohorts without changing our results.

markets, respectively. Aggregate changes in the export propensity are thus driven by the arrival of new cohorts.

In contrast with the export propensity, the domestic production threshold ω^*_{dt} and the mixed export threshold ω^*_{mt} are independent of the cohort but depend on the current date t. These two thresholds are falling in t as the domestic network size n_t expands over time (as derived below). The fall in the lower threshold ω^*_{dt} motivates a range of low ability agents to move from the traditional occupation into domestic production at older ages. The fall in the higher threshold ω^*_{mt} motivates a range of entrepreneurs previously specializing in exports to become mixed exporters at older ages. These changes affect all older cohorts in the same way.

We complete the discussion in this section by listing the key differences between our model and the canonical Melitz (2003) model, which also features sorting by ability into domestic production and exporting.

1. Decisions at the extensive margin: The Melitz model allows firms to enter and exit, solving for the steady-state equilibrium. In our dynamic model, there is no exit and the number of firms is increasing over time. This focus on the transition dynamics is reasonable in the context of a rapidly growing economy at initial stages of economic development. Moreover, our results would be retained if we added a uniform and exogenous death rate to the model. In particular, the propensity equations derived below to explain Facts 1 and 2 would be simply multiplied through by the survival rate. All of the empirical analysis in this paper is thus based on the stock of *surviving* firms at each point in time.

2. Decisions at the intensive margin: The Melitz model allows firms to adjust their size in both directions. In our model, capital investments are irreversible, which is once again reasonable in the context of a growing economy. We obtain qualitatively similar results in the absence of any irreversibility, where agents sort into domestic production, pure exporting and mixed exporting at each date and the myopia assumption is no longer necessary. The only change from the equilibrium derived above is that the cohort-specific pure export threshold, $\omega^*_{et'}$, would now vary over time, just like the domestic production threshold, ω^*_{dt}, and the mixed export threshold, ω^*_{mt}.

3. Pure exporters: In the Melitz model, the entire overhead production cost is accounted for in domestic profits and, hence, a firm will export if its additional revenues exceed the additional costs. This implies that no firm will ever export and not produce for the domestic market. In our model, some exporters will specialize in that activity if the scope diseconomy (measured by the β parameter) is sufficiently large. Pure exporters have been observed in many developing countries and we document their presence in China, by matching the economic censuses to the Customs database, in Appendix D.4. Pure exporters comprise around 15% of all exporters and their revenues lie between domestic-firm revenues and mixed-exporter revenues, as implied by the model. Although the number of pure exporters may not be substantial, they are critical to the analysis. If the marginal exporter were a mixed exporter, instead, then Fact 2 would not be obtained.

4. Occupational dynamics: In the Melitz model, business opportunities are restricted to the do-

mestic market to begin with. When export opportunities subsequently become available, domestic producers above an ability threshold become (mixed) exporters. This transition from domestic production to mixed exporting is absent in our model, as noted above, but could be generated if we allowed exports to commence in some period $\tau+1$, rather than the initial date. Then domestic producers from the τ preceding cohorts above an ability threshold would become mixed exporters once the new opportunities became available, with this process continuing over time as the threshold declined (with the expansion of the export network). The advantage of starting the domestic network and the export network at the same time is that this simplifies the analysis. The limitation of this approach is that the model does not account for high ability Melitz-type domestic producers who subsequently become mixed exporters. However, their absence does not qualitatively affect the analysis that follows in this section. The propensity of an incumbent domestic producer to add an export plant is increasing in the size of the export network, but is independent of the size of the domestic network. It is the pure exporters, whose numbers are decreasing in the size of the domestic network, as made precise below, that drive Fact 2. We will, however, take account of the Melitz-type mixed exporters when estimating the model in Section 5.

4.3 Explaining the Facts

Recall from Section 2.1 that potential entrepreneurs born in denser counties have a greater propensity to enter business (domestic production), but a lower propensity to enter exporting. We now verify that the model can generate both stylized facts, even though networks drawn from denser counties function more effectively in domestic production and exporting; $\theta'_d(p) > 0$ and $\theta'_e(p) > 0$.

Fact 1: Individuals with ability $\omega \in [\omega^*_{dt}, A]$ become entrepreneurs. Deriving the expression for ω^*_{dt} from (7), by setting $\Pi_{Ot}(\omega^*_{dt}) = \Pi_{Dt}(\omega^*_{dt})$, and unpacking C_{dt}:

$$n_t = ts(p)[A - \omega^*_{dt}] = ts(p)[A - \frac{\log\zeta}{1-\sigma} + \frac{q_{dt} + \theta_d(p)\log n_{t-1}}{(1-\sigma)(1-\alpha)}] \tag{9}$$

Recall that the initial number of firms, n_0, is assumed to be independent of p. From the preceding equation, entrepreneurial propensity in period 1, $\frac{n_1}{s(p)}$ and, hence, n_1 will be increasing in p because $\theta'_d(p) > 0$ and the number of potential entrepreneurs, $s(p)$, is increasing in p. By a recursive argument, entrepreneurial propensity in period t, $\frac{n_t}{ts(p)}$ is increasing in p to explain Fact 1.[19]

Fact 1 is obtained because more effective (higher-p) networks bring in lower ability entrepreneurs at the margin. This implies that the marginal entrant's ability and initial capital is decreasing in p in each cohort, as derived in Appendix D.5 and verified in Appendix Figure D2. The resulting variation in the ability of the marginal entering entrepreneur across birth counties is indicative of a misallocation. In particular, total output would increase if the marginal entrant from a higher population density network was replaced by the last (higher ability) individual to stay out of a lower

[19]The preceding result is derived for a given birth county and destination prefecture, whereas Fact 1 is based on all locations where firms from a given birth county are established. However, it is straightforward to verify that the result we have derived also goes through when we aggregate up across locations. The same is true for Fact 2 below.

population density network, as in Banerjee and Munshi (2004). Such reallocation is infeasible in practice because networks are restricted to individuals from the same birth county.

Fact 2: Individuals from cohort t' with ability $\omega \in [\omega^*_{et'}, A]$ become exporters. As noted, there is no further entry into exporting from the t' cohort after that period. Thus, the stock of exporters at any period t is just the sum of exporters supplied by all preceding cohorts. The marginal pure exporter in cohort t', with ability $\omega^*_{et'}$, is indifferent between domestic production and pure exporting. Following the same steps as above, we set $\Pi_{Dt'}(\omega^*_{et'}) = \Pi_{Et'}(\omega^*_{et'})$ to derive $\omega^*_{et'}$ from (7) and then unpack $C_{et'}$ to obtain:

$$n_{et} = ts(p)[A - \frac{\log\gamma}{\delta - 1}] + \frac{s(p)}{(\delta-1)(1-\alpha)}\sum_{t'=1}^{t}[q_{et'} - q_{dt'} + \theta_e(p)\log n_{e,t'-1} - \theta_d(p)\log n_{t'-1}] \quad (10)$$

As observed in the preceding equation, $\omega^*_{et'}$, which pins down the export propensity, is determined by market-time effects $(q_{et'}, q_{dt'})$ and network sizes $(n_{e,t'-1}, n_{t'-1})$, in exporting versus domestic production. Summing up over all previous cohorts, the export propensity in period t, $\frac{n_{et}}{ts(p)}$, is determined by the *net* network effect: $\frac{1}{t}\sum_{t'=1}^{t}[\theta_e(p)\log n_{e,t'-1} - \theta_d(p)\log n_{t'-1}]$. Given that $\theta'_e(p) > 0$, the export propensity would be increasing in p in the absence of the second term in square brackets. However, $\theta'_d(p) > 0$, and we know from Fact 1 that $n_{t'-1}$ is increasing in p. If the resulting (domestic) network "overhang," which dampens entry into exporting, is sufficiently large, then the net network effect and, hence, the export propensity will be decreasing in p to explain Fact 2.

The root cause of the network overhang in our model is the scope diseconomy, which introduces a nonseparability between domestic production and exporting. As a result, most active entrepreneurs, with the exception of the mixed exporters, must choose between these activities. The nonseparability does not arise in the Melitz model where, for example, a demand shock on the domestic market would have no bearing on the firm's export decision. However, it does arise in Fan et al. (2020) and Almunia et al. (2021), who extend the Melitz model by allowing for increasing marginal costs. Positive shocks on the domestic market now reduce the firm's exports, and while the focus of these recent papers is on the intensive margin, they could in principle generate the same tradeoff at the extensive margin between domestic production and exporting as in our model.

5 Testing the Model

5.1 Propensity Equations

We test the model and subsequently verify Facts 1 and 2 by estimating the structural propensity equations (9) and (10). Notice that the propensity equations are nonlinear in parameters but linear in variables. They can thus be rewritten as follows, with each "composite" parameter in the equations below corresponding to a set of structural parameters in equations (9) and (10). The ability distribution is assumed to be the same in all birth counties in the model to be consistent with Facts 1 and 2 (which are derived conditional on a set of covariates associated with entrepreneurial ability). Based on a comparison of conditional and unconditional estimates in Figure 1, however, we expect the unconditional ability distribution to vary across birth counties. Moreover, while the model is based on a single market or location, entrepreneurs from a given birth county will establish their firms in multiple prefectures in practice. We thus replace the A parameter in equations (9) and (10) with birth county-destination prefecture specific parameters, A_{jk}, where j refers to the birth county and k to the destination prefecture. Modifying the notation to allow for multiple origins and destinations, the propensity equations that we estimate can then be written as follows:

$$\frac{n_{jkt}}{P_{jt}} = \tilde{A}_{jk} + \tilde{\Phi}_{kt} + \tilde{\Theta}_d(p_j) \log n_{jk,t-1} + \tilde{\epsilon}_{jkt} \tag{11}$$

$$\frac{n_{ejkt}}{P_{jt}} = A_{jk} + \Phi_{kt} + \left[\Theta_e(p_j)\left(\frac{1}{t}\sum_{t'=1}^{t} \log n_{ejk,t'-1}\right) + \Theta_d(p_j)\left(\frac{1}{t}\sum_{t'=1}^{t} \log n_{jk,t'-1}\right)\right] + \epsilon_{jkt} \tag{12}$$

where P_{jt} measures the number of potential entrepreneurs and $\tilde{\Phi}_{kt}, \Phi_{kt}$ are destination prefecture-time period effects.[20] Comparing equations (9) and (11), $\tilde{\Theta}_d(p_j) \equiv \frac{\theta_d(p)}{(1-\sigma)(1-\alpha)}$. Comparing equations (10) and (12), $\Theta_e(p_j) \equiv \frac{\theta_e(p)}{(\delta-1)(1-\alpha)}$ and $\Theta_d(p_j) \equiv -\frac{\theta_d(p)}{(\delta-1)(1-\alpha)}$. Our estimates of the revenue and productivity equations in Section 3 imply that network effects are positive in both domestic production and exporting; $\theta_i(p) > 0$ for $i \in \{d, e\}$. This implies that $\tilde{\Theta}_d(p_j)$, $\Theta_e(p_j)$ will be positive and $\Theta_d(p_j)$ will be negative in the propensity equations. In addition, if $\theta_i(p)$ is linear in p: $\theta_i(p) \equiv \theta_{i0} + \theta_{ip} \cdot p$, as assumed in Section 4, then the Θ functions will be linear in p_j: $\tilde{\Theta}_d(p_j) \equiv \tilde{\Theta}_{d0} + \tilde{\Theta}_{dp} \cdot p_j$, $\Theta_i(p_j) \equiv \Theta_{i0} + \Theta_{ip} \cdot p_j$, $i \in \{d, e\}$. The network terms thus appear uninteracted and interacted with p_j in equations (11) and (12). Recall that our estimates in Section 3 also indicate that networks drawn from denser birth counties function more effectively; $\theta_i'(p) \equiv \theta_{ip} > 0$, for $i \in \{d, e\}$. This implies that the interaction coefficients in the propensity equations $\tilde{\Theta}_{dp}$, Θ_{ep} will be positive and that Θ_{dp} will be negative.

Although our analytical model does not include structural error terms, these terms can be introduced for the estimation by allowing for birth county-destination prefecture entry shocks. The discussion on identification that follows focuses on equation (12) for convenience, but it applies in exactly the same way to equation (11). The numerator of the dependent variable in equation (12) is the stock of export firms at each point in time; i.e. the sum of entry flows over preceding periods and, hence, the error term can be analogously characterized as the sum of per period entry shocks, v_{jkt}: $\epsilon_{jkt} = \epsilon_{jk,t-1} + v_{jkt}$. The error term, ϵ_{jkt}, is serially correlated by construction, and since the propensity equation includes lagged firm stocks (the network size terms) on the right hand side, biased estimates will be obtained if the equation is estimated in levels. The standard solution to this problem in the dynamic panel literature is to first-difference the estimating equation. This will purge the origin county-destination prefecture effects, A_{jk}, and leave us with v_{jkt} in the residual of

[20] We ignore sectors in the current analysis in order to leave us with a sufficient number of observations to construct the propensity variables. The propensities are measured at the birth county-destination prefecture-time period level, matching the specification of the network variables.

the estimating equation. If v_{jkt} is serially uncorrelated, OLS estimation of the differenced equation will yield unbiased estimates of the network effects. It is, however, entirely possible that v_{jkt} is serially correlated, in which case instruments need to be constructed for the network terms.

Since the network variables are measured in logs, the first-differenced variables that need to be instrumented are the network growth rate in period $t-1$ in equation (11) and the average network growth rate over all periods up to $t-1$, for all firms and for export firms, in equation (12). For this component of the analysis, we cannot base our instruments on the history of agricultural income shocks in the birth county, as we did when estimating the firm-level revenue and productivity equations in Section 3, because these shocks directly determine firm entry and, hence, the entrepreneurial and export propensities. What we do, instead, is to take advantage of the dynamic properties of the networks. There are 125,000 domestic networks and 5,000 export networks, defined at the birth county-destination prefecture level, in our data. These networks form at different points in time in a given prefecture, with the domestic network forming eight years earlier than the export network on average. Once a network drawn from a given birth county has formed in a destination prefecture, its size will grow from one period to the next; i.e. with its "duration," on account of the dynamic network multiplier effect. Moreover, the trajectory of the network will depend on the initial level of entry, which determines the size of the multiplier effect. The interaction of network duration with (log) initial entry can thus be used as an instrument for the growth rate. As commonly assumed in the migration literature, the identifying assumption (validated below) is that the factors that determine initial entry should not determine subsequent entry, except through the network multiplier effect.

Once we first-difference the propensity equations, the left hand side is approximately equal to the flow of new entrepreneurs or exporters from the birth county into a given prefecture divided by the stock of potential entrepreneurs (since the latter statistic changes little from one period to the next). In our model, there is a single destination prefecture and, hence, potential new entrepreneurs can be partitioned by ability into distinct activities. With multiple destinations, however, the same individual could possibly be willing to establish his firm in more than one prefecture. To avoid such double-counting, we assume that each potential entrepreneur receives a single referral, which is required to set up a business, from the birth county network. If there is an equal probability of receiving that referral from all prefectures, then the right hand side of the first-differenced propensity equations will be multiplied by a constant and the estimation proceeds without modification. For our benchmark specification, however, we make the more realistic assumption that the probability that a potential entrant receives a referral from a given prefecture, k, in period t is equal to the share of incumbent firms from the birth county who were located in that prefecture by the end of the preceding period, $S_{jk,t-1}$, with the shares across all prefectures summing to one. The right hand side of the first-differenced propensity equations is now multiplied by $S_{jk,t-1}$ or, equivalently, the left hand side is divided by $S_{jk,t-1}$ (which is what we do in practice).

The instrumental variable estimates with entrepreneurial propensity as the dependent variable are reported in Table 5, Column 1 and the corresponding estimates with export propensity as the dependent variable are reported in Column 2. While the model assumes that domestic production and exporting commenced simultaneously for analytical simplicity, we now allow for distinct regimes: the analysis of entrepreneurial propensity spans the 1994-2009 period and the analysis of export propensity spans the 2002-2009 period. Based on the Kleibergen-Paap statistic, our instruments have sufficient power (the F statistic is well above 10). The estimated coefficients also have the expected signs and are statistically significant. The fact that both the export network and the domestic network determine the export propensity provides empirical support for a key feature of the model. The negative coefficients on the domestic network terms, in addition, are indicative of the network overhang that is needed to generate Fact 2. Qualitatively similar coefficient estimates are obtained without the $S_{jk,t-1}$ correction in Appendix Table E1, although our preferred specification does a better job of predicting entry, especially for all entrepreneurs, in distant prefectures (where the share is smaller).[21]

Among the export firms in the 2008 economic census who were established after 2002, which is the starting point for the exporting regime in our analysis, 76% commenced exporting within two years. This is broadly in line with the equilibrium specified in our model, where exporters commence that activity immediately, once we take account of the time needed in practice to make connections with foreign buyers and receive government permissions. However, 68% of the exporters in the 2004 economic census and 37% of the exporters in the 2008 census established their firms prior to 2002. Most of these firms would have transitioned from domestic production to exporting when new opportunities became available with China's entry into the WTO, as in the Melitz model. Since the Melitz-type exporters do not appear in our model, we drop exporters who were established prior to 2002 when constructing the export propensity in Table 5, Column 3 to more accurately test its implications. Note that there is no change in the regressors of the estimating equation. As can be seen, the estimated coefficients with this alternative specification of the export propensity are broadly in line with the estimates based on all exporters in Column 2.

The identifying assumption with our instrumental variable estimates is that the factors that determine initial entry in each birth county-destination prefecture should only determine subsequent entry through the network multiplier effect; i.e. these factors should not be persistent. This assumption is plausible, given that there is often an accidental one-off aspect to (business) network formation, as described, for example, in Munshi (2011) and Kerr and Mandorff (2023). The analysis that follows provides independent support for the validity of the instrumental variable estimates.

The OLS estimates of the propensity equations, reported in Appendix Table E2, differ substantially from the IV estimates in Table 5. Our first validation test assesses whether the difference

[21]We measure the number of potential entrepreneurs, P_{jt}, by the number of 25-55 year old men who were born in county j at time t, as we did when deriving Facts 1 and 2. In the model, however, a fresh cohort of potential entrepreneurs arrives in each period and then remains active forever. We thus verify that the results are robust to an alternative measure of the number of potential entrepreneurs in Appendix Table E1: we start with the number of 25-35 year olds in 1994 and then add a fresh cohort of 25 year olds each year up to 2009. In addition, 81% of the initial entry levels in our birth county-destination prefecture networks consist of a single firm. Since the log of initial entry is zero in that case, which would result in no variation over time in those networks, we add a small constant equal to 0.1 to all initial entry levels when estimating the propensity equations. Appendix Table E3 verifies that the results are robust to adding 0.05 or 0.15 instead.

Table 5: Entrepreneurial and Export Propensity

Propensity to become:	entrepreneur	exporter	exporter post-WTO
	(1)	(2)	(3)
$\tilde{\Theta}_{d0}$	0.0050***	–	–
	(0.0012)		
$\tilde{\Theta}_{dp}$	0.1540***	–	–
	(0.0514)		
Θ_{e0}	–	-0.0004	-0.0003
		(0.0003)	(0.0002)
Θ_{ep}	–	0.0171**	0.0121**
		(0.0067)	(0.0049)
Θ_{d0}	–	-0.0000	-0.0000
		(0.0001)	(0.0001)
Θ_{dp}	–	-0.0063***	-0.0044**
		(0.0023)	(0.0017)
Birth county-prefecture FE	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes
Kleibergen-Paap F	188.9	15.41	15.41
Observations	699,531	16,559	16,559

Note: The number of firms is derived from the SAIC registration database and the Customs database.
The number of potential entrepreneurs is derived from the Population Census (1990, 2000).
The unit of observation is the birth county-destination prefecture-year.
$\tilde{\Theta}_{d0}$, Θ_{e0}, Θ_{d0} measure direct network effects, while $\tilde{\Theta}_{dp}$, Θ_{ep}, Θ_{dp} measure interaction effects.
The interaction of network duration with initial (log) entry and the triple interaction with birth county population density are used as instruments for each network term and its interaction with population density in the first-differenced equation (separately for the domestic network and the export network in Columns 2-3).
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

between these estimates can be plausibly explained by two potential sources of bias: measurement error in the network variables and serial correlation in the per period entry shocks after the network has formed, v_{jkt}. While a detailed, self-contained, description of this test is presented in Appendix E, the key steps are as follows: (i) Assuming that the IV estimates in Table 5 are unbiased, the error structure in the first-differenced propensity equations can be recovered from the estimated residuals. It turns out that the residuals or, equivalently, the entry shocks can be characterized by AR1 processes. (ii) We draw entry shocks from this error distribution over successive periods, taking initial entry in each birth county-destination prefecture network as given, to recursively predict the propensity change from one period to the next. Predicted network sizes, which can be recovered from the predicted propensity changes, are then used to re-estimate the OLS regressions. The OLS estimates with predicted (simulated) data in Appendix Table E2 are close to the IV estimates in Table 5. These OLS estimates are purged of measurement error, but continue to be biased due to serial correlation in the entry shocks (error term). We can thus conclude that measurement error is responsible for much of the observed difference between the OLS estimates with actual data and the

IV estimates. This is reassuring, since our instruments can correct such bias with some confidence. Moreover, the amount of measurement error that is needed to generate the observed bias is not implausibly large, as verified in Appendix E.

Our second validation test assesses whether the instruments satisfy the exclusion restriction. If the (unobserved) factors that determine initial entry are persistent, then the duration of the network will be correlated with these factors, violating the exclusion restriction. We examine this possibility in the following ways: First, we include duration directly as a covariate in the first-differenced entrepreneurial propensity and export propensity equations. There is now less variation in the instruments, but they continue to have sufficient statistical power and the estimated network effects, reported in Appendix Table E3, remain very similar to the benchmark estimates in Table 5. Second, we take account of the fact that even if the factors that determine network formation are persistent, their effects will dissipate over time, as commonly assumed in the time series literature. This implies that any bias in the estimated network effects will decline as we remove time periods from the sample. We thus proceed to re-estimate the propensity equations in Table 5, removing the first period after inception for each network from the sample and then sequentially deleting additional periods. Focussing on the economically meaningful interaction of the network terms with birth county population density in Appendix Figure E1, the magnitude of the estimated coefficients is (statistically) unchanged as the estimating sample moves further away in time from the point of inception of the network.

As a final validation test, we proceed to re-estimate the firm-level revenue and productivity equations with the instruments based on network duration and initial firm entry in Table 6. We now first-difference the estimating equations to purge the fixed effects, as we did with the propensity equations, which is why the number of observations is smaller than in Table 3. A comparison of the OLS estimates in Columns 1-3 of Table 3 and Table 6 indicates that the point estimates differ quite substantially. This is consistent with our finding that network sizes are measured with error, in which case the method used to purge the firm fixed effects – within estimation in Table 3 and first-differencing in Table 6 – matters for the OLS estimates. Once we instrument for network size, however, the estimates in Columns 4-6 of Table 3 and Table 6 come closer together. This consistency in the results with different sets of instruments, exploiting independent sources of exogenous variation, increases our confidence in their validity. Moreover, since the current instruments are based on (exogenous) initial firm entry, we are specifically identifying a *business* network effect, rather than a more general birth county-destination prefecture network effect.

We close the discussion in this section with a comment on the connection between Table 5 and Table 6. The positive and significant interaction effects in Table 6, Columns 4-6 explain the corresponding interaction effects in the propensity equations that we report in Table 5, when viewed through the lens of the model. This internal consistency is strong evidence in support of our model. The opposing effects of the export network and the domestic network in the export propensity equation also highlights the tension between networks that is a novel feature of our dynamic model.

Table 6: Revenue, TFP, and Network Effects (Alternative Instruments)

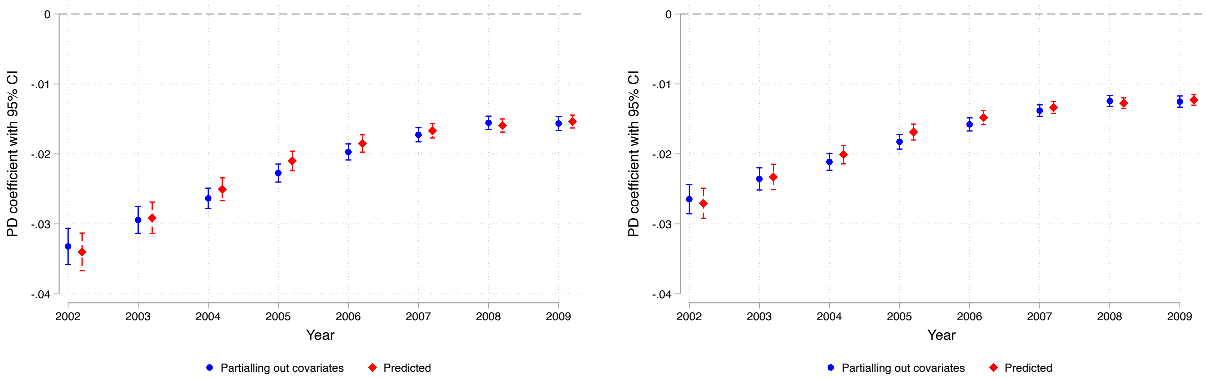
Model:	OLS			IV		
Dependent variable:	log revenue	log TFP	log(exporting revenue)	log revenue	log TFP	log(exporting revenue)
	(1)	(2)	(3)	(4)	(5)	(6)
$\log n_{jk,t-1}$	0.167***	0.185***	0.150***	0.358***	0.390***	-0.180*
	(0.009)	(0.010)	(0.028)	(0.036)	(0.046)	(0.092)
$p_j \times \log n_{jk,t-1}$	0.540**	0.424*	2.045***	2.774***	3.012***	2.517*
	(0.211)	(0.219)	(0.564)	(0.696)	(0.852)	(1.518)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	29.66	29.66	6.085
Observations	1,433,528	1,433,529	56,043	1,433,528	1,433,529	56,043

Note: Revenue and TFP are from the Inspection database, covering the 1998-2009 period. Export revenue is obtained from the Customs database, covering the 2002-2009 period.
log revenue, log TFP, and log exporting revenue are measured as a Z-score within the one-digit industry-prefecture-time period.
p_j denotes population density in 1982 for birth county j and $n_{jk,t-1}$ is the stock of firms from county j established in prefecture k by the end of the preceding period $t-1$. When the dependent variable is export revenue, $n_{jk,t-1}$ is measured by the stock of export firms.
The interaction of network duration with initial (log) entry and the triple interaction with birth county population density are used as instruments for each network term and its interaction with population density in the first-differenced equation.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

5.2 Generating Fact 2

While the preceding results indicate that a domestic network overhang is present, to reconcile Fact 2 with the model we need to establish that the overhang is sufficiently strong; i.e. that the net network effect in square brackets in equation (12) is decreasing in p_j. We do this in two ways: (i) by partialling out the prefecture-time period effects from the first-differenced equation and then estimating the association between export propensity (conditional on these effects) and population density, and (ii) by predicting the term in square brackets, based on the estimated coefficients and taking initial entry in each network as given, and then estimating its association with birth county population density. The estimated population density coefficients are reported for each year over the 2002-2009 period in Figure 3, with the symbol (blue circle or red diamond) denoting the point estimate and the vertical line demarcating the 95 percent confidence interval. The estimated coefficients are negative and significant, as required to generate Fact 2, but notice that they grow smaller (in absolute magnitude) over time. The drag of the domestic network weakens, but it does not disappear completely. Notice also that our point estimates based on (i) above, in blue, are very close to the corresponding estimates based on (ii), in red. This indicates that our parsimonious model fits the data well, conditional on the covariates in the estimating equation.

We complete the analysis in this section by quantifying the magnitude of the network effects. Based on the estimated entrepreneurial propensity equation and maintaining the estimated



(a) Net Network Effect (all exporters)

(b) Net Network Effect (post-WTO exporters)

Figure 3: Net Network Effect and Population Density

Source: The net network effect is derived from Table 5, Columns 2 and 3, and birth county population density is obtained from the 1982 Population Census.

prefecture-time effects, our counter-factual simulations indicate that the predicted number of domestic firms in 2009 would have declined by 39% if the domestic networks had not emerged. Focusing on the export propensity equation and maintaining the estimated prefecture-time effects once again, the predicted number of exporters would have increased by 16% in 2009 if the domestic network overhang were absent. While the domestic networks played an important role in stimulating entrepreneurship in China, they exerted a substantial drag on the subsequent transition to higher value exporting.

6 Conclusion

Despite its well documented inefficiencies, the Chinese economy has grown at an unprecedented rate over the past three decades. Our analysis provides a (partial) explanation for these apparently contradictory facts, based on the idea that networks of firms provide mutual help to each other in an environment where markets function imperfectly. Our estimates indicate that hometown (birth county) networks contributed substantially to the increase in the number of rural-born entrepreneurs, whose firms account for two-thirds of registered firms in China. Although the existence of community-based business networks has been documented historically and in contemporary industry studies, this constitutes the first economy-wide evidence to date of the important role played by these informal institutions.

While the domestic networks that we identify may have facilitated mobility in the initial transition, they slowed the growth of newly emerging export networks and the transition to the next stage of economic development. The export networks also facilitate mobility, but if the domestic network overhang is sufficiently large, then the entry rate of exporters in equilibrium could be even lower than the counter-factual rate in an economy without networks. Entrepreneurs do not internalize the effect of their entry on network performance and, hence, there is a role for policy.

Export subsidies (which have no consequence for domestic profits) are unambiguously efficiency enhancing. In contrast, entry subsidies must balance two opposing effects: their positive effect on domestic profits due to a larger domestic network and the negative effect on export profits due to a smaller export network (on account of the domestic network overhang). If the latter effect is sufficiently large, it may even be optimal to tax entry. Adding to the complexity, if the second transition is anticipated, then domestic policies during the first transition would need to take account of their future consequences for exporting. Although a complete characterization of dynamic optimal subsidies is left to future research, we note that industrial policy could have large positive impacts in economies where networks (with their dynamic multiplier effects) are active.

The organic process of economic development that we describe in this paper, in which networks emerge at each stage to facilitate the occupational mobility of their members, and pre-existing networks slow down the growth of the networks that follow, is not specific to China or to business. For example, there are many anecdotal examples of working-class communities, who historically benefited from mobility-enhancing labor networks, subsequently getting locked into traditional industrial occupations. At the same time, the analysis in this paper, will only be relevant in populations where community networks are already active or have the potential to be activated and this will, in general, depend on the underlying social structure. Both China, the setting for the current analysis, and India, where the role of caste networks has been previously documented, have high population densities. This gives rise to well functioning networks, as we have shown. In other, more sparsely populated regions of the world, such as Africa, community-based networks will function less effectively and, thus, will play a less important role during the process of development. While the political economy of African development has been studied extensively, and differences in the complexity of Asian and African societies have been previously noted (Diamond, 1997), this particular aspect of African society has received less attention and may be responsible (in part) for the observed variation in trajectories across these regions.

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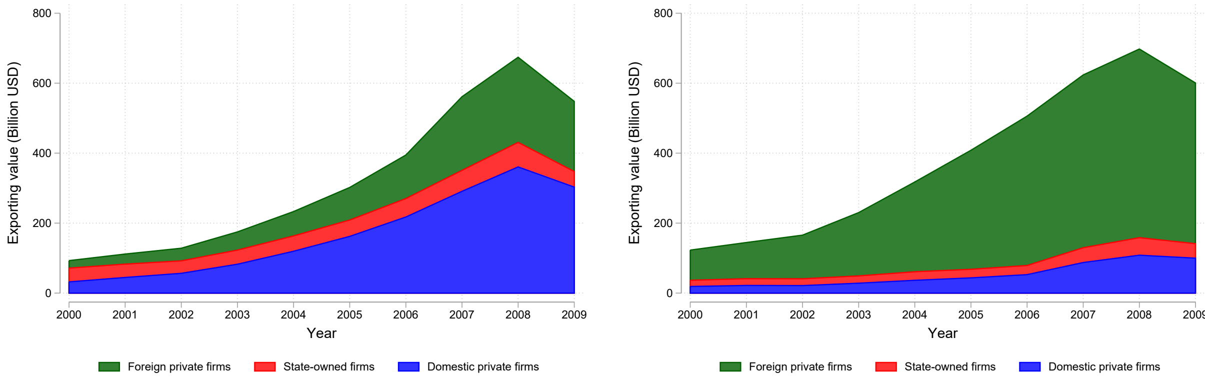
Appendix A: Export Accounting

There are two types of exports in China: production exports and processing exports. Given our interest in the transition from domestic production to higher value exporting, and the evidence provided by Dai, Maitra and Yu (2016), we thus restrict attention to production exports. The Customs database, which indicates the type of export for each shipment over the 2000-2009 period, can be merged with the SAIC registration database, which provides the ownership structure of each supplying firm. The merged data, reported in Figure A1, indicate that private domestically owned firms are largely involved in production exports in any case, whereas processing exports are dominated by foreign owned firms.



(a) Production Export

(b) Processing Export

Figure A1: Production and Processing Export, By Ownership

Source: Customs Data

Production exports can be further divided into direct exports and indirect exports through intermediaries or trading firms. Indirect exporters are less productive than direct exporters in China (Ahn, Khandelwal and Wei, 2011). We thus expect them to supply lower quality products and Table A1 provides empirical support for this claim. The Customs database provides information on the price (unit value) and the destination of each shipment. The SAIC registration database, which can be merged with the Customs database, indicates whether the supplier is a direct exporter (producer) or trading firm (operating in the wholesale or retail sector). As observed in Table A1, trading firms (and, hence, indirect exporters) receive lower prices for their goods and are less likely to ship to OECD countries where the demand for quality is higher. Notice that this result is obtained within narrowly defined (4-digit) goods categories in each year; i.e. with goods-year fixed effects in the estimating equation.

While indirect exporters may be less productive than direct exporters, how do they compare with domestic producers? To answer this question, we turn to the Above Scale database, which provides total revenues and export revenues for all firms with annual revenues above 5 million Yuan, in each year over the 2000-2009 period. The Above Scale database can be merged with the Customs database. This allows us to measure direct exports for each above-scale firm that appears in the Customs database in a given year. It also allows us to measure indirect exports for firms that

Table A1: Unit Price and Destination of Exported Goods

Dependent variable:	price per unit	OECD destination
	(1)	(2)
Trading firms	-15.857***	-0.074***
	(2.703)	(0.001)
Constant	82.018***	0.474***
	(1.978)	(0.001)
Goods-year fixed effects	Yes	Yes
Observations	9,062,560	9,062,560

Note: Trading firms are identified as exporters in the Customs Data who operate in the wholesale and retail sector. Direct exporters are the reference group.
Price per unit is calculated at the 8-digit HS code level. Firm-goods in the bottom and top 5 percentile of each 5-digit Standard International Trade Classification (SITC) code are excluded from the analysis.
Standard errors clustered at the good - year level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

report positive export revenues in the Above Scale database, as the difference between reported total exports and direct exports (from the Customs database, if relevant). While direct exports can also be computed for below-scale firms if they appear in the Customs database, we cannot directly measure their indirect exports. As shown in Figure A2 below, the contribution of these firms to total indirect exports is small in any case.

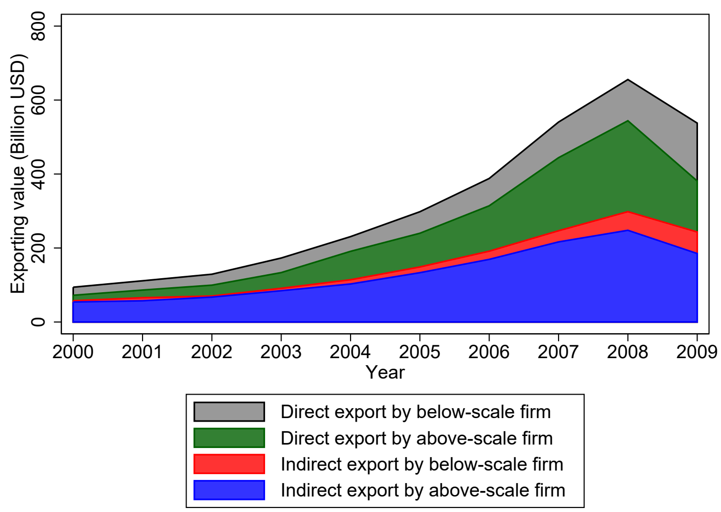


Figure A2: Export Accounting

Source: SAIC registration database, Customs database, and Above Scale database.

The blue area in Figure A2 represents the sum of indirect exports supplied by all above-scale firms, based on the method described above. The red area represents the contribution of below-scale firms to indirect exports. This is derived by subtracting above-scale indirect exports from total indirect exports; i.e. the amount supplied by trading firms in the Customs data. As can be seen, the contribution of below-scale firms to indirect exports is negligible. To compare the productivity of indirect exporters and domestic producers we thus begin by focusing on above-scale firms. Since a given firm could be engaged in multiple activities, we examine the association between the capital-labor ratio, a common measure of firm productivity, and the share of the firm's revenue accounted for by direct exports and indirect exports, respectively, in Table A2, Column 1. Note that domestic production is the reference category, measured by the constant term, in this specification. Conditioning for industry-year effects and the firm's total revenue (linear and quadratic terms), we observe that the capital-labor ratio is increasing in the direct export ratio and decreasing in the indirect export ratio.

Table A2: Capital Intensity of Different Type of Firms

Data source:	Above Scale: 2000-2009	Census: 2004, 2008
Dependent variable:	log (K/L)	
	(1)	(2)
Direct export share	0.029*	0.094***
	(0.016)	(0.028)
Indirect export share	-0.368***	-0.290***
	(0.009)	(0.014)
Constant	15.861***	11.755***
	(0.204)	(0.120)
Industry-year fixed effects	Yes	Yes
Observations	654,408	775,722

Note: The estimating equations include log firm revenue (linear and quadratic terms) and industry-year effects. Standard errors clustered at 4-digit industry - year level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

While indirect exporting is concentrated among above-scale firms, notice from Figure A2 that a substantial fraction of direct exports are supplied by below-scale firms. These firms also comprise the bulk of domestic producers. We thus expand the sample in Table A2, Column 2 by using data from the Economic Census, which includes all firms not just above-scale firms, but only at two points in time (2004 and 2008). The Economic Census provides revenues for each firm, but not export revenues, and thus indirect exports must be obtained from the Above Scale database as above. Indirect exports for below-scale firms are set to zero. The estimates with the augmented sample of firms in Column 2 match what we obtain with above-scale firms in Column 1. Direct exporting is more productive and indirect exporting is less productive than domestic production (the reference category in these regressions). Given our interest in the transition to higher quality (productivity) exporting, we thus define "exporting" more narrowly in our analysis by direct exporting. Less productive indirect exporting is clubbed together with domestic production.

Appendix B: Descriptive Evidence

1. Entrepreneurship in China

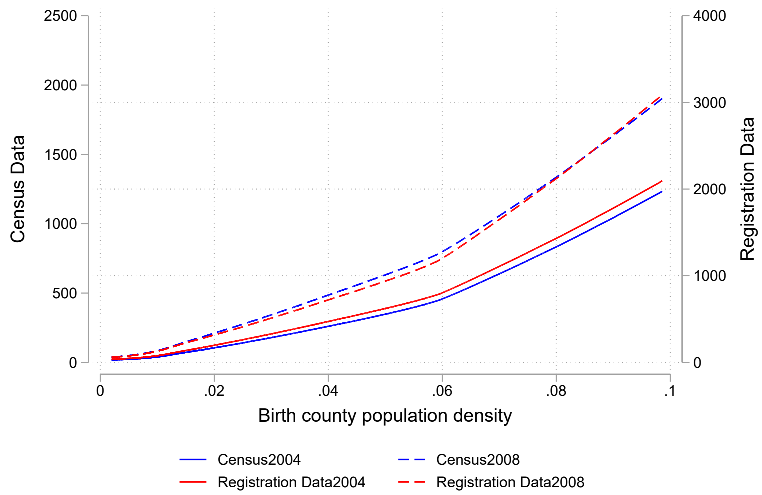
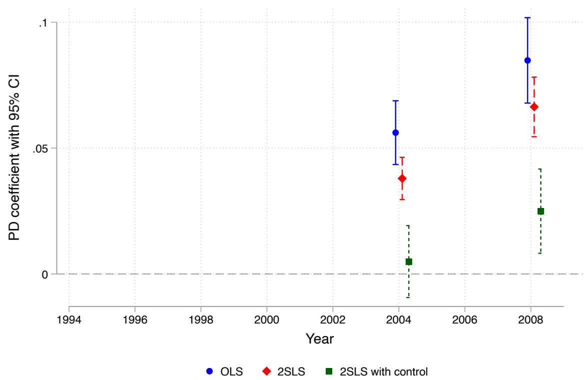
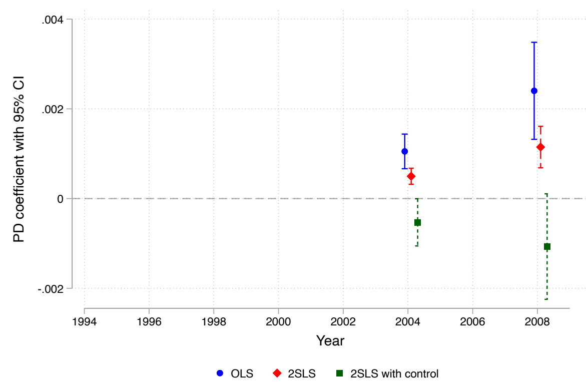


Figure B1: Number of Manufacturing Firms

Source: SAIC registration database and Economic Census (2004, 2008).



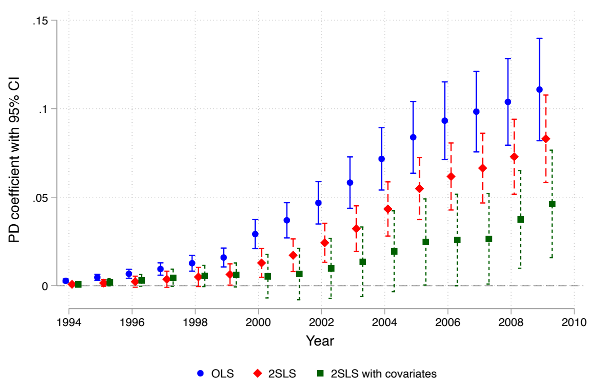
(a) Entrepreneurial Propensity and Population Density



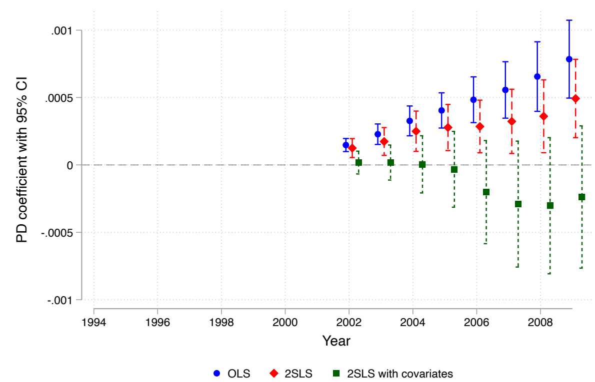
(b) Export Propensity and Population Density

Figure B2: Entrepreneurial and Export Propensity

Source: Economic Census (2004, 2008) and Customs database.
2SLS estimates use potential crop yields as instruments for population density in 1982.
Covariates measure education distribution, occupational structure and industry structure in the birth county in each year.



(a) Entry into Business



(b) Entry into Exporting

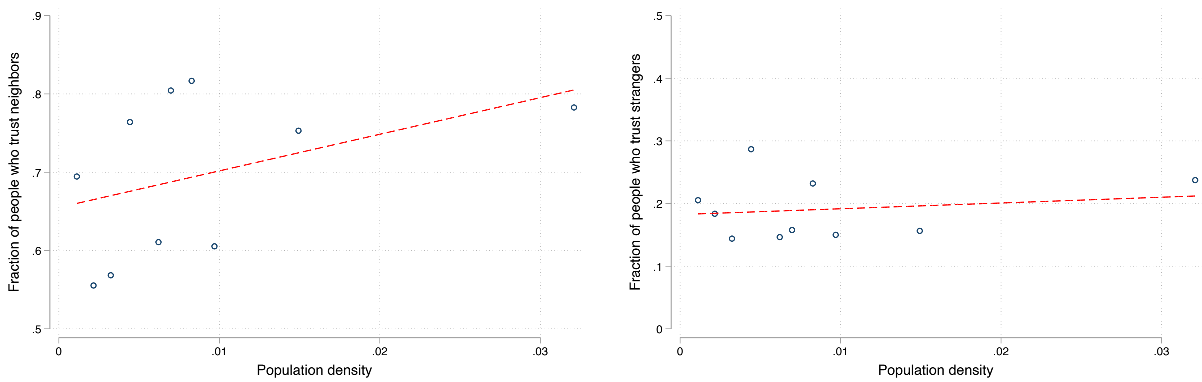
Figure B3: Entrepreneurial Propensity, Export Propensity, and Population Density: Outside the Birth County

Source: Registration database, Customs database and Population Census 1982, 1990, 2000.
2SLS estimates use potential crop yields as instruments for population density in 1982.
Covariates measure education distribution, occupational structure and industry structure in the birth county in each year.

2. Trust and population density across the world

The trust-population density association is not China-specific and we expect to observe the same positive association in other settings. The most recent (sixth) round of the World Values Survey (WVS) asks the same questions about trust in neighbors and trust in strangers; i.e. people that the respondent would meet for the first time as the CFPS. The WVS provides the fraction of respondents for a given country in each category: trust completely, trust somewhat, trust not very much, trust not at all. We combine the first two categories and the latter two categories to construct a binary measure of trust.

While the advantage of the WVS data is that they cover many countries, one limitation is that responses from rural and urban residents cannot be distinguished. We partially address this limitation by only including large developing countries with large rural populations (GDP per capita less than \$20,000 and area greater than 100,000 km^2) in the sample. This leaves us with 31 countries in the binned scatter plots reported below.



(a) Trust in neighbors

(b) Trust in strangers

Figure B4: Trust and Population Density: Cross-Country Comparison

Source: World Values Survey and World Development Index.

3. Derivation of the Adjusted HHI

Suppose that there are n trials, that each outcome j from the set of k possible outcomes has an independent probability of occurring p_j, and that the random variable X_j is the number of occurrences of outcome j. Then the multivariate random variable $\mathbf{X} = (X_1, \cdots, X_k)$ has a multinomial distribution with parameters $(n, k, p_1, \cdots, p_k)$. Applied to our context, (i) n is the total number of firms from a given birth county, (ii) k is the total number of destinations (prefectures) that they are allocated to, and (iii) $p_1, \cdots, p_k$ are the probabilities that a firm allocated randomly would end up in each of those destinations. We assume that there is an equal probability of choosing any destination; $p_j = \frac{1}{k}, \forall j$.

The expected HHI when firms make decisions independently can be expressed as,

$$E(HHI) = E\left(\frac{1}{n^2}\sum_{i=1}^{k} X_i^2\right) = E\left(\frac{1}{n^2}\mathbf{X}^T\mathbf{X}\right).$$

Based on the general properties of the multinomial distribution,

$$E(HHI) = \frac{1}{n^2}\left([E(\mathbf{X})]^T E(\mathbf{X}) + tr[cov(\mathbf{X})]\right).$$

It follows that,

$$E(HHI) = \frac{1}{n^2}\left(k\left(\frac{n}{k}\right)^2 + k\left[n\frac{1}{k}\left(1-\frac{1}{k}\right)\right]\right) = \frac{1}{k} + \frac{1}{n}\frac{k-1}{k}.$$

For large n, $E(HHI) \approx \frac{1}{k}$. For small n, $E(HHI)$ is decreasing in n. We account for this by constructing a normalized HHI statistic, which is simply the unadjusted HHI, based on the observed distribution of firms across destinations, divided by $E(HHI)$. If firms are allocated randomly, then the adjusted HHI will be close to one, providing a useful benchmark for this statistic.

Appendix C: Identifying Network Effects

1. Accuracy and representativeness of SAIC inspection data

Table C1: Accuracy of Inspection Data

Data:	Economic Census 2004		Economic Census 2008	
Difference in:	log assets	log revenues	log assets	log revenues
	(1)	(2)	(3)	(4)
PD	-0.038	1.419	0.532	0.255
	(0.374)	(2.666)	(0.503)	(3.452)
Province fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	30,717	30,717	209,578	209,578

Note: The dependent variable is measured as the difference between log assets(revenues) in the Economic Census and the Inspection database, for firms who appear in both datasets.
Birth county population density (PD) is obtained from the 1982 Population Census.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table C2: Representativeness of Inspection Data

Data:	Economic Census 2004		Economic Census 2008	
Dependent variable:	log assets	log revenues	log assets	log revenues
	(1)	(2)	(3)	(4)
Reporting inspection	0.705***	0.551***	0.476***	0.548***
	(0.060)	(0.073)	(0.044)	(0.052)
PD	1.950***	5.118***	3.774***	5.286***
	(0.576)	(0.641)	(0.953)	(1.272)
Reporting $\times$ PD	0.679	0.129	0.303	-0.604
	(1.666)	(2.110)	(1.124)	(1.416)
Province fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	122,649	122,649	228,089	228,089

Note: Reporting inspection indicates whether a firm in the Economic Census is also in the SAIC inspection database.
Birth county population density (PD) is obtained from the 1982 Population Census.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

2. Measuring firm productivity: Consider a standard Cobb-Douglas production function, as in Hsieh and Klenow (2009):

$$R_{it} = z_{it}^{1-\eta} \left(K_{it}^{1-\beta} L_{it}^{\beta} \right)^{\eta}.$$

If the firm's revenue, capital and labor are observed, then its productivity, z_{it}, can be computed directly. However, the SAIC inspection data do not provide information on labor. Assuming that all firms in a sector-prefecture-time period face the same wage, w, we can nevertheless solve for the profit maximizing labor input and then rewrite the revenue equation as follows:

$$R_{it} = z_{it}^{\frac{1-\eta}{1-\beta\eta}} \left(\frac{\beta\eta}{w} \right)^{\frac{\beta\eta}{1-\beta\eta}} K_{it}^{\frac{(1-\beta)\eta}{1-\beta\eta}}.$$

Taking logs,

$$\log z_{it} = \frac{(1-\beta\eta)}{1-\eta} \log R_{it} - \frac{(1-\beta)\eta}{1-\eta} \log K_{it} - \frac{\beta\eta}{1-\eta} \log \left(\frac{\beta\eta}{w} \right).$$

β at the one-digit sector level and η can be obtained from Hsieh and Klenow. The last term on the right hand side of the preceding equation is common to all firms in a sector-prefecture-time period and, hence, will drop out when productivity is measured as a Z-score.

3. Constructing the Shift-share Instruments: The instrument for network size, at the birth county-destination prefecture-year level, is constructed in the following steps:

Step 1: To construct the "shift" of the shift-share instrument, we calculate a crop-specific price shock for the same set of 11 crops that we use to predict population density, over the 1992-2009 period. Agricultural Producer Prices (APP) at the "farm gate" are available for each producing country in USD between 1991 and 2016 from the FAO. Following Imbert et al. (2022), the world price of each crop c is the average price across countries (excluding China) weighted by their yearly share of global exports. As in Imbert et al. (2022), the crop price shock, ϵ_{ct}, is calculated by estimating the following equation:

$$\log P_{c,t} = \theta \log P_{c,t-1} + \eta_t + \nu_c + \epsilon_{ct}.$$

Step 2: To construct the first (inner) component of the "share" in the shift-share instrument, we construct a weight for each crop that reflects its contribution to total agricultural output, by value, in county j. The weighted sum of the crop price shocks then provides us with a measure of the income shock in county j in year t:

$$S_{jt} = \sum_c \left(\frac{\overline{P}_c \cdot \overline{A}_{cj} \cdot y_{cj}}{\sum_c \overline{P}_c \cdot \overline{A}_{cj} \cdot y_{cj}} \right) \epsilon_{ct}$$

where $\overline{P}_c$ is the world price of crop c in a reference year (1997), $\overline{A}_{cj}$ is the acreage allocated to crop c in county j in that year, and y_{cj} is the potential crop yield (obtained from the FAO-GAEZ database). The acreage statistic is obtained from the 2000 World Census of Agriculture (WCA), which provides a geocoded map of harvest area for each crop at a 30 arc-second (approximately 10 km.) resolution. We aggregate the harvest areas to the county level to construct the acreage statistic. We choose 1997 as the reference year when constructing the crop weights because the WCA provides acreage in that year for China.

Step 3: Our measure of network size is based on the stock of firms. To predict this stock, we begin with the entry decision. This is a major decision that is unlikely to be determined by a single income shock. We thus assume that the number of entrants in year t from county j is determined by the average income shock over the preceding five years (or as long as available):

$$AS_{jt} = \frac{1}{5} \sum_{\tau=t-5}^{t-1} S_{j\tau}.$$

For the analysis with all firms, we construct AS_{jt} from 1993 onwards and S_{jt} is available from 1991. In the early years (prior to 1997), AS_{jt} is thus computed as the average income shock over a shorter period of time (less than five years). For exporters, we construct AS_{jt} from 2001 onwards and, hence, AS_{jt} can always be computed as the average income shock over five years.

To construct a predictor of the stock of firms from birth county j in year t, n_{jt}, we sum up

$AS_{j\tau}$ from $\tau = 0$ to t:

$$TS_{jt} = \sum_{\tau=0}^{t} AS_{j\tau}$$

where period 0, corresponding to the first cohort of entering firms, is specified to be 1993 for domestic producers and 2001 for exporters.

Step 4: While we have constructed a predictor of the total stock of firms from county j in period t, our measure of network size is more precisely the stock of firms from county j in destination prefecture k in year t, n_{jkt}. To construct a predictor of network size we assume that the probability of establishing a firm in a given prefecture k is declining in its distance, d_{jk}, from birth county j. If a firm locates in its birth prefecture, the distance is set to zero. If not, the distance is measured from the centroid of the birth county to the centroid of the destination prefecture. To derive the probability, we estimate a gravity equation as in the New Economic Geography literature; e.g. Tombe and Zhu (2019) :

$$\log\left(\frac{n_{jkt}}{n_{jt}}\right) = \eta_{jt} + \eta_{kt} + \kappa \log(d_{jk}) + \varepsilon_{jkt}.$$

The estimated "migration" elasticity, κ, equals -0.865 for all firms and -0.404 for exporters. This allows us to construct the second (outer) "share" of our shift-share instrument for n_{jkt}:

$$IV = d_{jk}^{\kappa} TS_{jt}.$$

To construct the instrument for the interaction of network size with birth county population density, we interact the shift-share instrument derived above with potential crop yields in the county for all 11 crops.

Table C3: First Stage Estimates

Dependent variable:	$\log n_{jk,t-1}$	
Sample:	all firms	exporters
	(1)	(2)
IV	-10.321***	-10.142***
	(0.192)	(0.406)
Birth county-prefecture fixed effects	Yes	Yes
Observations	148,856	11,673

Note: The unit of observation is birth county-destination prefecture-year.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

4. Validating the Shift-share Instruments

Table C4: Revenue, TFP, and, Network Effects: Located outside Birth County

Model:	OLS			IV		
Dependent variable:	log revenue	log TFP	log (exporting revenue)	log revenue	log TFP	log (exporting revenue)
	(1)	(2)	(3)	(4)	(5)	(6)
$\log n_{jk,t-1}$	0.267***	0.188***	0.186***	0.165***	0.077***	0.213
	(0.007)	(0.007)	(0.040)	(0.031)	(0.029)	(0.153)
$p_j \times \log n_{jk,t-1}$	1.188***	0.686***	2.482***	3.317***	1.965***	3.628
	(0.183)	(0.178)	(0.720)	(0.732)	(0.706)	(2.659)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	25.90	25.90	11.42
Observations	1,324,210	1,324,210	26,751	1,324,210	1,324,210	26,751

Note: Revenue and TFP are derived from the Inspection database, covering the 1998-2009 period. Export revenue is obtained from the Customs database, covering the 2002-2009 period. Network size is constructed from SAIC registration data and Customs data.
log revenue, log TFP, and log exporting revenue are measured as a Z-score within the one-digit industry-prefecture-time period.
p_j denotes population density in 1982 for birth county j and $n_{jk,t-1}$ is the stock of firms from county j established in prefecture k by the end of the preceding period $t-1$. When the dependent variable is export revenue, $n_{jk,t-1}$ is measured by the stock of export firms.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table C5: Revenue, TFP, and, Network Effects: Excluding Agricultural Processing

Model:	OLS			IV		
Dependent variable:	log revenue	log TFP	log (exporting revenue)	log revenue	log TFP	log (exporting revenue)
	(1)	(2)	(3)	(4)	(5)	(6)
$\log n_{jk,t-1}$	0.238***	0.152***	0.282***	0.095***	-0.012	0.209***
	(0.007)	(0.006)	(0.024)	(0.025)	(0.026)	(0.072)
$p_j \times \log n_{jk,t-1}$	1.780***	1.143***	1.519***	4.546***	3.727***	2.575**
	(0.186)	(0.177)	(0.398)	(0.636)	(0.759)	(1.201)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	26.57	26.57	12.79
Observations	2,177,788	2,177,788	73,745	2,177,788	2,177,788	73,745

Note: Revenue and TFP are derived from the Inspection database, covering the 1998-2009 period. Export revenue is obtained from the Customs database, covering the 2002-2009 period. Network size is constructed from SAIC registration data and Customs data.
log revenue, log TFP, and log exporting revenue are measured as a Z-score within the one-digit industry-prefecture-time period.
p_j denotes population density in 1982 for birth county j and $n_{jk,t-1}$ is the stock of firms from county j established in prefecture k by the end of the preceding period $t-1$. When the dependent variable is export revenue, $n_{jk,t-1}$ is measured by the stock of export firms.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table C6: Revenue, TFP, and, Network Effects: Conditional on Agriculture Income Shock in the Birth County

Model:	OLS			IV		
Dependent variable:	log revenue	log TFP	log (exporting revenue)	log revenue	log TFP	log (exporting revenue)
	(1)	(2)	(3)	(4)	(5)	(6)
$\log n_{jk,t-1}$	0.247***	0.167***	0.286***	0.162***	0.093***	0.492***
	(0.007)	(0.006)	(0.023)	(0.032)	(0.031)	(0.083)
$p_j \times \log n_{jk,t-1}$	2.005***	1.470***	1.594***	4.337***	3.368***	0.850
	(0.188)	(0.174)	(0.404)	(0.574)	(0.574)	(1.085)
Agriculture income shock	0.474***	0.703***	0.449**	0.481***	0.684***	1.662***
	(0.053)	(0.045)	(0.184)	(0.125)	(0.121)	(0.334)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	9.575	9.575	8.541
Observations	2,251,473	2,251,473	79,307	2,251,473	2,251,473	79,307

Note: Revenue and TFP are derived from the Inspection database, covering the 1998-2009 period. Export revenue is obtained from the Customs database, covering the 2002-2009 period. Network size is constructed from SAIC registration data and Customs data.
log revenue, log TFP, and log exporting revenue are measured as a Z-score within the one-digit industry-prefecture-time period.
p_j denotes population density in 1982 for birth county j and $n_{jk,t-1}$ is the stock of firms from county j established in prefecture k by the end of the preceding period $t-1$. When the dependent variable is export revenue, $n_{jk,t-1}$ is measured by the stock of export firms.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table C7: Revenue, TFP, and, Network Effects: Conditional on Distance Interacted with Time Fixed Effects

Model:	OLS			IV		
Dependent variable:	log revenue	log TFP	log (exporting revenue)	log revenue	log TFP	log (exporting revenue)
	(1)	(2)	(3)	(4)	(5)	(6)
$\log n_{jk,t-1}$	0.214***	0.136***	0.279***	0.097***	-0.012	0.227***
	(0.007)	(0.006)	(0.022)	(0.024)	(0.026)	(0.068)
$p_j \times \log n_{jk,t-1}$	1.651***	1.040***	1.457***	4.435***	3.647***	2.248**
	(0.195)	(0.160)	(0.383)	(0.621)	(0.746)	(1.141)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	23.02	23.02	11.29
F stat. of Distance Multiplier	212.11	103.98	1.14	161.39	93.74	1.07
Observations	2,251,473	2,251,473	79,307	2,251,473	2,251,473	79,307

Note: Revenue and TFP are derived from the Inspection database, covering the 1998-2009 period. Export revenue is obtained from the Customs database, covering the 2002-2009 period. Network size is constructed from SAIC registration data and Customs data.
log revenue, log TFP, and log exporting revenue are measured as a Z-score within the one-digit industry-prefecture-time period.
p_j denotes population density in 1982 for birth county j and $n_{jk,t-1}$ is the stock of firms from county j established in prefecture k by the end of the preceding period $t-1$. When the dependent variable is export revenue, $n_{jk,t-1}$ is measured by the stock of export firms.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Appendix D: The Model

1. Revenue and productivity equations The revenue obtained by a domestic producer with ability ω, $R_{dt} = C_{dt}\omega^{1-\alpha}K_{dt}^{\alpha}$. Taking logs, substituting the value of the profit maximizing capital investment, and unpacking C_{dt}:

$$\log R_{dt} = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r}\right) + \frac{\theta_d(p)\log n_{t-1}}{1-\alpha} + \frac{q_{dt}}{1-\alpha} + \frac{[(1-\alpha)^2+1]}{1-\alpha}\log\omega. \tag{13}$$

The corresponding expression for export revenue is obtained as:

$$\log R_{et} = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r(1+I)}\right) + \frac{\theta_e(p)\log n_{e,t-1}}{1-\alpha} + \frac{q_{et}}{1-\alpha} + \frac{\delta[(1-\alpha)^2+1]}{1-\alpha}\log\omega. \tag{14}$$

When revenue is replaced by productivity, P_{dt}, as the outcome, the specification of the structural equation is qualitatively unchanged. $P_{dt} = C_{dt}\omega^{1-\alpha}$ and, hence,

$$\log P_{dt} = \theta_d(p)\log n_{t-1} + q_{dt} + (1-\alpha)\log\omega. \tag{15}$$

Comparing the structural equations with the specification of the revenue and productivity equation (2) in Section 3, the market-time effects, q_{dt} and q_{et}, are accounted for when firm outcomes are measured as Z-scores, within the sector-prefecture-time period. Ability, ω, is subsumed in the firm fixed effect. If $\theta_d(p)$, $\theta_e(p)$ are specified to be linear in p, then the structural equations match the equations that we estimate and the coefficients can be interpreted accordingly.

2. Proposition 1

For the discussion that follows we assume that log ability ω is uniformly distributed with constant density $s(p)$ on support $[a, a+\mu]$. Our model sets the dispersion parameter $\mu = 1$, with $a \equiv A - 1$, to simplify notation.

We impose the following parameter restrictions, which ensure existence of a unique equilibrium featuring positive, interior shares of different occupations at each date for each cohort:

$$\log\zeta > \frac{1}{1-\alpha}[q_{dT} + \theta_d(\overline{p})\log T] + a \tag{16}$$

$$\log\gamma > \frac{(\delta-1)\log\zeta}{1-\sigma} - \frac{(\delta-\sigma)q_{d1}}{(1-\sigma)(1-\alpha)} + \frac{1}{1-\alpha}[q_{dT} + \theta_e(\overline{p})\log T] \tag{17}$$

$$\log\beta > \frac{\log\gamma}{\delta-1} - \log\zeta + \frac{\delta}{(\delta-1)(1-\alpha)}[q_{dT} + \theta_d(\overline{p})\log T] - \frac{q_{e1}}{(\delta-1)(1-\alpha)} \tag{18}$$

$$a + \mu > \log\beta + \log\zeta - \frac{q_{d1}}{1-\alpha} \tag{19}$$

Proof of Proposition 1:

To prove the Proposition, we show that ability thresholds are interior and ordered, as in (8), given the parameter restrictions (16-19).

We begin by showing that $\log \omega^*_{dt} > a$ if (16) is satisfied. From (7):

$$\log \omega^*_{dt} = \frac{\log \zeta}{1-\sigma} - \frac{\log C_{dt}}{(1-\alpha)(1-\sigma)}$$

Observe that T is an upper bound on network size. Hence, $\theta_d(\overline{p}) \log T$ is an upper bound on the network effect in the domestic market. It follows that (16) is a sufficient condition for $\log \omega^*_{dt} > a$.

Next, we show that $\log \omega^*_{et'} > \log \omega^*_{dt}$, for all $t \geq t'$, if (17) is satisfied. From (7):

$$\log \omega^*_{et'} = \frac{1}{\delta - 1}\left[\log \gamma + \frac{\log C_{dt'} - \log C_{et'}}{1-\alpha}\right]$$

It follows that $\log \omega^*_{et'} > \log \omega^*_{dt}$ if

$$\log \gamma > \frac{(\delta-1)\log \zeta}{1-\sigma} - \frac{(\delta-1)\log C_{dt}}{(1-\sigma)(1-\alpha)} - \frac{\log C_{dt'} - \log C_{et'}}{1-\alpha}$$

$\log C_{dt}$, $\log C_{dt'}$ are bounded below by q_{d1}, assuming min. $n_0 = 1$. $\log C_{et'}$ is bounded above by $q_{eT} + \theta_e(\overline{p}) \log T$. It follows that (17) is a sufficient condition for the preceding inequality to be satisfied.

A similar bounding argument shows that (18) implies $\omega^*_{mt} > \omega^*_{et'}$ for any $t \geq t'$, and that (19) implies $a + \mu > \max\{\omega^*_{mt}, \omega^*_{dt}\}$ for all p, t.

Condition (16) ensures that some low ability agents always choose the traditional occupation, as ζ (e.g., interest rate r) is high enough relative to ability lower bound a, terminal output market size and maximum network size. Condition (17) sets γ (i.e., incremental cost of exporting plant investments I) large enough relative to the export market premium δ, home and export market sizes, interest rate and technology parameters, to ensure that the ability threshold for specializing in exports will always be higher than for entry into the home market. As in the Melitz model, this ensures positive selection into exports. Condition (18) imposes a lower bound on the scope diseconomy cost β relative to the other parameters, to ensure that the threshold for mixed exporters exceeds that for entry into export specialization. Unlike the Melitz model, this ensures existence of an intermediate range of entrepreneurs who specialize in exports. Finally, (19) requires ability to be sufficiently dispersed to ensure a positive mass of mixed exporters in every cohort.

3. Extending the model to allow for forward looking behavior

We now explain how our model extends to the case where agents are non-myopic, and apply a discount factor $\phi \in (0, 1)$ to future profits. We show that expressions for optimal capital stocks and profits at any date (conditional on entry into any market) are unchanged. Moreover, the entrepreneurial propensity equation is unchanged for small values of ϕ. The same is not true in general for the export propensity, for which a closed form expression can no longer be obtained, but (a) the expression for the case of myopic agents is an approximation for the case of small ϕ and (b) forward looking behavior is likely to induce an additional source of the domestic network overhang effect.

Suppressing notation for market and network sizes at different dates, the dynamic optimization decision faced by an agent of ability ω at date t with inherited capital stocks $K_{d,t-1}, K_{e,t-1}$ is represented by the following Bellman equations. If the agent is a mixed exporter at $t-1$, i.e., $K_{d,t-1}K_{e,t-1} > 0$:

$$W_{mt}(\omega; K_{d,t-1}, K_{e,t-1}) = \max_{K_{dt} \geq K_{d,t-1}, K_{et} \geq K_{e,t-1}} [\pi_{dt}(\omega; K_{dt}) + \pi_{et}(\omega; K_{et}) - \beta + \phi W_{m,t+1}(\omega; K_{dt}, K_{et})] \tag{20}$$

where $\pi_{dt}(\omega; K_{dt}) \equiv C_{dt}\omega^{1-\alpha}K_{dt}^{\alpha} - rK_{dt}$ and $\pi_{et}(\omega; K_{dt}) \equiv C_{et}\omega^{\delta(1-\alpha)}K_{et}^{\alpha} - r(1+I)K_{dt}$.

If the agent is a pure exporter at $t-1$ (i.e., $K_{e,t-1} > 0, K_{d,t-1} = 0$):

$$\begin{aligned} W_{et}(\omega; K_{e,t-1}) &= \max_{K_{dt} \geq 0, K_{et} \geq K_{e,t-1}} [\pi_{et}(\omega; K_{et}) + \mathcal{I}_{K_{dt}>0}[\pi_{dt}(\omega; K_{dt}) - \beta \\ &\quad + \phi W_{m,t+1}(\omega; K_{dt}, K_{et})] + (1 - \mathcal{I}_{K_{dt}>0})\phi W_{e,t+1}(\omega; K_{et})] \end{aligned} \tag{21}$$

where $\mathcal{I}_x$ is an indicator function taking value one if event x happens and 0 otherwise.

If the agent is a pure domestic producer at $t-1$ (i.e., $K_{d,t-1} > 0, K_{e,t-1} = 0$):

$$\begin{aligned} W_{dt}(\omega; K_{d,t-1}) &= \max_{K_{et} \geq 0, K_{dt} \geq K_{d,t-1}} [\pi_{dt}(\omega; K_{dt}) + \mathcal{I}_{K_{et}>0}[\pi_{et}(\omega; K_{et}) - \beta \\ &\quad + \phi W_{m,t+1}(\omega; K_{d,t-1}, K_{e,t-1})] + (1 - \mathcal{I}_{K_{et}>0})\phi W_{d,t+1}(\omega; K_{dt})] \end{aligned} \tag{22}$$

and finally if the agent has not already entered either market at $t-1$ (i.e., $K_{d,t-1} = K_{e,t-1} = 0$):

$$W_{ot}(\omega) = \max\{\omega^{\sigma} + \phi W_{o,t+1}(\omega); W_{dt}(\omega, 0); W_{et}(\omega, 0); W_{mt}(\omega; 0, 0)\} \tag{23}$$

Observe first that it continues to be the case that capital irreversibility constraints do not bind on the intensive margin, i.e., conditional on entering either domestic or export market, the associated optimal capital stocks are myopically optimal (e.g., $K^*_{dt}(\omega; K_{d,t-1}, K_{e,t-1})$) maximizes $\pi_{dt}(\omega; K_{dt})$ without any irreversibility constraint. The same proof applies: if we consider the relaxed problem where the irreversibility constraint is dropped, the constraint does not bind since market and network sizes are growing. Hence the solution to the relaxed problem is a solution to the true problem. And in the relaxed problem, current capital stock (conditional on being positive) does not affect future profits, so it must be myopically optimal.

This implies that the value functions reduce to the following simpler expressions:

$$\begin{aligned} W_{mt}(\omega) &= \Pi_{Dt}(\omega) + \Pi_{Et}(\omega) - \beta + \phi W_{m,t+1}(\omega) \\ W_{et}(\omega) &= \max\{\Pi_{Et}(\omega) + \phi W_{e,t+1}(\omega); W_{mt}(\omega)\} \\ W_{dt}(\omega) &= \max\{\Pi_{Dt}(\omega) + \phi W_{d,t+1}(\omega); W_{mt}(\omega)\} \\ W_{ot}(\omega) &= \max\{\omega^{\sigma} + \phi W_{o,t+1}(\omega); W_{dt}(\omega); W_{et}(\omega); W_{mt}(\omega)\} \end{aligned} \tag{24}$$

where Π_{Dt}, Π_{Et} denote static profits at date t associated with myopically (unconstrained) optimal capital stocks provided in the text.

If all parameters lie in a compact set, these value functions are bounded and uniformly continuous. Hence for ϕ in a neighborhood of 0, these value functions are close to those corresponding to $\phi = 0$, implying that the pattern of sorting will be similar, with ability thresholds for different options ordered as in the case of myopic agents (given in Proposition 1 of the text).

Claim: *For ϕ in a right neighborhood of 0, the ability threshold ω^*_{dt} for entry into the domestic sector is the same as when agents are myopic ($\phi = 0$).*

The reasoning is as follows. As the pattern of sorting for small ϕ is similar to that where $\phi = 0$, the threshold ω^*_{dt} is determined by indifference between staying in the traditional occupation o and entering the domestic market at t. In other words, it solves

$$\omega^\sigma + \phi W_{o,t+1}(\omega) = \Pi_{Dt}(\omega) + \phi W_{d,t+1}(\omega) \tag{25}$$

and in a neighborhood of this threshold both these options strictly dominate either export specialization or mixed exporting:

$$W_{ot} = \max\{\omega^\sigma + \phi W_{o,t+1}(\omega); W_{dt}(\omega)\} \tag{26}$$

at all dates t. (26) shows that the choice for these agents effectively reduces to a date $\tilde{t} \geq t$ when they enter the domestic market (and until $\tilde{t} - 1$ they remain in the traditional occupation); after $\tilde{t}$ the continuation value is the same. It follows that the optimal date of entry is the first $\tilde{t} \geq t$ at which $\omega^\sigma \leq \Pi_{D\tilde{t}}(\omega)$, which coincides with the choice made by myopic agents. Hence the threshold ω^*_{dt} is same as for a myopic agent.

The threshold ω^*_{et} for export specialization solves $W_{dt}(\omega) = W_{et}(\omega)$, i.e.,

$$\Pi_{Dt}(\omega) + \phi W_{d,t+1}(\omega) = \Pi_{Et}(\omega) + \phi W_{e,t+1}(\omega) \tag{27}$$

Since the corresponding continuation values $W_{d,t+1}(\omega), W_{e,t+1}(\omega)$ of specializing in the domestic and export markets will typically differ, this threshold will typically vary with ϕ even for small values of ϕ. The threshold is of course continuous in ϕ, so the expression for the export propensity in the text is an approximation for the true threshold for small values of ϕ. Observe also that the greater the difference between growth of market or network size in the domestic and export markets between t and $t+1$, the greater is the corresponding difference in change in the value of domestic specialization $\Pi_{D,t+1}(\omega) - \Pi_{Dt}(\omega)$ versus export specialization $\Pi_{E,t+1}(\omega) - \Pi_{Et}(\omega)$, and the higher will be ω^*_{et}, resulting in a lower export propensity at t. This is a dynamic extension of the domestic network overhang effect amplifying the latter when agents are non-myopic.

4. Composition of Firms: Our ability to explain Fact 2 relies on the presence of pure exporters. Such firms have been observed in many developing countries and we now proceed to document their presence in China. We do this with data from the economic census, available in 2004 and 2008. These data provide revenues for all manufacturing firms and can be matched with the Customs database. Those firms whose revenues exceed their exports are designated as mixed exporters. Those firms whose revenues match their exports are classified as pure exporters. The economic census is the most reliable data-source that we have at our disposal. Nevertheless, there will be inaccuracies in reported revenues. We thus allow for up to 10% slippage between revenues and exports when classifying a firm as a pure exporter. Finally, those firms that do not appear in the customs data are assumed to be domestic producers.

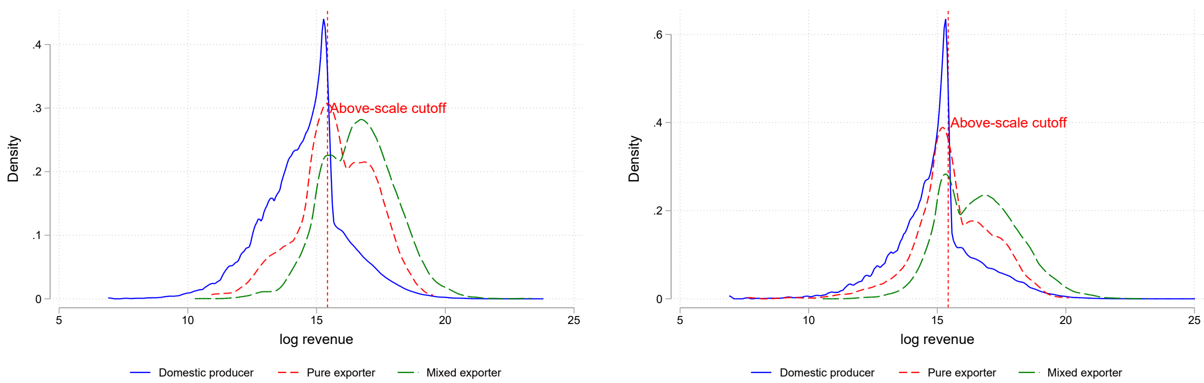
Table D1 describes the composition of firms in 2004 and 2008, based on the preceding classification. Export firms constitute a tiny fraction, around 2-3%, of all manufacturing firms and pure exporters comprise around 15% of all exporters. Notice that these firms can be ranked with respect to their revenue: domestic producers have the lowest revenues, followed by pure exporters and then mixed exporters. This ranking matches the ordering of firms in our model with respect to revenues (and ability). Figure D1 subjects the ranking to closer scrutiny by reporting the distribution of revenues for each type of firm. It can be seen that the distributions for domestic producers, pure exporters and mixed exporters, in that order, are increasingly shifted to the right.

Table D1: Composition of Firms

Year	2004		2008	
Type:	number	log revenue	number	log revenue
Domestic producer	234,998	14.48	471,961	14.87
Pure exporter	572	15.75	2,086	15.58
Mixed exporter	4,102	16.52	10,300	16.42

Source: Economic Census (2004,2008) and Customs database.
Data restricted to manufacturing firms. Revenue measured in Yuan.

The vertical line in Figure D1 marks the 5 million Yuan cutoff above which firms are selected into the Above Scale database, which is maintained by the National Bureau of Statistics and has been used in many previous studies. Above Scale firms are subjected to increased government oversight, which is presumably why there is bunching just below the threshold (especially for domestic firms). Firms in the Above Scale database are evidently highly selected, which is why we prefer the economic censuses and the SAIC databases for our analyses. The SAIC inspection database, which we use for the analysis of network effects, also provides firm revenues. However, this is only for a sample of firms and, as noted in Appendix C, there are discrepancies between the revenues reported in the inspection database and the economic census. This is especially important for the current analysis because revenues and exports must match closely to identify pure exporters.



(a) 2004

(b) 2008

Figure D1: Revenue Distribution

Source: Economic Census (2004,2008) and Customs Database.
Revenue measured in Yuan.

5. Marginal initial capital: To show that marginal initial capital is decreasing in birth county population density, we first derive marginal ability from the model by setting $\Pi_{Ot}(\omega^*_{dt}) = \Pi_{Dt}(\omega^*_{dt})$ and then solving for ω^*_{dt} from (7):

$$\log \omega^*_{dt} = \frac{\log \zeta}{1-\sigma} - \frac{\log C_{dt}}{(1-\sigma)(1-\alpha)}. \tag{28}$$

Recall that $\log C_{dt} = q_{dt} + \theta_d(p) \log n_{t-1}$. We assume that $\theta'_d(p) > 0$ and $\log n_{t-1}$ is increasing in p from Fact 1. It follows that $\log \omega^*_{dt}$ is decreasing in p; i.e. the marginal entrant's ability is decreasing in birth county population density.

To verify that this result also applies to the marginal entrant's initial capital, K^*_{dt}, we solve for that agent's optimal capital investment by maximizing his profit: $C_{dt}(\omega^*_{dt})^{1-\alpha} K^{\alpha}_{dt} - rK_{dt}$. Substituting the expression for C_{dt} from (28), it follows that

$$\log K^*_{dt} = \frac{1}{1-\alpha} \log \left(\frac{\alpha}{r}\right) + \log \zeta + \sigma \log \omega^*_{dt}. \tag{29}$$

$\log K^*_{dt}$ is an affine transform of $\log \omega^*_{dt}$, which implies that $\log K^*_{dt}$ is also decreasing in p.

The SAIC registration database provides the registration year and the initial capital of each firm. The initial (registered) capital represents the total amount paid up by the shareholders. This amount is deposited with the firm's bank and can be used to pay the firm's operating expenses before it becomes cash flow positive. Access to bank credit is also dependent on the firm's registered capital, which is why firms will often choose to increase their registered capital over time. We account for the fact that capital requirements will vary across sectors by measuring marginal initial capital within each birth county-sector in each year, with sectors defined at the 2-digit level. Marginal initial capital is thus regressed on birth county population density, measured in 1982, with sector fixed effects included in the estimating equation. We measure marginal initial capital as the bottom (first) percentile of the initial capital distribution among new entrants in each birth county-sector-year. As can be seen in Appendix Figure D2 below, the population density coefficient is negative and significant in each year. This is also true for the 2SLS estimates.

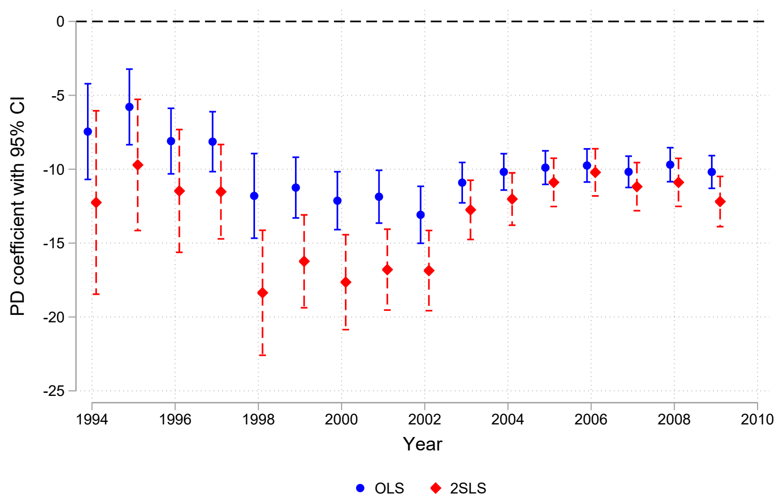


Figure D2: Marginal Initial Capital and Population Density
Source: Registration database and 1982 Population Census.

Appendix E: Testing the Model

1. Alternative Construction of the Propensity Variable

Table E1: Alternative Propensity Construction

Propensity to become:	entrepreneur		exporter	
Construction:	without $S_{jk,t-1}$	accumulated P_{jt}	without $S_{jk,t-1}$	accumulated P_{jt}
	(1)	(2)	(3)	(4)
$\tilde{\Theta}_{d0}$	0.0157***	0.0051***	–	–
	(0.0012)	(0.0014)		
$\tilde{\Theta}_{dp}$	0.0686***	0.1657***	–	–
	(0.0141)	(0.0568)		
Θ_{e0}	–	–	-0.0004	-0.0004
			(0.0003)	(0.0003)
Θ_{ep}	–	–	0.0172**	0.0190***
			(0.0071)	(0.0073)
Θ_{d0}	–	–	0.0000	-0.0000
			(0.0001)	(0.0001)
Θ_{dp}	–	–	-0.0091***	-0.0070***
			(0.0031)	(0.0025)
Birth county-prefecture FE	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes
Kleibergen-Paap F	188.9	188.9	15.41	15.41
Observations	699,531	699,531	16,559	16,559

Note: The number of firms is derived from the SAIC registration database and the Customs database.
The number of potential entrepreneurs is derived from the Population Census (1990, 2000).
The unit of observation is the birth county-destination prefecture-year.
$\tilde{\Theta}_{d0}$, Θ_{e0}, Θ_{d0} measure direct network effects, while $\tilde{\Theta}_{dp}$, Θ_{ep}, Θ_{dp} measure interaction effects.
The interaction of network duration with initial (log) entry and the triple interaction with birth county population density are used as instruments for each network term and its interaction with population density in the first-differenced equation (separately for the domestic network and the export network in Columns 3-4).
The accumulated P_{jt} measure of potential entrepreneurs starts with 25-35 year olds in 1994 and adds a fresh cohort of 25 year olds in each subsequent year.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

2. Comparing OLS and IV estimates of the propensity equations The OLS estimates of the entrepreneurial propensity and export propensity equations are reported in Appendix Table E2, Columns 1 and 3. To explain the (substantial) difference between these OLS estimates and the corresponding IV estimates in Table 5, we proceed to simulate the model. The simulation exercise is based on the assumption that the IV estimates are unbiased and, hence, that the underlying error structure can be recovered from the estimated residuals. Based on our estimates, the residuals or, equivalently, the entry shocks in the first-differenced entrepreneurial propensity and export propensity equations can be characterized by AR1 processes, with reasonably sized autoregressive coefficients (see Appendix Table E2). We draw entry shocks from this error distribution over successive periods, taking initial entry in each birth county-destination prefecture network as given, to recursively predict the propensity change from one period to the next. Predicted network sizes, which can be recovered from the predicted propensity changes, are then used to re-estimate the OLS regressions in Appendix Table E2, Columns 2 and 4 where we see that the point estimates are now similar in magnitude to the IV estimates in Table 5.

Although the predicted (simulated) network sizes are purged of measurement error, the OLS estimates with the simulated data continue to be biased due to serial correlation in the per period entry shocks (error term). Our interpretation of the preceding finding is thus that the bulk of the bias in this setting is due to measurement error. The measurement error for a network at a given point in time is computed as the difference between observed and predicted network size (in logs). The variance in this error across all networks and time periods is approximately equal to the corresponding variance in predicted ("true") network sizes, also measured in logs (see Appendix Table E2). With a canonical univariate regression model, where an analytical solution for the magnitude of the bias is available, the level of measurement error that we estimate across all networks and time periods would halve the estimated coefficient. With our multivariate dynamic panel model, the same (not unduly large) measurement error generates greater bias.

Table E2: OLS Estimation with Actual and Simulated Data

Propensity to become:	entrepreneur		exporter	
Data:	actual	simulated	actual	simulated
	(1)	(2)	(3)	(4)
$\tilde{\Theta}_{d0}$	0.0003	0.0091***	–	–
	(0.0018)	(0.0001)		
$\tilde{\Theta}_{dp}$	0.0251	0.1655***	–	–
	(0.0329)	(0.0033)		
Θ_{e0}	–	–	-0.0001	-0.0004***
			(0.0001)	(0.0000)
Θ_{ep}	–	–	0.0063**	0.0179***
			(0.0032)	(0.0004)
Θ_{d0}	–	–	-0.0000	0.0001***
			(0.0000)	(0.0000)
Θ_{dp}	–	–	0.0009*	-0.0016***
			(0.0005)	(0.0003)
Birth county-prefecture FE	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes
Autoregressive coefficient	–	0.2527	–	0.3522
SD of measurement error	–	1.9206	–	1.5564
SD of "true" (simulated) network size	–	2.1152	–	1.7632
Observations	699,531	653,697	16,559	13,592

Note: The number of firms is derived from the SAIC registration database and the Customs database.
The number of potential entrepreneurs is derived from the Population Census (1990, 2000).
The unit of observation is the birth county-destination prefecture-year.
$\tilde{\Theta}_{d0}$, Θ_{e0}, Θ_{d0} measure direct network effects, while $\tilde{\Theta}_{dp}$, Θ_{ep}, Θ_{dp} measure interaction effects.
Autoregressive coefficients estimated with residuals from the first-differenced instrumental variable regressions in Table 5, Columns 1-2.
Taking initial (log) entry in each birth county-destination prefecture network as given, we draw from the AR1 distribution to recursively predict the change in entrepreneurial (export) propensity over successive time periods. The resulting predicted network sizes are used for first-differenced OLS estimation in Columns 2 and 4.
Measurement error in each network-time period is constructed as the difference between observed and predicted (simulated) network size.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

3. Validating the Propensity Equation Estimates

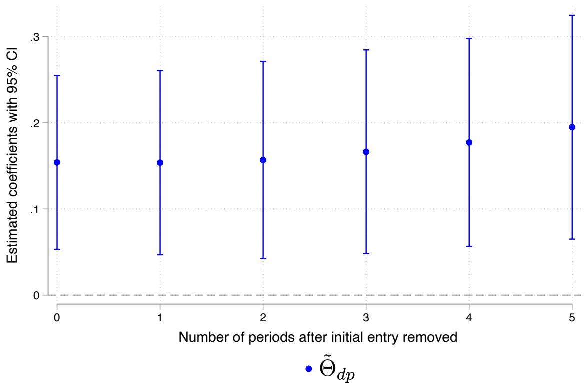
3.1 Alternative construction of instrumental variables

Table E3: Alternative Construction of Instrumental Variables

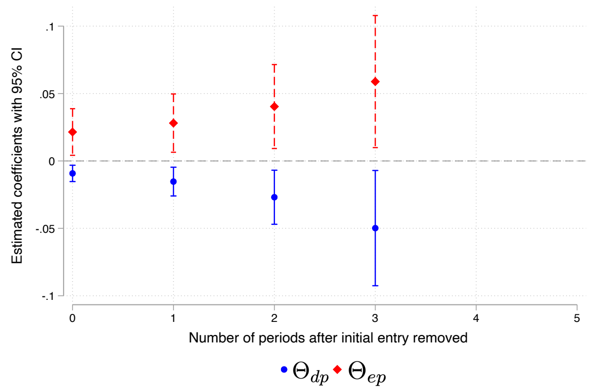
Propensity to become:	entrepreneur			exporter		
Specification:	$n_0 + 0.05$	$n_0 + 0.15$	conditional on duration	$n_0 + 0.05$	$n_0 + 0.15$	conditional on duration
	(1)	(2)	(3)	(4)	(5)	(6)
$\tilde{\Theta}_{d0}$	0.0047***	0.0052***	0.0056***	–	–	–
	(0.0012)	(0.0012)	(0.0017)			
$\tilde{\Theta}_{dp}$	0.1595***	0.1499***	0.1544***	–	–	–
	(0.0517)	(0.0512)	(0.0514)			
Θ_{e0}	–	–	–	-0.0003	-0.0005	0.0002
				(0.0003)	(0.0003)	(0.0004)
Θ_{ep}	–	–	–	0.0139**	0.0203***	0.0190***
				(0.0062)	(0.0073)	(0.0064)
Θ_{d0}	–	–	–	-0.0001	0.0001	-0.0003*
				(0.0001)	(0.0001)	(0.0002)
Θ_{dp}	–	–	–	-0.0051**	-0.0075***	-0.0098***
				(0.0020)	(0.0026)	(0.0030)
Birth county-prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	190.9	187.8	95.06	21.24	12.57	13.87
Observations	699,531	699,531	699,531	16,559	16,559	16,559

Note: The number of firms is derived from the SAIC registration database and the Customs database.
The number of potential entrepreneurs is derived from the Population Census (1990, 2000).
The unit of observation is the birth county-destination prefecture-year.
$\tilde{\Theta}_{d0}$, Θ_{e0}, Θ_{d0} measure direct network effects, while $\tilde{\Theta}_{dp}$, Θ_{ep}, Θ_{dp} measure interaction effects.
The interaction of network duration with initial (log) entry and the triple interaction with birth county population density are used as instruments for each network term and its interaction with population density in the first-differenced equation (separately for the domestic network and the export network in Columns 4-6).
Instead of using $\log(n_0 + 0.1)$ to construct the initial entry variable, we now use $\log(n_0 + 0.05)$ or $\log(n_0 + 0.15)$ in Columns 1-2 and 4-5.
Network duration is included as a covariate in the estimating equation in Columns 3 and 6.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

3.2 Testing the exogeneity of initial entry



(a) Entrepreneurial Propensity Estimation



(b) Export Propensity Estimation

Figure E1: Testing the Exogeneity of Initial Entry

Source: The coefficients are estimated using the same equation as in Table 5, sequentially removing time periods in each network.