Entrepreneurship in China's Structural Transitions: Network Expansion and Overhang*

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June 1, 2023

Abstract

This research examines the determinants of entrepreneurship in the initial transition from agriculture to industrial production and the subsequent transition to higher value exporting in China. Using data covering the universe of registered firms over the 1994-2009 period, we find that individuals born in rural counties with higher agricultural productivity and population density had a greater propensity to enter domestic production in the first transition, but that this association was reversed in the second transition to exporting. Standard models of occupational choice and trade, based on individual characteristics, cannot explain the facts that we document in this paper. We subsequently add a community-based component to the analysis by allowing for the presence of productivity enhancing hometown (birth county) networks. More densely populated rural counties give rise to networks of firms that are more effective at improving the outcomes of their members (both in domestic production and exporting, based on our shift-share instrumental variable estimates). While this generated faster transition in the first stage, the more successful domestic networks drawn from denser counties created a disincentive to subsequently enter exporting. Our analysis identifies and quantifies a novel dynamic inefficiency that could arise in any developing economy where (overlapping) networks are active.

Keywords. Entrepreneurship. Structural transformation. Transition to exporting. Firms in developing countries. Cooperation in networks. Enforceable trust.

*This paper includes some results from an unpublished manuscript that was previously circulated under the title "The Community Origins of Private Enterprise in China." We are grateful to numerous seminar and conference participants and, especially, Paul Goldsmith-Pinkham for their constructive comments. Research support from the Economic Development and Institutions (EDI) RA4 program, Cambridge-INET, China National Science Foundation (project number 71874008,72192844, and 72203252) and the Agence Nationale de la Recherche (ANR) under the EUR Project ANR-17-EURE-0010 is gratefully acknowledged. We are responsible for any errors that may remain.

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1 Introduction

The process of economic development is often characterized by an initial transition from agriculture to industry, followed by a second transition to higher value exporting. It is well known that entrepreneurship plays a critical role in this process. 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 industrialization, as well as in the subsequent shift to exporting (Melitz, 2003; Atkin and Khandelwal, 2020). However, they will not fully explain the patterns of entrepreneurship that we document in China's structural transitions. Adding a community-level dimension to standard economic models of occupational choice and trade, our analysis identifies and quantifies the important role played by hometown networks in supporting (and distorting) the entry of private firms in China.

The transition out of agriculture in China commenced in the early 1980's with the establishment of township-village enterprises (TVE's) and then accelerated with 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]

A distinguishing feature of Chinese entrepreneurship is that it 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). We designate the firm's principal 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 are approximately 2000 counties in China, accounting for 74 percent of its population, and our initial objective is to determine which counties were better positioned to supply entrepreneurs in the first transition into domestic production, as well as in the second transition to exporting.

Based on the conventional view, entry into business following privatization would have been determined by pre-industrial economic development or, equivalently, agricultural productivity, which are positively associated with the entrepreneurial traits listed above. For example, counties with higher agricultural productivity would have accumulated greater wealth that could be subsequently

[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.

channelled into manufacturing (Bustos, Garber and Ponticelli, 2020). 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 measures of entrepreneurial propensity and pre-industrial economic development in the birth county. The former statistic is measured by the number of registered firms drawn from a given birth county in a given year divided by the number of potential entrepreneurs from that county, obtained from the population census. The latter statistic 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 when constructing this measure of historical economic development is that greater agricultural productivity would have supported a larger population density (Diamond, 1997; Acemoglu, Johnson and Robinson, 2002). We find in Section 2.1 that there is a positive and significant association between entrepreneurial propensity and birth county population density, which is retained when we use only that part of the variation in population density that can be explained by exogenous agricultural productivity (crop suitability). The association does weaken, as expected, when county-level characteristics that proxy for wealth, education and occupational experience (relevant for business) are included in the estimating equation, but it remains positive and significant [Fact 1].

Having documented that entry into business (domestic production) conforms to the conventional view of entrepreneurship, we turn next to entry into exporting. The export propensity is measured by the number of active exporters from a given birth county in a given year, obtained from the Customs database which includes all shipments out of China, divided by the number of potential entrepreneurs, as above. As with the entrepreneurial propensity, there is a positive and significant association between the export propensity and birth county population density. However, this association turns *negative* (and marginally significant) when the county-level covariates that proxy for wealth, education and occupational experience are included in the estimating equation [Fact 2]. Conditional on a set of covariates that are associated with entrepreneurial ability, birth county population density has a positive effect on entry into domestic production and a negative effect on entry into exporting. Much of the paper is devoted to explaining these twin facts, which we argue are broadly informative about the process of economic development.

One explanation for the facts we have uncovered is based on (unobserved) ability heterogeneity not accounted for by the covariates. Departing from the standard assumption that ability has a single dimension, suppose, as in Acemoglu, Aghion and Zilibotti (2006), that ability has one dimension that is relevant for domestic production and another that is relevant for exporting. If the resulting ability heterogeneity gives an advantage to denser counties in domestic production and less dense counties in exporting, then both facts could be obtained. Alternatively, if firms from denser counties have preferred access to locations (including their birth county) where domestic production is more profitable for exogenous reasons, whereas the converse is true for exporting, then Facts 1 and 2 could once again be obtained.[3] Finally, it is well known that domestic producers

[3]Bustos, Caprettini and Ponticelli (2016) document that agricultural productivity, which we proxy with population density, is positively associated with the speed of structural transformation under specific conditions. These conditions might well have applied to our rural counties in which case denser counties would have industrialized faster.

and exporters benefit from government connections in China (Bai et al., 2020; Khandelwal, Schott and Wei, 2013). Both facts could be obtained if these connections place domestic producers from denser counties and exporters from less dense counties at an advantage relative to their competitors, within the locations where they are established.

To shed further light on these alternative explanations, we proceed to examine firm-level outcomes that underlie the decision to enter domestic production and exporting in Section 2.2. The SAIC inspection database provides revenues and assets for a subset of registered firms and the Customs database provides export revenues for all exporting firms. Net of firm fixed effects, revenues (and productivity) are observed to increase more steeply over time for firms drawn from denser counties, both in domestic production and exporting. Moreover, firms from these counties perform better relative to other firms *within* the sector-locations where they are established. These results would not be generated by the explanations for Facts 1 and 2 listed above: (i) ability heterogeneity across birth counties is subsumed in the firm fixed effects and, hence, cannot explain the additional (conditional) variation in firm outcomes across birth counties, (ii) differential access to more profitable production locations would not explain why firms from denser counties grow faster within sector-locations, and (iii) differential access to government connections is inconsistent with the superior performance of those firms in both domestic production and exporting. The novel mechanism that we propose in this paper, which can explain all our empirical findings, is based on the idea that networks of firms organized around the hometown are active in China and that firms from denser birth counties have access to better functioning networks that increase the productivity of their members, both in domestic production and exporting. This differential increase in productivity, with its accompanying increase in revenues, brings more firms from denser counties into domestic production to explain Fact 1. At the same time, the 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.[4]

The idea that business networks are active in China and that these networks are organized around the birth county (hometown) 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).[5] However, the assumption that birth county networks drawn

[4]One explanation for the results in Section 2.2 posits that entrepreneurs from denser counties are selected with higher ability, both in domestic production and exporting, while also allowing ability to have a differential effect on firm experience over time or, equivalently, with experience, as in Banerjee and Munshi (2004). While this mechanism can explain the superior performance of firms from denser counties, net of fixed effects, it cannot be easily reconciled with Facts 1 and 2.

[5]Chambers of commerce that bring entrepreneurs from the same origin together (*yidi shanghui*) are commonly found in Chinese cities. Based on anecdotal accounts in Chinese media and academic journals, entrepreneurs from a single rural county can, in exceptional cases, dominate an entire industry.

from denser counties function more effectively has not been previously examined.

Our explanation for the preceding assumption is based on the idea that population density in rural areas is positively associated with the frequency of local social interactions, which, in turn, gives rise to higher levels of enforceable trust (among neighbors but not strangers). We verify each element of this argument with nationally representative data from the China Family Panel Study in Section 2.3. While these micro-foundations are important, our primary interest is in the networks of firms that emerge from the rural counties. If links between firms from denser counties are subjected to higher levels of enforcement by the origin social network, as implied by our trust results, then they can sustain higher levels of cooperation (mutual help) and are thus more valuable. The implication of this argument, which we verify with SAIC registration data is that firms from these counties will be (i) more likely to remain connected to their birth county, even when they are established elsewhere and (ii) be more likely to form business links with firms from the same origin (operating in the same prefecture). In addition, we document that links between firms from denser counties are more likely to be "supported" – a measure of cooperation proposed by Jackson, Rodriguez-Barraquer and Tan (2012) – by mutually linked firms from their origin operating in the same prefecture.[6]

Building on the preceding descriptive evidence, we develop a model of occupational choice in Section 3 that adds a network component and a trade component to the Roy (1951) model. In our model, members of a network provide mutual help to each other that increases their productivity. A longstanding literature describes how firms respond to the difficulty in enforcing formal contracts in developing economies by establishing relational contracts (McMillan and Woodruff, 1999; Macchiavello and Morjaria, 2015, 2021). Community networks can expand the scope of such bilateral arrangements; for example, a firm in a long-term relationship with a buyer or supplier can provide a (credible) referral for another member of its network. Members of a network can also provide information about new technologies and business opportunities to each other. Such help is inherently local and, hence, we 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. If mutual help is complementary, then firms will benefit from a larger (birth county-prefecture) network, with the domestic network defined by the (lagged) stock of all firms and the export network defined by the corresponding stock of export firms, as in Fernandes and Tang (2014). The first implication of our model, for firm outcomes, is thus that revenues and productivity, net of entrepreneurial ability and exogenous prefecture-level factors, will be increasing in network size. The additional implication, in light of the descriptive evidence that networks drawn from denser birth counties function more effectively, is that network effects will be increasing in birth county population density. We verify that these implications of the model are consistent with the observation in Section 2.2 that revenues are increasing more steeply over time for firms drawn from denser counties, both in domestic production and exporting.

[6]Although the recent literature on networks in developing countries has largely focussed on information diffusion and program targeting, a few papers; e.g. Karlan et al. (2009); Jackson, Rodriguez-Barraquer and Tan (2012); Blumenstock, Chi and Tan (2019) examine cooperation in networks, but not between firms.

To explain Facts 1 and 2 through the lens of the model, we next derive occupational choices in equilibrium, drawing on the implications for firm outcomes described above. 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. This implies that there are three 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). The fraction of individuals who select into business is increasing in domestic network size and its interaction with birth county population density, which improves firm outcomes as described above and thus shifts down the lower threshold, to explain Fact 1.[7] 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). The first 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 could be declining in population density to explain Fact 2.

We begin our tests of the model in Section 4.1 by estimating the revenue (and productivity) equations with SAIC inspection data and Customs data. The estimating equations include firm fixed effects, which subsume entrepreneurial ability, network size as specified above, and its interaction with birth county population density. Firm outcomes are measured as a Z-score, relative to other firms in the same prefecture-sector-time period, and while this will account for agglomeration effects, government infrastructure and all factors that affect firms in the prefecture equally, it will 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 effects will be evidently biased, and we address this possibility by constructing an instrument for network size that is based on agricultural shocks in the birth county that *push* individuals into business. Specifically, the interaction of world crop price shocks, crop shares in the birth county, and the distance from the origin to the destination prefecture are used to construct a shift-share instrument, following Imbert et al. (2022).

Our estimates indicate that firm revenues and productivity within sector-locations are increasing in network size, with the estimated network size effect increasing in birth county population density.

[7]For this result to be obtained, network size also needs to be increasing in birth county population density. We use a recursive argument to establish this result in Section 3.

These results are obtained for both domestic production and exporting and are robust to the validation tests proposed for shift-share instruments by Goldsmith-Pinkham, Sorkin and Swift (2020). Although there is an extant literature on networks of firms in developing countries; e.g. Fafchamps (2000); Fisman (2003); Banerjee and Munshi (2004); Munshi (2011), our analysis is the first to estimate the causal effect of these networks on the outcomes of their members with a comprehensive (economy-wide) sample of firms.

The final step in the empirical analysis is to estimate the propensity equations that allow us to interpret Facts 1 and 2 through the lens of the model. Pure exporters, who must choose between domestic production and exporting, are key to explaining Fact 2. 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, accounting for approximately 15 percent of all exporters, in Section 4.2. Next, we estimate the propensity equations implied by the model in Section 4.3. 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.[8] While this result is consistent with the model, we noted that the domestic network "overhang" must be sufficiently large for the net network effect to be decreasing in population density. Completing the empirical analysis, we verify in Section 4.4 that this is indeed the case to explain Fact 2. The analysis of networks in the trade literature has examined how connections to foreign buyers can improve firm outcomes; e.g. Rauch and Trindade (2002); Chaney (2014); Burchardi, Chaney and Hassan (2019). The analysis of networks in macroeconomics has focussed on the role played by production (upstream-downstream) networks in propagating and amplifying aggregate shocks; e.g. Carvalho et al. (2021). Our research adds to both literatures by documenting the role played by networks of domestic firms in macroeconomic structural transformation; spanning the initial transition from agriculture to industrial production and the subsequent transition to exporting (international trade).

While our counter-factual simulations with the estimated model indicate that the domestic network contributed substantially to the entry of firms in the first transition, they also tell us that it had an important dampening effect on the number of exporters in the second transition. Trade economists have devoted much attention to the factors that constrain the upgrading to exporting in developing countries (Verhoogen, 2021). Our analysis uncovers a new network-based mechanism that increases export productivity in these countries, while at the same time discouraging the transition to higher value exporting (on account of the successful domestic networks that are already

[8]We cannot use agricultural income shocks 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. As with the shift-share analysis, this instrument survives a number of robustness tests that are discussed in Section 4.3.

in place). The stock of domestic firms has no effect on export revenues or productivity, and *vice versa*, and, hence, a social planner choosing the number of domestic and export firms to maximize aggregate profit would make these decisions independently. The domestic network overhang we have uncovered thus results in a sub-optimal number of exporters.[9] We conclude in Section 5 by discussing policies, such as timely (and temporary) export subsidies, that could target the dynamic inefficiency we have documented. Whether such interventions are needed at all will depend on whether networks are active in a given economy. The networks that we identify in this paper are not specific to China or to business. However, as discussed in the concluding section, their importance in other settings will depend on the underlying social structure and this will vary across regions of the world.

2 Descriptive Evidence

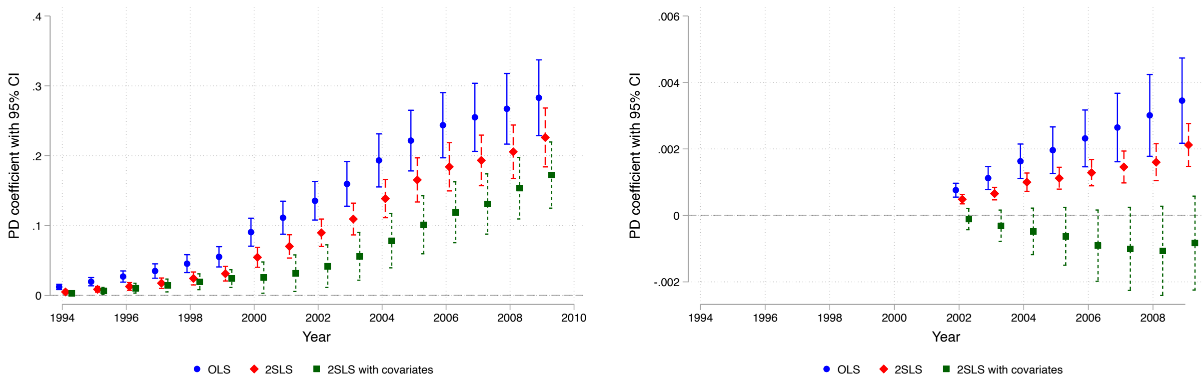
2.1 Entrepreneurship in China

Which rural populations were better positioned to supply entrepreneurs in China, following privatization the early 1990's? As discussed in the previous section, the conventional view is that entrepreneurship at early stages of industrialization is positively associated with historical economic development, which, in turn, is associated with agricultural productivity. We measure historical (pre-industrial) economic development by county-level population density in 1982, prior to privatization, when the Chinese economy was still largely agrarian. Entrepreneurial propensity in a given year is measured by the number of registered private firms from a given birth county 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.[10] Our analysis of entrepreneurship (domestic production) runs from 1994, when company registration was made mandatory, up until 2009 and the financial crisis. While entrepreneurial propensity increases over this period with the growth of the Chinese economy, from 0.05% in 1994 to 1.5% in 2009, our focus is on how this statistic varies across counties at each point in time. We thus proceed to estimate the association between entrepreneurial propensity and 1982 birth county population density, separately in each year over the 1994-2009 period. The population density (PD) coefficients are reported in Figure 1a

[9] In our model, the domestic network overhang arises because the scope diseconomy creates a nonseparability between domestic production and exporting for the marginal pure exporter who must choose between these activities. A nonseparability also arises in Fan et al. (2020) and Almunia et al. (2021), who extend the Melitz model by allowing for increasing marginal costs; shocks in the domestic market now affect the firm's export profits and *vice versa*. However, this nonseparability does not give rise to an inefficiency because firms internalize the tradeoffs with respect to domestic and export profits when they make choices at the intensive margin.

[10] The SAIC registration database provides the gender and age for a subset of legal representatives. Among those representatives 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.

– the blue circle is the point estimate and the blue vertical line demarcates the 95 percent confidence interval – and, as can be seen, these coefficients are positive and significant in each year.[11] In line with the conventional view, individuals born in historically developed (higher population density) counties have a greater propensity 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 would have been determined by crop suitability, which, in turn, is determined by geoclimatic 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.[12] The estimated 2SLS population density coefficients, reported in red in Figure 1a, are qualitatively similar, albeit smaller in magnitude, than the corresponding benchmark coefficient estimates in blue. Although the 2SLS estimates do not have the standard causal interpretation, since population density is treated as a proxy for historical economic development, they indicate that exogenously greater agricultural productivity in the pre-industrial economy has a positive and significant effect on entrepreneurial propensity at early stages of economic development. This is in line, once again,

[11]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.

[12]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 in order to match as closely as possible with historical output.

with the conventional view.

Although agricultural productivity may be exogenously determined by agroclimatic conditions, there are many channels through which it could determine the propensity to become an entrepreneur. For example, greater agricultural productivity and resulting pre-industrial economic development could be associated with a greater inherited wealth, higher levels of human capital, and experience in non-farming (industrial) activities. We account for some of these potentially coexisting channels by including the education distribution, occupational structure and industry structure among potential entrepreneurs in the birth county in each year in the estimating equation.[13] Conditional on these covariates, the population density coefficient marked in green does decline, as expected, since population density (our proxy for historical development) will be correlated with them. However, it remains positive and significant in each year [Fact 1].

While privatization in China commenced 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, higher population density counties were better positioned to support entry into domestic production 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 produces goods that are shipped directly to foreign buyers. Using this definition, and linking the SAIC registration database with the Customs database, 0.7% of registered manufacturing firms were engaged in exporting in 2002, with an increase to 1.6% by 2009.

While the preceding statistics indicate that the number of exporters was growing faster than the number of firms, our primary interest is in how the propensity to export, measured by the number of active exporters from a given birth county divided by the number of potential entrepreneurs as in Figure 1a, varies across counties at each point in time. The export propensity is regressed on 1982 birth county population density over the 2002-2009 period, with the estimated population density

[13] As with the number of potential entrepreneurs, we use the one percent sample from the 1990 and 2000 censuses to construct these covariates 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 directly, but it will be positively correlated with these covariates.

coefficient 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 covariates. While the export propensity is increasing in population density with the benchmark and 2SLS specifications, as in Figure 1a, the key difference between the two figures is that the sign of this association is reversed (turns negative and marginally significant) in Figure 1b when the covariates are included in the estimating equation [Fact 2].[14] Much of the analysis that follows will be devoted to explaining this difference.

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 Firm-Level Outcomes

We next proceed to examine the firm-level outcomes (revenues) that underlie the decision to enter domestic production and exporting. The SAIC inspection database collects assets and revenues for a subset of registered firms over time.[15] The Customs database, which provides information on all shipments out of China, can be linked to the SAIC registration database to compute export revenues for all exporting firms at each point in time. Since these are panel data sets, firm fixed effects that subsume entrepreneurial ability can be included in the estimating equations, together with a time trend and its interaction with birth county population density. To be consistent with the instrumental variable analysis in the subsequent section, we "instrument" for population density

[14]We observe that the same set of covariates weakens the association between birth county population density and the propensity to become an entrepreneur and an exporter. This is consistent with the view that the conventional individual-specific constraints to entrepreneurship (domestic production) also apply to exporting in developing countries. For example, Manova (2013); Manova, Wei and Zhang (2015) study how access to credit constrains the transition to exporting. Melitz (2003); Verhoogen (2008); Fieler, Eslava and Xu (2018) examine the role played by ability, broadly defined by productivity, in this transition.

[15]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. Although firm profits are not observed, profits and revenue will only differ by a constant term if all firms have the same production technology and face the same interest rate.

with potential crop yields. The estimating equation also includes the firm's initial capital (in logs) interacted with a time trend because, as observed in Appendix Figure B4, the marginal entering firm from a denser birth county has lower initial capital. Although this observation is consistent with our network-based model, as shown in Appendix C, we allow for the possibility that the observed variation in initial capital arises for other reasons, in which case firms from denser counties that start smaller could subsequently grow faster. As observed in Table 1, Column 1, firm revenue is increasing more steeply over time for entrepreneurs born in higher population density counties, conditional on the covariates discussed above. This result is retained in Column 2 when revenue is replaced by TFP as the dependent variable, constructed as in Brandt et al. (2022). Column 3 examines the same association as Column 1, but with exporters rather than all firms. We see that export revenues are also increasing more steeply over time for entrepreneurs born in denser counties.

Table 1: Revenue, TFP, and Population Density

Measurement:	level			Z-score within sector-location-year		
Dependent variable:	log revenue	log TFP	log (export revenue)	log revenue	log TFP	log (export revenue)
	(1)	(2)	(3)	(4)	(5)	(6)
Time	0.136***	0.125***	0.127***	0.053***	0.031***	0.057***
	(0.006)	(0.018)	(0.024)	(0.002)	(0.002)	(0.013)
PD×time	0.447**	2.330***	1.341***	0.290***	0.241***	0.858***
	(0.206)	(0.619)	(0.444)	(0.062)	(0.058)	(0.228)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	3.949	-5.612	5.950	–	–	–
Kleibergen-Paap F	74.05	74.05	10.69	74.05	74.05	10.69
Observations	2,235,509	2,235,509	70,579	2,235,509	2,235,509	70,579

Note: Revenue and TFP are obtained from the Inspection database, covering the 1998-2009 period. Export revenue is obtained from the Customs database, covering the 2002-2009 period. Population density is obtained from the 1982 Population Census.
We "instrument" for PD (birth county population density in 1982) with potential crop yields, reporting the corresponding Kleibergen-Paap F statistics.
The firm's initial capital (in logs) interacted with a time trend is included in the estimating equation.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

What is the source of the advantage enjoyed by firms from denser counties? One explanation is based on the idea that there are moving costs that are increasing with distance. Entrepreneurs thus tend to establish their firms close to where they are born. If denser counties or production centers (cities and Special Economic Zones) close to denser counties were growing relatively fast for exogenous reasons, then this would explain the results in Table 1. These results could also be obtained if the sectors in which firms from denser counties were concentrated, perhaps for accidental reasons, were growing relatively fast. However, if this were the story, then firms from all origins would grow at the same rate *within* the sector-locations where they were established. The SAIC data provide the sector and location of each firm and so we examine the preceding argument by constructing a Z-score for the firm's revenue or TFP, based on the distribution within each sector-location-time period. As can be seen in Columns 4-6, entrepreneurs from higher population density counties remain at an advantage, both in domestic production and exporting. There is some factor that is giving these firms a boost, within the sector-locations where they are established, at each point in time. We will propose and verify an explanation for this observation – based on birth county networks – in the sections that follow.

We complete the analysis in this section by assessing the robustness of the preceding result in a number of ways: (i) The SAIC inspection data are self-reported by firms. We check the accuracy of these data by comparing them with matched data at the firm level from the economic census in 2004 and 2008. Reporting error only confounds our interpretation of the results if it varies with birth county population density and over time. The more stringent test, implemented in Appendix Table B1, indicates that reporting error does not vary with population density at each point in time (2004 and 2008). (ii) The SAIC inspection database consists of a subset of registered firms. As with the accuracy of the self-reported data, non-representativeness of these firms does not confound our interpretation of the results in Table 1 unless it varies with birth county population density and over time. Firms listed in the inspection database have significantly higher assets and revenues than (representative) firms in the economic census in Appendix Table B2. However, this bias in sample selection does not vary with population density (the interaction terms are small in magnitude and statistically insignificant, without exception). (iii) Firms from denser counties could perform better on average simply because they have access to a more favorable business environment in their birth county, as opposed to the network-based explanation proposed below. However, Appendix Table B3 verifies that the results in Table 1 hold up when the sample is restricted to firms located outside the birth county.

2.3 Birth County Networks

As discussed in the Introduction, a number of mechanisms are consistent with Facts 1 and 2. However, just one, based on networks of firms, will explain these facts and the additional empirical results on firm outcomes that we reported above. These networks provide various forms of mutual support to their members. Entrepreneurs in developing economies rely on each other for credit, connections to buyers and suppliers, as well as for information about new technologies and markets. 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 is based, instead, on community enforcement, backed by social ties among the entrepreneurs in each network (as described by Nee and Opper (2012) for China). We noted in the Introduction 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).[16] For the purpose of our analysis, we thus assume that business networks are

[16]In the economics literature, Fisman et al. (2018) document the importance of hometown connections in Chinese academia.

organized around the birth county. The additional assumption needed to explain the results in the preceding section is that networks drawn from denser counties are more effective at improving the outcomes of their members. The analysis that follows provides descriptive evidence supporting these assumptions.

Why do we expect business networks drawn from higher population density counties to be more effective? Our point of departure is the idea that the frequency of social interactions is increasing in population density (spatial proximity) in relatively sparsely populated rural counties. This, in turn, helps 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 interconnectedness; for example, the probability that the two nodes in any link have mutual connections. The level of cooperation that can be sustained in a network has been shown to be increasing in the number of "supporting" mutual links that are severed when either node in a given link unilaterally deviates (Jackson, Rodriguez-Barraquer and Tan, 2012). It follows that cooperation or enforceable trust is likely to be increasing in population density in our rural counties.

We provide support for the preceding argument using nationally representative data from the China Family Panel Studies (CFPS), which were conducted in 2010, 2012 and 2014. The 2012 CFPS included questions on (i) trust in neighbors, which we interpret as measuring localized enforceable trust, and (ii) trust in strangers; individuals that the respondent would meet for the first time, which cannot be supported by social sanctions. We find that there is a positive and significant association between trust in neighbors (but not trust in strangers) and population density among respondents residing in rural counties. In contrast, there is no association between either measure of trust and population density in the urban sample, where spatial proximity is not a constraint to social interactions. 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. Complementing these results, data from the 2010 CFPS indicate that the frequency of social interactions (chatting) between neighbors is increasing in population density, once again in counties but not cities. While the association between enforceable trust and population density, supported by underlying social interactions, provides micro-foundations for the analysis of birth county networks that follows, it is not the focus of our analysis. The preceding results are thus collected in Appendix B, with the key findings on trust and social interactions among rural residents reported in Table 2 below.

Turning to the business networks that are drawn from the rural counties, the mutual help provided by firms to each other, such as connections and information, is inherently local in nature. We thus examine inter-firm linkages in this paper within prefectures. 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

Table 2: Trust, Social Interactions, and Population Density

Data source:	CFPS 2012 individual module		CFPS 2010 family module	CFPS 2010 individual module
Dependent variable:	trust in neighbors	trust in strangers	chatted with neighbors in the past week	chat most frequently with neighbors
	(1)	(2)	(3)	(4)
Population density	5.425***	-1.113	2.145**	1.267***
	(1.971)	(2.774)	(0.833)	(0.421)
Mean of dependent variable	6.429	2.194	0.690	0.198
Observations	20,047	20,047	8,294	20,652

Note: Trust, social interactions, household income and individual education are obtained from the China Family Panel Studies (2010, 2012). See Appendix B for variable construction. Population density is obtained from the 1982 Population Census.
Column 4 is based on a question that asks whether the respondent chats most frequently with neighbors, relatives or friends/colleagues (see Appendix B).
Outcomes are measured as binary variables and the sample is restricted to residents of rural counties.
Income and education are included as covariates in the estimating equation.
Standard errors clustered at the county level are reported in parentheses.

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.[17] How does localized enforceable trust in the birth county affect the functioning of these networks? Our measure of trust is not a portable cultural trait but must, instead, be supported by the threat of social sanctions (applied by the entrepreneur's origin community). We thus assume that county-born entrepreneurs remain connected to their rural origins, despite the fact that the majority of these entrepreneurs establish their firms elsewhere, and that business links between firms from the same birth county can thus be "supported" (in the sense of Jackson, Rodriguez-Barraquer and Tan (2012)) by the origin social network. Based on our analysis of trust in Chinese counties, the level of support and associated social enforcement that is provided by the origin social network is increasing in population density. This implies that links between firms from higher population density origins will sustain higher levels of mutual help; i.e. are more valuable. It follows that firms from denser birth counties should (i) be more likely to remain connected to their origin, and (ii) be more likely to form business links with other firms from the same origin operating in the same prefecture.[18]

In addition to the principal, the SAIC registration database also lists other key personnel in the

[17] We define the network at the birth county-destination prefecture level rather than the birth county-destination prefecture-sector level because many forms of support, such as help with government connections, will cross sectoral lines.

[18] This argument is based on the assumption that links between firms reduce information and enforcement problems and, thereby, support higher levels of cooperation. Moreover, these links and the "supporting" links in the origin social network are complements. If they were substitutes, instead, then firms from denser counties with higher levels of trust would be less likely to make connections with each other, which is at odds with the results reported below.

firm.[19] We begin our examination of the preceding argument in Table 3, Column 1 by estimating the relationship between the fraction of listed individuals born in the same county as the principal and his birth county's population density. The sample in all of the analysis that follows in this section is restricted to firms located outside their birth county since the focus is on the firm's connection to the origin. We also restrict attention to firms that were active in 2009, the end point of our analysis, to emphasize the persistence of these connections. The birth county population density coefficient is positive and significant. Notice that the population density coefficient as well as the mean of the dependent variable, which measures average birth county homophily, are many times larger than what would be obtained if listed individuals were randomly assigned across firms in each prefecture. Since links between firms from higher population density counties are more valuable, as discussed above, we expect that they should have a greater propensity to form such links. As observed in Table 3, Column 2, firms from higher population density counties are indeed more likely to report having external links, where two firms (located in the same prefecture) are defined as being linked if the same individual is listed in both of them. Moreover, conditional on being linked, firms from those counties are more likely to be linked to firms from the same origin (established in the same prefecture) in Column 3. Once again, this homophily is an order of magnitude larger than what would be obtained if firms with links in each prefecture were randomly matched.

Table 3: Birth County Connections and Population Density

Unit of observation:	firm			network	
Dependent variable:	fraction of listed individuals from the same birth county	whether firm has links in the prefecture	whether linked firms are linked to a firm from the same birth county	fraction of links that are supported	number of supporting firms conditional on support
	(1)	(2)	(3)	(4)	(5)
PD	1.630***	0.332***	1.644***	1.640***	15.522***
	(0.389)	(0.107)	(0.480)	(0.246)	(3.507)
Mean of dependent variable	0.488	0.268	0.499	0.288	1.797
Counter-factual PD	0.082	–	0.048	–	–
Counter-factual mean	0.013	–	0.014	–	–
Observations	1,436,699	1,436,699	385,210	1,611	1,291

Note: the sample is restricted to firms established outside their birth counties and active in 2009.
Two firms are "linked" if the same individual is listed in both of them. A link is "supported" if the nodal firms have mutual links to at least one other firm.
The counter-factual estimates are based on the random assignment of listed individuals and the random matching of linked firms in the prefectures where they are located.
The birth county of the principal and other listed individuals is obtained from the SAIC registration database and birth county population density (PD) is derived from the 1982 Population Census.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Appendix Table B7, Columns 1-3 repeats the preceding exercise, replacing listed individuals with shareholders. While we expect to observe the same relationships as we did with listed in-

[19] The principal, who is designated as the "legal representative" in the SAIC registration database, has the authority to enter into binding obligations on behalf of the company. This individual typically functions as the firm's president, chairman or proprietor. Other listed individuals include directors, senior managers, and external "supervisors."

dividuals above, there is an additional reason why firms from higher population density counties are more likely to have shareholders from the origin; i.e. a higher level of birth county homophily. Although we have discussed the role of the network in providing connections and information, it could also channel capital to them. One way that this can be done is through joint ownership (shared equity).[20] Individuals at the origin are more likely to invest in a firm located far away when there are higher levels of (enforceable) trust in the population. As predicted, we see in Appendix Table B7 that higher birth county population density is associated with (i) a higher fraction of shareholders from the principal's birth county, (ii) a higher fraction of firms with cross-ownership in the prefectures where they are established, and (iii) a higher fraction of such links that are between firms from the same origin. Once again, the observed homophily is on average an order of magnitude larger than what would be obtained by random assignment of shareholders and random matching of firms with shareholder links, within each prefecture.

Our analysis of business networks thus far has been based on the idea that links between firms from higher population density origins are more strongly "supported" by the overlapping origin social network. Recall that a link is supported if the two nodal firms, or key personnel and shareholders in those firms, have mutual links to one or more individuals in the origin social network. Although the architecture of the origin social network is not observed, this information is available for the business network. We thus turn next to the complementary support that can be provided by the destination business network, based on mutual links to firms from the same origin. When we motivated the positive association between trust and population density above, we argued that higher degree; i.e. a larger number of links per capita was (mechanically) positively associated with the level of support in the origin social network. Having established that firms from higher population density origins are more likely to be linked with each other at a given destination, we expect by the same argument that their destination-based business network will be associated with a higher level of support. Focusing on links between firms from the same origin located in the same prefecture (but outside their birth county) we observe in Table 3, Columns 4-5 that such links between firms from higher population density counties are (i) more likely to be supported by mutually linked firms, and (ii) supported by a greater number of firms, conditional on being supported.[21]

The results in Table 3 indicate that while all firms maintain ties with their birth county, even when located elsewhere, firms from higher population density counties display higher levels of birth county homophily. Firms from these counties are more likely to be linked to other firms in the prefectures where they are located and these links are more likely to be with firms from the same origin.[22] The individual links between firms from higher population density counties will be stronger for two reasons: First, they will be supported more strongly by the more inter-

[20] Bai et al. (2020) also examine cross-ownership using the SAIC registration data. However, they do not investigate how these linkages vary with birth county population density.

[21] This is also true if links are defined by cross-ownership, as shown in Appendix Table B7, Columns 4 and 5.

[22] A particularly useful feature of our network data is that all firms and all links between firms are observed. As with any empirical analysis of networks, the preceding results are obtained for specific types of links (cross-listing and cross-ownership). Nevertheless, given the consistency of the results and their micro-foundations, we expect that they would hold up if other (possibly informal) linkages between firms were included in the analysis.

connected social network at the origin, which has been shown to be associated with higher levels of localized enforceable trust. Second, these links will be supported more strongly by the business network at the destination, as documented above. This explains why networks of firms drawn from higher population density counties can support higher levels of cooperation (mutual help) and thus function more effectively. The model that follows incorporates these network properties when deriving Facts 1 and 2. Section 4.1 subsequently estimates the effect of the birth county networks on the business outcomes of their members, documenting that networks drawn from denser counties are indeed more effective.[23]

3 The Model

3.1 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 ability distribution is homogeneous across counties, although we will reintroduce the heterogeneity later in Section 4 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 in a specific prefecture (we ignore sectors to simplify the exposition). 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 $i = d, e$ 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:

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

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 term C_{it}, which we describe in greater detail below.

[23]The sample size is too small to permit an analysis of support with the network restricted to export firms. However, we will see in Section 4.1 that domestic networks and export networks drawn from denser counties function more effectively.

Capital costs for domestic and export plants are as follows:

$$E_{dt} = rK_{dt}, E_{et} = r(1 + I)K_{et} \tag{2}$$

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.[24] 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 is represented by a fixed cost β in addition to plant costs (2). 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.

We now turn to the productivity term, C_{it}, which is determined by exogenous market size in the prefecture, 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 size component of the productivity term incorporates agglomeration effects and other exogenous business opportunities associated with product demand, government support and infrastructure, that apply equally to all firms in the prefecture regardless of their origin. This term is growing 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 network component of the productivity term reflects the idea that mutual help is complementary and so larger networks are more effective at improving the outcomes of their members: the size of the network is determined by the number of (experienced) firms from the birth county that are established in the prefecture by the end of the preceding period.

Notice that the domestic network consists of all firms, n_{t-1}, whereas the export network only consists of exporting firms, $n_{e,t-1}$. This reflects the idea that experience acquired on the export market is relevant for domestic production, but not *vice versa*.[25] Notice also that other birth county networks do not affect the firm's revenue; 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 origin account for 6.3% of firms in the prefectures where they locate, on average (within narrow two-digit sectors). This statistic is based on all entrepreneurs, including those who

[24] 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.

[25] 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.

locate their firms in their county of birth. The corresponding statistic for the capital share is 5.9%. The common view in China that entire industries are dominated by firms from a single hometown appears to be the exception rather than the rule. Moreover, while previous research indicates that pricing may be non-competitive in China (Brooks, Kaboski and Li, 2016), the origin-based networks do not appear to be responsible for these distortions.

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 on account of $\theta_d(p)$ and $\theta_e(p)$, which measure the effectiveness of the domestic and export network, respectively. Based on the descriptive evidence from the previous section, we assume that $\theta'_d(p) > 0$, $\theta'_e(p) > 0$.

3.2 Occupational Choice in Equilibrium

To simplify the dynamics, we assume that agents are myopic and that network sizes at past dates are observable by all agents. Consider date t with given productivity $C_{it}, i = d, e$. 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} to maximize

$$[C_{dt}\omega^{1-\alpha}K_{dt}^{\alpha} - rK_{dt}] + [C_{et}\omega^{\delta(1-\alpha)}K_{et}^{\alpha} - r(1+I)K_{et}] - \beta\mathbb{I}(K_{dt}K_{et}) \tag{3}$$

subject to the irreversibility constraints

$$K_{it} \geq K_{i,t-1}, i = d, e \tag{4}$$

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.

We assume that market sizes expand over time and noted above that network sizes are non-decreasing. This implies that productivity $C_{it}, i = d, e$, is increasing over time and, hence, that plant sizes must increase over time for incumbents. It follows that the irreversibility constraint can be ignored. Maximizing profit with respect to capital in each market and then substituting back in the profit function, the equilibrium profit for an entrepreneur with ability ω in period t can be derived for each market $W \in \{T, D, E, M\}$, where T refers to the traditional occupation, D is domestic production, E is pure exporting, and M is mixed exporting:

$$
\begin{aligned}
\Pi_{Tt}(\omega) &= \omega^{\sigma} \\
\Pi_{Dt}(\omega) &= \omega[\frac{1}{\zeta}]C_{dt}^{\frac{1}{1-\alpha}} \\
\Pi_{Et}(\omega) &= \omega^{\delta}[\frac{1}{\zeta\gamma}]C_{et}^{\frac{1}{1-\alpha}} \\
\Pi_{Mt}(\omega) &= \Pi_{Dt}(\omega) + \Pi_{Et}(\omega) - \beta
\end{aligned} \tag{5}
$$

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 market entry decision W on the extensive margin. We now turn to equilibrium choices of (extensive form) market entry decisions. Observe from (5) that the return to ability is increasing as we progress from the traditional occupation (Π_{Tt}) 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, with parametric restrictions specified in Appendix C ensuring the existence of a unique equilibrium featuring positive shares of each occupation at each date for each cohort:

Proposition 1 *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:*

$$A - 1 < \log \omega^*_{dt} < \log \omega^*_{et'} < \log \omega^*_{mt} < A \tag{6}$$

and a unique Nash equilibrium involving the following strategies:

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

(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 regularity condition $\log \omega^*_{et'} < \log \omega^*_{mt}$ for all t maintains the ordering of the three ability thresholds for any cohort t' at each point in time.[26] 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

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

export propensity may vary across different cohorts, depending on the evolution of market sizes and network sizes in the domestic and export 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 close the discussion in this section by listing the differences between our model and the canonical Melitz (2003) model, which also features sorting by ability into domestic production and exporting.

1. Production technology and market structure: In the Melitz model, each firm produces a differentiated product (variety) with a constant returns to scale technology. It faces a downward sloping CES demand curve and thus sets its profit-maximizing price at a constant markup over its unit cost, resulting in a revenue function that exhibits constant elasticity (less than one) with respect to scale. In our model, each firm produces a homogeneous good and is a price taker. However, the production technology is specified such that the revenue function continues to exhibit diminishing returns to scale. We could, instead, have specified the production technology and market structure as in Melitz (2003) without changing any of the results.

2. Decisions at the extensive margin: The Melitz model allows firms to enter and exit, solving for the steady-state equilibrium. In our 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, the main result would be retained if we added a uniform and exogenous death rate to the model. The propensity equations derived below to explain Facts 1 and 2 would be simply multiplied through by the survival rate.

3. 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}^*.

4. 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 cost accounting implies that no firm will ever export and not produce for the domestic market. In our model, restrictions on the δ, I, parameters ensure that entrepreneurs above an ability threshold produce for the export market. Those entrepreneurs would also produce for the domestic market, as in the Melitz model, in the absence of the scope diseconomy (measured by the

β parameter). If the diseconomies of scope are sufficiently large, however, then some exporters will specialize in that activity and their presence is key to explaining Fact 2 below.

5. Occupational dynamics: In the Melitz model, business opportunities are restricted to the domestic 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 $\tau + 1$. 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 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 exporters when estimating the model in Section 4.

3.3 Firm-Level Outcomes

Recall from Section 2.2 that firm-level revenue and productivity are increasing more steeply over time for firms drawn from denser counties, both in domestic production and exporting. To verify that the model can explain these results, we begin by deriving the corresponding structural equations for revenue and productivity.

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}:

$$\log R_{dt} = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r}\right) + \frac{\theta_d(p)\log n_{t-1}}{1-\alpha} + \frac{q_{dt}}{1-\alpha} + \frac{[(1-\alpha)^2+1]}{1-\alpha}\log\omega. \tag{7}$$

The corresponding expression for export revenue is obtained as:

$$\log R_{et} = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r(1+I)}\right) + \frac{\theta_e(p)\log n_{e,t-1}}{1-\alpha} + \frac{q_{et}}{1-\alpha} + \frac{\delta[(1-\alpha)^2+1]}{1-\alpha}\log\omega. \tag{8}$$

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,

$$\log P_{dt} = \theta_d(p)\log n_{t-1} + q_{dt} + (1-\alpha)\log\omega. \tag{9}$$

Comparing the structural equations with the reduced form specification of the revenue and productivity equations in Table 1, the market size terms, q_{dt} and q_{et}, are accounted for in Columns 4-6 when revenue and productivity are measured as Z-scores, within the sector-location-time period.

Ability, ω, is subsumed in the firm fixed effect that is included in the reduced form equations. To reconcile the model with the reduced form result that domestic revenues and productivity are increasing more steeply over time for firms drawn from denser counties, equations (7) and (9) imply that the following condition must be satisfied:

$$\frac{d^2\theta_d(p)\log n_{t-1}}{dpdt} = \theta_d'(p)\frac{d}{dt}\log n_{t-1} + \theta_d(p)\frac{d^2\log n_{t-1}}{dpdt} > 0$$

This condition is evidently feasible, since $\theta_d'(p) > 0$ by assumption and domestic network size, n_{t-1} is non-decreasing. By an analogous argument, the structural equation (8) for export revenues is consistent with the corresponding reduced form result in Table 1 because $\theta_e'(p) > 0$ by assumption and export network size, $n_{e,t-1}$ is non-decreasing

3.4 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 explain 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 (5), by setting $\Pi_{Tt}(\omega_{dt}^*) = \Pi_{Dt}(\omega_{dt}^*)$, and unpacking C_{dt}:

$$n_t = ts(p)[A - \omega_{dt}^*] = ts(p)[A - \frac{\log\zeta}{1-\sigma} + \frac{q_{dt} + \theta_d(p)\log n_{t-1}}{(1-\sigma)(1-\alpha)}] \tag{10}$$

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.[27]

Note that Fact 1 implies that the marginal entrant's initial capital is decreasing in p in each cohort, as derived in Appendix C, which, in turn, is consistent with Appendix Figure B4. More successful (higher-p) networks bring in smaller firms (with lower entrepreneurial ability) at the margin. This generates variation in the ability of the marginal entering entrepreneur across birth counties, which results in 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 population density network, as in Banerjee and Munshi (2004). Such reallocation is infeasible 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

[27]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.

at any period t is just the sum of exporters supplied by all preceding cohorts. Following the same steps as above, we set $\Pi_{Dt'}(\omega^*_{et'}) = \Pi_{Et'}(\omega^*_{et'})$ to derive $\omega^*_{et'}$ from (5) and then unpack $C_{et'}$ to obtain:

$$n_{et} = ts(p)[A - \frac{\log\gamma}{\delta - 1}] + \frac{s(p)}{(\delta-1)(1-\alpha)} \sum_{t'=1}^{t} [q_{et'} - q_{dt'} + \theta_e(p)\log n_{e,t'-1} - \theta_d(p)\log n_{t'-1}] \tag{11}$$

The ability of the marginal pure exporter in each cohort $\omega^*_{et'}$, which pins down the export propensity, is determined by market sizes and network sizes 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.

In the decentralized equilibrium described by our model, potential exporters do not account for the positive network externality associated with their entry into that activity, which implies that there is too little entry. A social planner choosing the optimal number of exporters to maximize total export profits would take account of this externality, but their choice would be independent of the size of the domestic network since the latter has no effect on export productivity (or profits). Regardless of its magnitude, the negative domestic network overhang is thus unambiguously associated with a dynamic inefficiency, which reduces entry into exporting.

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. Note, however, that the nonseparability in the model with increasing marginal costs does not generate an inefficiency because firms internalize the tradeoffs with respect to domestic and export profits when they make their production decisions.

4 Evaluating the Model

4.1 Firm-Level Outcomes

We showed above that the structural equations for firm-level revenues and productivity implied by the model can be reconciled with the reduced form results reported in Section 2.2. We now proceed to estimate these equations (7)-(9) to verify the key assumption that networks drawn from denser counties function more effectively; i.e. $\theta'(p) > 0$, with this function parameterized to be linear in p: $\theta(p) = \theta_0 + \theta_p(p)$. If birth county networks are active, then $\theta_0 > 0$. If networks drawn from denser birth counties are more effective, as assumed, then $\theta_p > 0$. Although the model is based on a single birth county and a single destination prefecture, the empirical tests that follow allow for multiple origins and for multiple destinations for each origin and, hence, the notation in the estimating equations is modified accordingly:

$$\log y_{ijkt} = (\theta_0 + \theta_p p_j) \log n_{jk,t-1} + \gamma \log K_{i0} \cdot t + f_i + u_{jkt}, \tag{12}$$

where y_{ijkt} measures the Z-score for 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 and $n_{jk,t-1}$ measures the stock of firms from county j located in prefecture k in period $t-1$; i.e. prior to period t. Note that network size $n_{jk,t-1}$ is based on the stock of exporting firms when the outcome is export revenues, following Fernandes and Tang (2014) and as assumed in our model.[28] The ability terms in the structural equations are captured by a firm fixed effect f_i and the market-size terms that affect all firms in a prefecture equally are implicitly accounted for when we measure outcomes by Z-scores. Matching the reduced form specification estimated in Table 1, we also include the firm's initial capital interacted with a time trend, $\log K_{i0} \cdot t$, as a covariate. The structural error term, which does not appear in the model but which we motivate below, is denoted by u_{jkt}.

As seen in Table 4, 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 prefecture-sector-time period level, such as infrastructure 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 over time, u_{jkt}, give 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 (12), does not solve the problem when shocks are serially correlated, in which case a spurious network effect could be obtained.

One strategy to address the identification problem described above 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

[28] The network mechanism in Fernandes and Tang (2014) is based on social learning rather than mutual help and, hence, their specification of the estimating equation also includes proxies for the signals inferred from neighbors. However, their definition of the network is based on all firms operating in a given location and thus the effects they identify are fully accounted for when we construct the dependent variable as a Z-score.

Table 4: Revenue, TFP, and Network Effects

Model:	OLS			IV		
Dependent variable:	log revenue	log TFP	log (export revenue)	log revenue	log TFP	log (export revenue)
	(1)	(2)	(3)	(4)	(5)	(6)
$\log n_{jk,t-1}$	0.242***	0.150***	0.266***	0.117***	0.008	0.184**
	(0.006)	(0.006)	(0.026)	(0.024)	(0.021)	(0.075)
$p_j \times \log n_{jk,t-1}$	1.756***	1.201***	1.245***	4.155***	3.567***	2.363*
	(0.186)	(0.153)	(0.420)	(0.605)	(0.557)	(1.278)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	25.45	25.45	12.41
Observations	2,235,509	2,235,509	70,579	2,235,509	2,235,509	70,579

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. The network terms are constructed with SAIC registration data.
The firm's initial capital interacted with a time trend is included in the estimating equation.
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%.

entrepreneurs, as instruments for the size of the business networks that emerge from those counties (and are established in different prefectures). Following Imbert et al. (2022), 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 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, 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). (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 shift-share instrument. Details of instrumental variable construction are provided in Appendix D. The instrumental variable estimates of the network effects are reported in Table 4, Columns 4-6. Network effects continue to be positive and significant (with one exception) and to be increasing in birth county population density.

The shift-share instrument we have constructed consists of quasi-random crop price shocks (shifts) interacted with fixed birth county-destination prefecture characteristics (shares). This instrument is seen to have a strong (first-stage) effect on the network variables, for all firms and for export firms, in Appendix Table D1. The assumption that networks drawn from denser counties function more effectively is critical to our analysis and, hence, the discussion that follows examines the validity of each component of the shift-share instrument.

We begin with the shift. 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 D2. As can be seen, the estimates are very similar to what we obtain with the full sample in Table 4. 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 D3 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 sector-location in which they are active and will result in a decline in their revenues. Note, however, that our first-stage estimates indicate that a negative agricultural price shock increases firm entry and, with it, network size. These effects work in opposite directions and, hence, by ignoring a potential wealth effect we are (if anything) reporting conservative estimates of the network effect.

Next we turn to the share, which consists of two components: (i) the distance term, which maps the total stock of firms from a given birth county into destination prefectures, and (ii) the crop multiplier, which maps crop-specific shocks into the income shock for that county. The share is a fixed characteristic and, hence, its 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 share with time must also be considered when examining the validity of the shift-share instrument. For example, 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 absolute 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-location. The greater threat to identification stems from the potential endogeneity of the crop shares. 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, perhaps for extraneous reasons, 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 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 5 reports results with firm revenue as the dependent variable, using the share for each crop interacted with time effects 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 shift-share 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 4, Column 4. This indicates that no crop has a separate and independent effect on firm performance, validating the exogeneity of the corresponding shares.

Table 5: 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)
$\log n_{jk,t-1}$	0.203***	0.186***	0.185***	0.242***	0.177***	0.245***
	(0.013)	(0.016)	(0.015)	(0.023)	(0.016)	(0.021)
$p_j \times \log n_{jk,t-1}$	3.140***	3.453***	3.903***	2.928***	3.987***	2.266***
	(0.421)	(0.479)	(0.528)	(0.716)	(0.509)	(0.655)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	17.58	12.21	12.41	48.53	27.64	6.178
Observations	2,235,509	2,235,509	2,235,509	2,235,509	2,235,509	2,235,509

Note: Revenue is derived from the Inspection database, covering the 1998-2009 period. Network size is constructed with SAIC registration data.
The firm's initial capital interacted with a time trend is included in the estimating equation.
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%.

We complete the instrumental variable analysis with a comment on the interpretation of the estimates. Negative income shocks in the birth county will also increase labor migration, as documented by Imbert et al. (2022). Given that the cost of moving is increasing in distance, entrepreneurs and workers from a birth county could end up in the same locations. If entrepreneurs are more likely to hire workers from their hometown, then the estimates in Table 4 could reflect an inter-firm business network effect and a complementary labor network effect. While we are comfortable with a more inclusive interpretation, the descriptive evidence in Section 2.3, which is based on observed links between firms, provides explicit support for the hypothesis that inter-firm networks are active.

4.2 Composition of Firms

Our ability to explain Fact 2 relies crucially 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.[29] Finally, those firms that do not appear in the customs data are assumed to be domestic producers.

Table 6 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 2 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 6: Composition of Firms

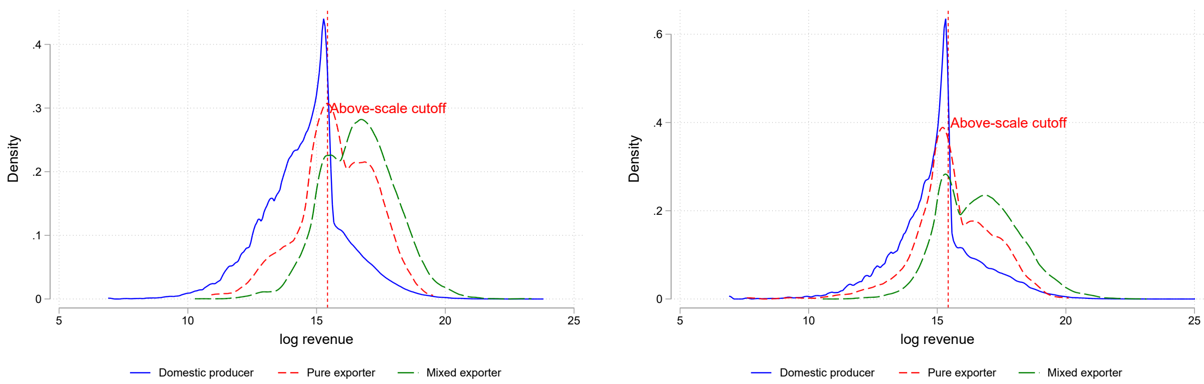
Year	2004		2008	
Type:	number	log revenue	number	log revenue
Domestic producer	234,998	14.48	471,961	14.87
Pure exporter	572	15.75	2,086	15.58
Mixed exporter	4,102	16.52	10,300	16.42

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

The vertical line in Figure 2 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.[30]

[29] 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.

[30] 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 B, there are discrepancies between the revenues



(a) 2004

(b) 2008

Figure 2: Revenue Distribution

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

4.3 Entrepreneurial and Export Propensity

The final step in the empirical analysis is to explain Facts 1 and 2 through the lens of the model by estimating the propensity equations (10) and (11). 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 (10) and (11). 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 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 destination prefecture, entrepreneurs from a given origin will establish their firms in multiple destinations, with different proximities, in practice. Entrepreneurs have a greater propensity to set up their firms in closer prefectures. We thus replace the A parameter in equations (10) and (11) 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:

$$\frac{n_{jkt}}{P_{jt}} = A_{jk} + \Phi_{kt} + \tilde{\Theta}_d(p_j) \log n_{jk,t-1} + \epsilon_{jkt} \tag{13}$$

$$\frac{n_{ejkt}}{P_{jt}} = A_{jk} + \Phi_{kt} + \left[\Theta_e(p_j \left(\frac{1}{t} \sum_{t'=1}^{t} \log n_{ejk,t'-1} \right) - \Theta_d(p_j) \left(\frac{1}{t} \sum_{t'=1}^{t} \log n_{jk,t'-1} \right) \right] + \epsilon_{jkt} \tag{14}$$

where P_{jt} measures the number of potential entrepreneurs and Φ_{kt} is a destination prefecture-

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.

time period effect.[31] The Θ functions are assumed to be linear in p_j: $\tilde{\Theta}_d(p_j) \equiv \tilde{\Theta}_{d0} + \tilde{\Theta}_{dp} \cdot p_j$, $\Theta_i(p_j) \equiv \Theta_{i0} + \Theta_{ip} \cdot p_j$, $i \in \{e, d\}$. The network terms thus appear uninteracted and interacted with p_j in the propensity equations, which can be estimated by Ordinary Least Squares.

Although our deterministic model does not include structural error terms, it is relatively straightforward to introduce these terms by allowing for birth county-destination prefecture entry shocks, ϵ_{jkt}. The numerator of the dependent variable in the propensity equations is the stock of all firms or 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: $\epsilon_{jkt} = \epsilon_{jk,t-1} + v_{jkt}$. The error term, ϵ_{jkt}, is serially correlated by construction, and since the propensity equations include lagged firm stocks (the network size terms) on the right hand side, biased estimates will be obtained if the equations are estimated in levels. However, if we first-difference to purge the origin county-destination prefecture effects, A_{jk}, then we will be left with v_{jkt} in the residual of the estimating equations. If v_{jkt} is serially uncorrelated, OLS estimation of the differenced equations will yield unbiased estimates of the network effects. It is, however, entirely possible that v_{jkt} is serially correlated. Moreover, the network variables are likely measured with error.

The standard solution to correct the biases described above is to construct instruments for network size. 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 outcome equations in Section 4.1, because these shocks directly determine entry into business 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 and 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. 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 (13) and the average network growth rate over all periods up to $t-1$, for all firms and for export firms, in equation (14). In addition, we need to instrument for the interaction of these growth rates with birth county population density. Based on the preceding discussion, two time-varying instruments are available for each growth rate and for its interaction with birth county population density: the interaction of the network's duration with (log) initial entry and the triple interaction with population density. As commonly assumed in the migration literature, the identifying restriction is that the factors that determine initial entry should not determine subsequent entry, except through the network multiplier effect. A detailed discussion on the validity of this assumption and the instrumental variable estimates more generally, with

[31] 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.

supporting tests, is provided below and in Appendix D.

Once we first-difference the propensity equations, the left hand side is approximately equal to the flow of new entrepreneurs or exporters 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 7, 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).[32] The estimated coefficients also have the expected signs and are statistically significant, with a couple of exceptions. The negative coefficients on the domestic network terms in the export propensity equation, in particular, are indicative of the network overhang that is a key feature of our model. Qualitatively similar coefficient estimates are obtained without the $S_{jk,t-1}$ correction in Appendix Table D4, although our preferred specification does a better job of predicting entry, especially for all entrepreneurs, in distant prefectures (where the share is smaller).[33]

68% of the exporters in the 2004 economic census and 37% of the exporters in the 2008 census

[32]Although we use the same set of instruments – the interaction of network duration with the initial entry level and the triple interaction with birth county population density – for the domestic network terms and the export network terms in Column 2, we are still identified because the domestic network and the export network (typically) start at different points in time in a given prefecture.

[33]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 D4: 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 D6 verifies that the results are robust to adding 0.05 or 0.15 instead.

Table 7: 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%.

registered their firms prior to 2002, which is the starting point for the exporting regime in our analysis.[34] Most of these firms would have transitioned from domestic production to exporting when new opportunities became available with China's entry into the WTO in 2002, as in Melitz (2003). Although our model does not permit such transitions, it can be easily extended to account for these firms once we specify that exporting commenced with a lag, as noted above. Nevertheless, since the Melitz-type exporters do not appear in our model as it is currently formulated, we drop exporters who were registered prior to 2002 when constructing the export propensity in Table 7, 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.

[34] Among the export firms in the 2008 economic census who were registered after 2002; i.e. during the exporting regime, 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.

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). The analysis that follows provides independent support for the validity of the instrumental variable estimates.

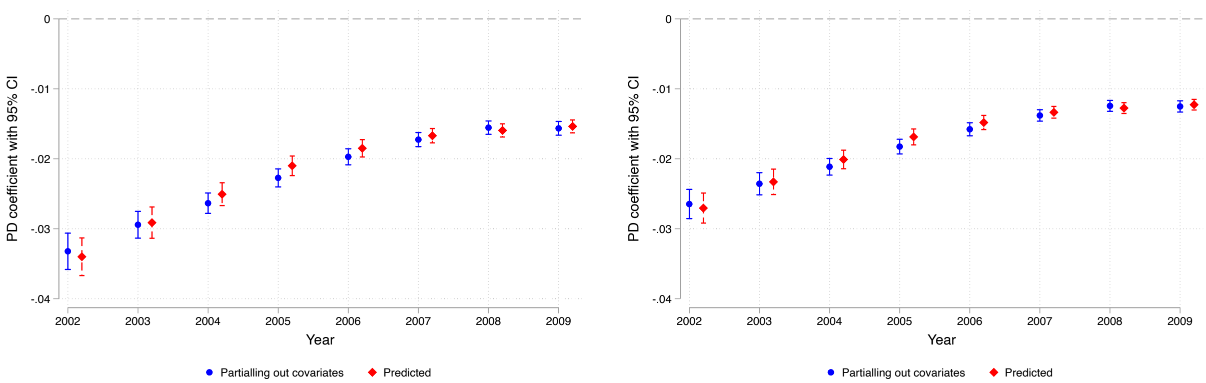
Our first validation test compares the OLS and IV estimates of the propensity equations, assessing whether the (sizeable) difference between these estimates can be plausibly explained by the sources of bias that we consider: measurement error in the network variables and serial correlation in the per period entry shocks after the network has formed, v_{jkt}. While a detailed, self-contained, description of this test is presented in Appendix D, the key findings can be summarized as follows. Based on our simulations of the model, and the OLS estimates with simulated data, we conclude that the bulk of the bias in this setting is due to measurement error.[35] 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.

Our second validation test assesses whether the instruments satisfy the exclusion restriction. As noted, our identification strategy is based on the assumption that the initial shocks that jump-start the birth county-destination prefecture networks are one-off accidental events. The threat to identification is that the factors that determine the initial shock are persistent. The duration of the network will then be correlated with these unobserved 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 D6, remain very similar to the benchmark estimates in Table 7. 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 7, 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 D1, 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. Based on the validation tests that we implement, there is no evidence that the instrumental variable estimates are biased.

[35]The OLS estimates with simulated data in Appendix Table D5 are close to the IV estimates. These estimates are purged of measurement error, but continue to be biased due to serial correlation in the error term. We can thus conclude that measurement error is responsible for much of the observed (substantial) difference between the OLS estimates with actual data, also reported in Appendix Table D5, and the IV estimates.

4.4 Reconciling the Model with Fact 2

While the preceding results indicate that a domestic network overhang is present, to reconcile the model with Fact 2 we need to establish that the overhang is sufficiently strong; i.e. that the net network effect in square brackets in equation (14) is decreasing in p_j. We do this in two ways: (i) by partialling out the remaining covariates in the estimating equation and then estimating the association between export propensity (conditional on those covariates) and population density, and (ii) by predicting the term in square brackets, based on the estimated coefficients, 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 (circle or 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 even in the long run. 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.



(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 7, Columns 2 and 3, and birth county population density is obtained from the 1982 Population Census.

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 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.

5 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 support 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, over the 1994-2009 period. 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 institutions in the process of development.

While the networks that we identify may have contributed to the growth in domestic production, they create inefficiencies of their own. In the decentralized equilibrium described by our model, potential entrants into exporting (and domestic production) do not internalize the positive network externality that they generate by selecting into those activities. While this results in a sub-optimal level of entry, the additional dynamic inefficiency that we identify arises because pre-existing domestic networks discourage potential exporters from selecting into that activity. There is a common view that Chinese exporters receive anti-competitive government subsidies. Although we cannot assess whether the level of these subsidies is optimal, our analysis provides an efficiency-based rationale for their presence. In developing economies where networks are active, timely promotion of new (more advanced) activities, that may only need to be temporary, can prevent or reduce the lock-in that we document in this paper.

We conclude with a comment on external validity. Although our findings are not specific to business or to China, the preceding arguments and, indeed, the analysis in this paper, will only be relevant in populations where community networks are already active or have the potential to be activated. 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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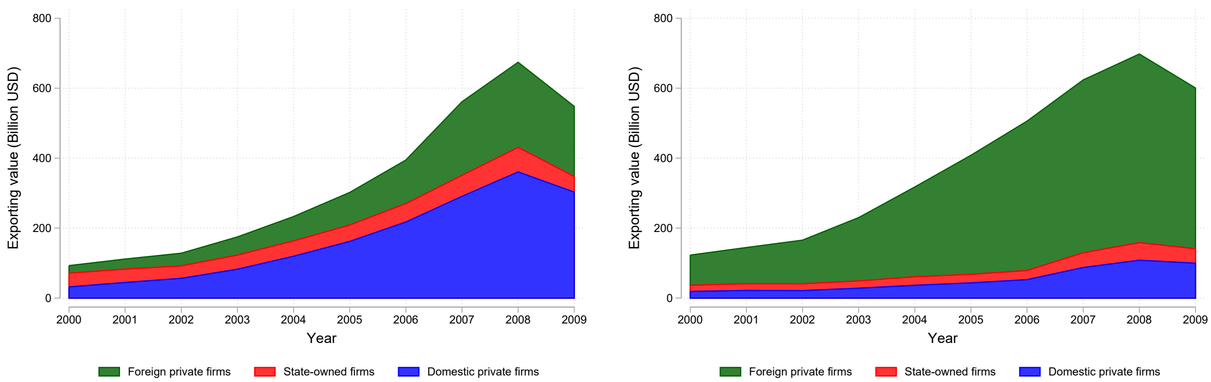
Appendix A: Export Accounting

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). Following Verhoogen (2008), 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. It also 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 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 report positive export revenues in the Above Scale database, as the difference between reported

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 FE	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%.

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.

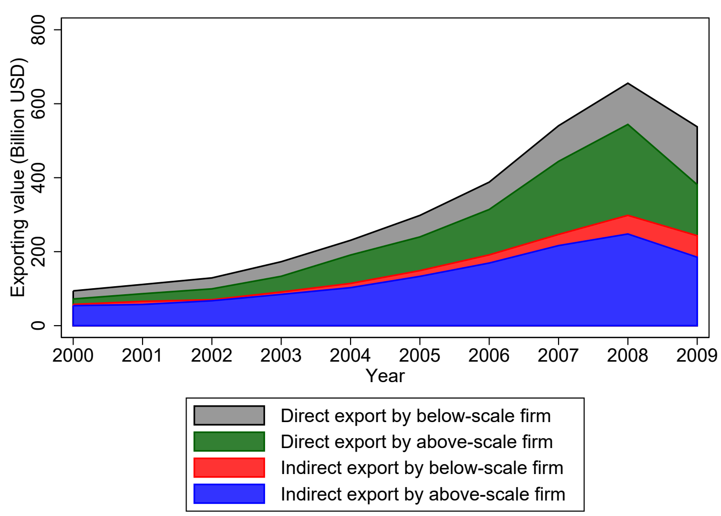


Figure A2: Export Accounting

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)
Observations	654,408	775,722

Note: The estimating equations include 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

A. Entrepreneurship in China

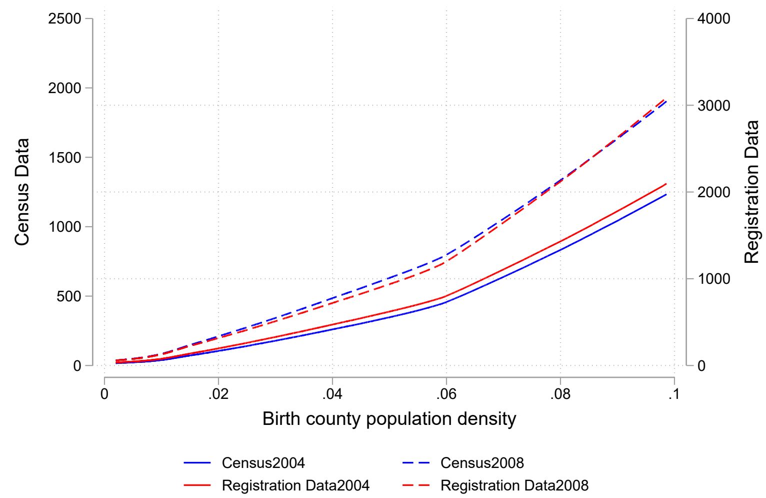
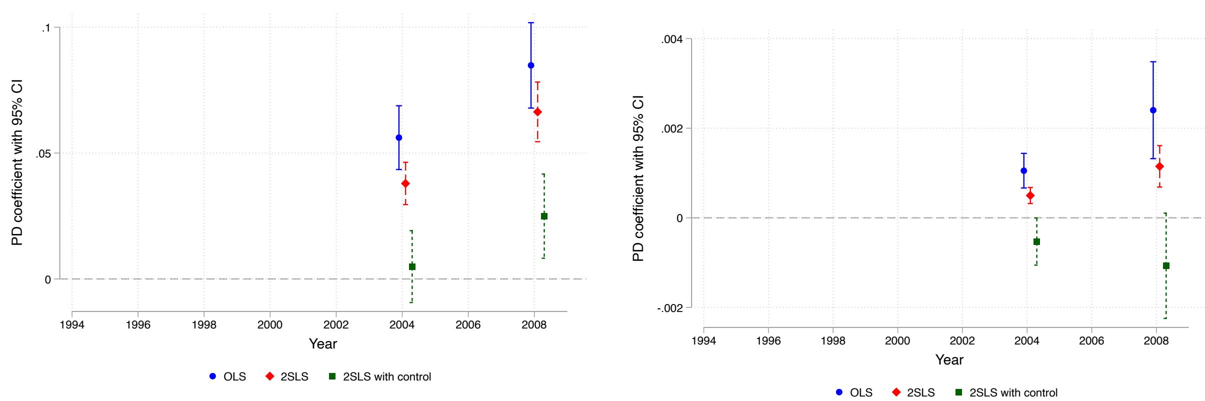


Figure B1: Number of Manufacturing Firms

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

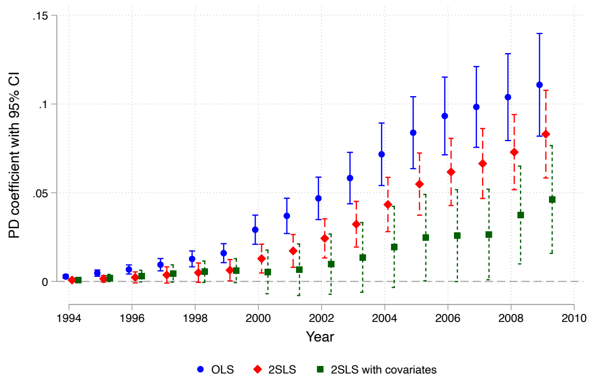


(a) Entrepreneurial Propensity and Population Density

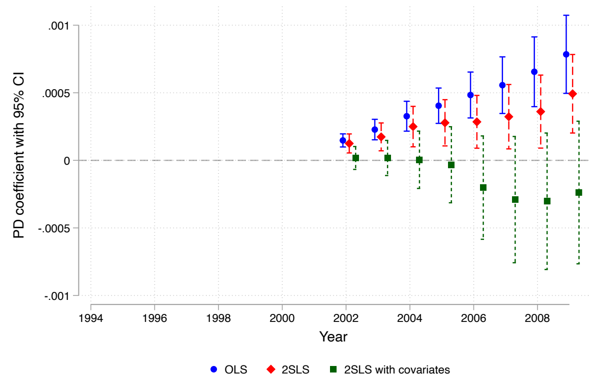
(b) Export Propensity and Population Density

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.

B. Firm-Level Outcomes

1. Marginal initial capital and birth county population density: 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 SAIC 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 then 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 the figure below, the population density coefficient is negative and significant in each year. This is also true for the 2SLS estimates.

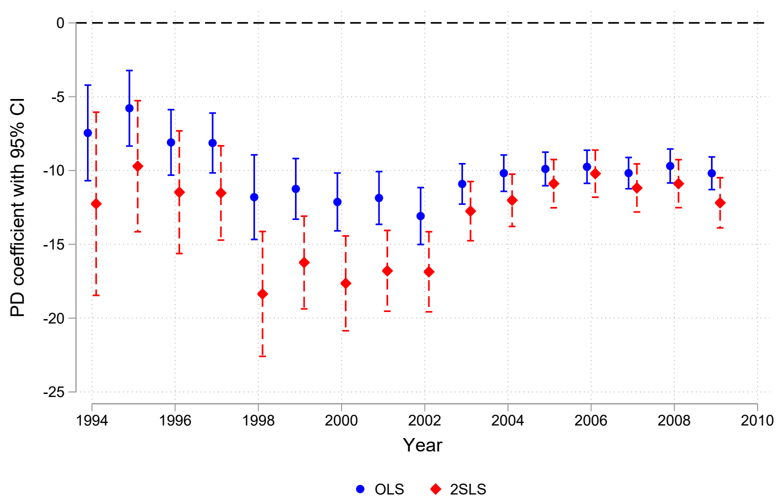


Figure B4: Marginal Initial Capital and Population Density
Source: Registration database and 1982 Population Census.

2. Accuracy and representativeness of SAIC inspection data

Table B1: 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 B2: 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%.

3. Outcomes for firms located outside the birth county

Table B3: Revenue, TFP, and Population Density: Outside the Birth County

Measurement:	Level			Z-score within sector-location-year		
Dependent variable:	log revenue	log TFP	log(exporting revenue)	log revenue	log TFP	log(exporting revenue)
	(1)	(2)	(3)	(4)	(5)	(6)
Time	0.146***	0.194***	0.131***	0.065***	0.041***	0.032**
	(0.006)	(0.018)	(0.030)	(0.002)	(0.003)	(0.015)
PD $\times$ Time	0.479***	1.918***	1.393**	0.280***	0.217**	1.342***
	(0.182)	(0.606)	(0.644)	(0.071)	(0.086)	(0.359)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	3.564	-6.187	5.537	–	–	–
Kleibergen-Paap F	96.78	96.78	33.41	96.78	96.78	33.41
Observations	1,272,673	1,272,673	26,223	1,272,673	1,272,673	26,223

Note: Revenue and TFP are obtained from the Inspection database, covering the 1998-2009 period. Export revenue is obtained from the Customs database, covering the 2002-2009 period. Population density is obtained from the 1982 Population Census.
We "instrument" for PD (birth county population density in 1982) with potential crop yields, reporting the corresponding Kleibergen-Paap F statistics.
The firm's initial capital (in logs) interacted with a time trend is included in the estimating equation.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

C. Birth County Networks

1. Trust and population density in China: The CFPS is a nationally representative, longitudinal, general social survey conducted at the individual, household, and community level that was launched in 2010, with subsequent rounds in 2012 and 2014. Different rounds of the CFPS include one-off modules; the adult individual module of the 2012 CFPS included questions on trust, which were harmonized with the World Values Survey (WVS) discussed below.

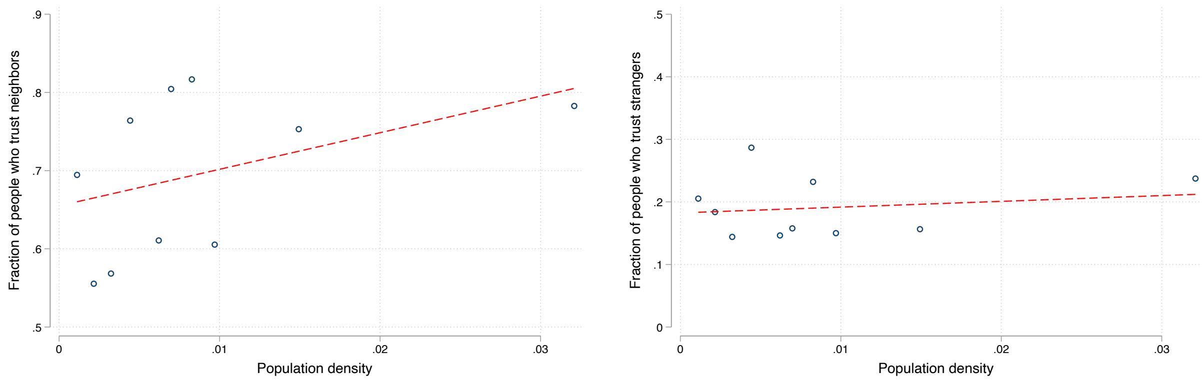
Table B4: Trust and Population Density

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 Study (2012). 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.

2. Trust and population density across the world: 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. The CFPS measures trust as an ordinal variable, taking values from 0 to 10. To construct a binary trust measure that is consistent with the WVS, we selected a cutoff, which turns out to be 5, such that trust in neighbors and strangers obtained from the CFPS matches most closely with the corresponding statistics for China from the WVS.

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) Localized trust

(b) Generalized trust

Figure B5: Trust and Population Density: Cross-Country Comparison

Source: World Values Survey and World Development Index.

3. Social interactions with neighbors and population density: The family module of the 2010 CFPS asks whether the household has had the following social interactions with neighbors in the past week: chatting, group entertainment/gatherings, visits to neighbors' homes. We construct a binary variable for each type of interaction that indicates whether it occurred.

Table B5: Interactions with Neighbors and Population Density

Repondent's location:	county			city		
Social interactions with neighbors:	chatting	group entertainment	visits to homes	chatting	group entertainment	visits to homes
	(1)	(2)	(3)	(4)	(5)	(6)
Population density	2.145**	-0.594	0.480	0.029	-0.260	-0.422**
	(0.833)	(0.510)	(0.910)	(0.224)	(0.166)	(0.167)
Mean of dependent variable	0.690	0.168	0.250	0.639	0.141	0.249
Observations	8,294	8,294	8,294	3,314	3,314	3,314

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

4. Most frequent interactions and population density: The adult individual module of the 2010 CFPS asks who the respondent chats most with: neighbors, different types of relatives; e.g. parents, spouse, etc., friends/classmates, colleagues, or others. We construct three binary variables that indicate whether the respondent lists neighbors, relatives, and friends/colleagues as their most frequent chatting partners, respectively.

Table B6: Most Frequent 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 Study (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.

5. Birth county connections and population density:

Table B7: Birth County Connections and Population Density: Shareholders

Unit of observation:	firm			network	
Dependent variable:	fraction of shareholders from the same birth county	whether firm has links in the prefecture	whether linked firms are linked to a firm from the same birth county	fraction of links that are supported	number of supporting firms conditional on support
	(1)	(2)	(3)	(4)	(5)
PD	1.711***	0.293***	1.759***	1.186***	2.310
	(0.389)	(0.094)	(0.503)	(0.199)	(1.459)
Mean of dependent variable	0.476	0.248	0.436	0.174	1.382
Counter-factual PD	0.062	–	0.059	–	–
Counter-factual mean	0.012	–	0.013	–	–
Observations	1,435,015	1,435,015	355,826	1,581	1,035

Note: the sample is restricted to firms established outside their birth counties and active in 2009.
The counter-factual mean is based on the random assignment of shareholders and the random matching of linked firms in the prefectures where they are located.
The birth county of the principal and other shareholders is obtained from the SAIC registration database and birth county population density (PD) is derived from the 1982 Population Census.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Appendix C: The Model

A. 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:

$$\log\zeta > \frac{1}{1-\alpha}[q_{dT} + \theta_d(\overline{p})\log T] + a \tag{15}$$

$$\log\gamma > \frac{(\delta-1)\log\zeta}{1-\sigma} - \frac{(\delta-\sigma)q_{d1}}{(1-\sigma)(1-\alpha)} + \frac{1}{1-\alpha}[q_{dT} + \theta_e(\overline{p})\log T] \tag{16}$$

$$\log\beta > \frac{\log\gamma}{\delta-1} - \log\zeta + \frac{\delta}{(\delta-1)(1-\alpha)}[q_{dT} + \theta_d(\overline{p})\log T] - \frac{q_{e1}}{(\delta-1)(1-\alpha)} \tag{17}$$

$$a + \mu > \log\beta + \log\zeta - \frac{q_{d1}}{1-\alpha} \tag{18}$$

Proof of Proposition 1

To prove the Proposition, we show that ability thresholds are interior and ordered, as in (6), given the parameter restrictions (15-18).

We begin by showing that $\log\omega^*_{dt} > a$ if (15) is satisfied. From (5):

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

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 (15) 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 (16) is satisfied. From (5):

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

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 (16) is a sufficient condition for the preceding inequality to be satisfied.

A similar bounding argument shows that (17) implies $\omega^*_{mt} > \omega^*_{et'}$ for any $t \geq t'$, and that (18) implies $a + \mu > \max\{\omega^*_{mt}, \omega^*_{dt}\}$ for all p, t.

Condition (15) 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 (16) 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 (17) 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, (18) requires ability to be sufficiently dispersed to ensure a positive mass of mixed exporters in every cohort.

B. Marginal initial capital is decreasing in birth county population density

As observed in Appendix Figure B4, marginal initial capital, K^*_{dt}, is decreasing in p. To show that this is consistent with the model, set $\Pi_{Tt}(\omega^*_{dt}) = \Pi_{Dt}(\omega^*_{dt})$ and solve for ω^*_{dt} from (5):

$$\log \omega^*_{dt} = \frac{\log \zeta}{1-\sigma} - \frac{\log C_{dt}}{(1-\sigma)(1-\alpha)}. \tag{19}$$

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.

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 (19), it follows that

$$\log K^*_{dt} = \frac{1}{1-\alpha} \log\left(\frac{\alpha}{r}\right) + \log \zeta + \sigma \log \omega^*_{dt}. \tag{20}$$

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

Appendix D: Instrumental Variable Construction and Validation

A. 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 D1: 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%.

B. Validating the Shift-share Instruments:

Table D2: Revenue, TFP and Network Size: 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)
$\log n_{jk,t-1}$	0.286***	0.192***	0.188***	0.216***	0.120***	0.143
	(0.006)	(0.007)	(0.044)	(0.031)	(0.032)	(0.140)
$p_j \times \log n_{jk,t-1}$	1.188***	0.663***	2.133***	2.800***	1.580**	4.098*
	(0.172)	(0.160)	(0.779)	(0.699)	(0.723)	(2.281)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	25.14	25.14	11.80
Observations	1,270,632	1,270,632	22,714	1,270,632	1,270,632	22,714

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.
The firm's initial capital interacted with a time trend is included in the estimating equation.
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%.

Table D3: Revenue, TFP and Network Size: 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)
$\log n_{jk,t-1}$	0.258***	0.157***	0.276***	0.119***	0.013	0.184**
	(0.007)	(0.006)	(0.027)	(0.024)	(0.022)	(0.082)
$p_j \times \log n_{jk,t-1}$	1.736***	1.106***	1.226***	4.544***	3.491***	2.377*
	(0.185)	(0.159)	(0.426)	(0.590)	(0.558)	(1.382)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	25.48	25.48	11.78
Observations	2,091,979	2,091,979	66,777	2,091,979	2,091,979	66,777

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.
The firm's initial capital interacted with a time trend is included in the estimating equation.
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%.

C. Alternative Construction of the Propensity Variable

Table D4: 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 4-6).
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%.

D. Validating the Propensity Equation Estimates

1. 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 D5, Columns 1 and 3. To explain the (sizeable) difference between these OLS estimates and the corresponding IV estimates in Table 7, we proceed to simulate the model. The simulation exercise is based on the assumption that the (first-differenced) propensity equations are correctly specified, 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 in the entrepreneurial propensity and export propensity equations can be characterized by AR1 processes, with reasonably sized autoregressive coefficients (see Appendix Table D5). We draw 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 D5, Columns 2 and 4 where we see that the point estimates are now similar in magnitude to the IV estimates in Table 7.

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. 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 D5). 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 D5: 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 7, 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%.

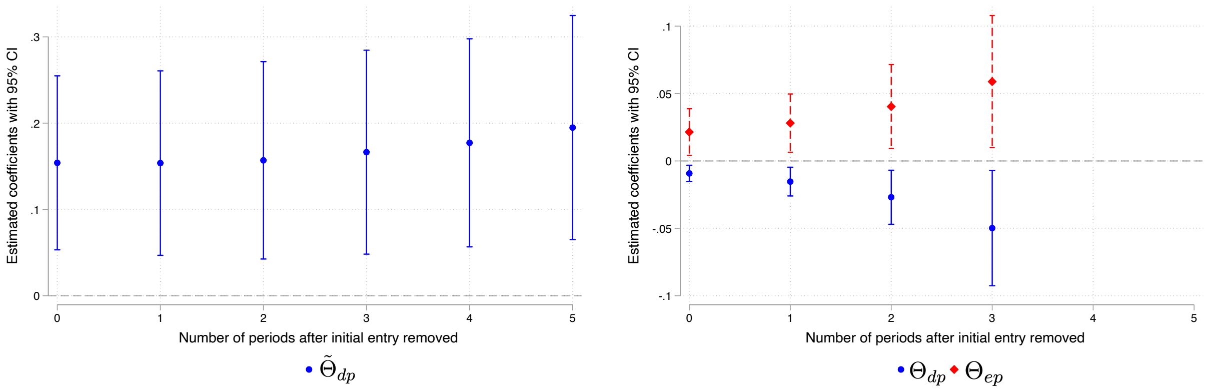
2. Alternative construction of instrumental variables

Table D6: 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. Testing the exogeneity of initial entry



(a) Entrepreneurial Propensity Estimation

(b) Export Propensity Estimation

Figure D1: Testing the Exogeneity of Initial Entry

Source: The coefficients are estimated using the same equation as in Table 7, sequentially removing time periods in each network.