Community Networks, Entrepreneurship and the Process of Economic Development*

Ruochen Dai[†] Dilip Mookherjee[‡] Kaivan Munshi[§] Xiaobo Zhang[¶]

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Abstract

This paper examines the determinants of entrepreneurship in China's transition from agriculture to domestic production in the 1990's and the subsequent transition to exporting in the 2000's. The model that we develop and test to describe these transitions incorporates a productivity enhancing role for community (birth county) networks, which emerge in response to weak market institutions at early stages of economic development. Using administrative data covering the universe of registered firms over the 1994-2012 period and the universe of exporters over the 2002-2012 period, we provide causal evidence that these networks of firms were active and effective in increasing the revenues of their members, both in domestic production and exporting. While this substantially increased entry into domestic production in the first transition, the incumbent domestic networks created a disincentive to enter exporting in the second transition that outweighed the direct positive effect of the export networks. Our analysis provides a novel characterization of the development process in which community-based networks emerge at each stage to support the economic activities of their members, and pre-existing networks slow down the growth of networks (drawn from the same population) that follow.

Keywords. Business networks. Agglomeration. Entrepreneurship. Occupational mobility. Structural transformation. Economic history.

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[†]Central University of Finance and Economics r.dai@cufe.edu.cn

[‡]Boston University dilipm@bu.edu

[§]Yale University and Toulouse School of Economics kaivan.munshi@yale.edu

[¶]Peking University and IFPRI x.zhang@gsm.pku.edu.cn

1 Introduction

The process of economic development is often characterized by an initial transition from agriculture to domestic production, followed by a second transition to higher value exporting. It is well known that entrepreneurs play a critical role in this process by setting up firms. The conventional individual-specific view of entrepreneurship is that it is determined by talent (Murphy, Shleifer and Vishny, 1991), education (Levine and Rubinstein, 2017) and inherited wealth when credit is constrained (Banerjee and Newman, 1993). These factors have been seen to be relevant in the initial phase of development, as well as in the subsequent shift to exporting (Melitz, 2003; Atkin and Khandelwal, 2020). Adding a new dimension to the analysis of entrepreneurship, this research documents the important role played by community networks at early stages of economic development in China. These informal institutions facilitated the entry of domestic producers in the first stage. However, their contribution turns out to be more nuanced in the second stage, as our analysis indicates that the incumbent domestic networks created a disincentive to enter exporting that more than offset the positive direct effect of newly emerging export networks.

Over the past decades, the Chinese economy has grown at an unprecedented rate (Zhu, 2012). Its transition out of agriculture commenced in the early 1980's with the establishment of township-village enterprises (TVE's) and then accelerated with market reforms and the entry of private firms in the 1990's. Starting with almost no private firms in 1990, there were 10 million registered private firms in 2012, accounting for 94 percent of all registered firms.[1] Past studies have focused on the increase in agricultural productivity and the reallocation of resources across sectors, especially from the state sector to the non-state (private) sector, to explain China's rapid growth (Hsieh and Klenow, 2009; Brandt and Zhu, 2010; Song, Storesletten and Zilibotti, 2011; Brandt, Van Biesebroeck and Zhang, 2012). However, this literature does not tell us how entrepreneurs without a business background were able to set up their firms, which is a prerequisite for growth, at this early stage of development when many markets were missing or incomplete. There is a common view that the government played a key role in supporting (favored) enterprises; e.g. Bai et al. (2020), but this would not explain the emergence of *millions* of private firms.

Our analysis aims to fill the preceding gap in the literature. It is based in large part on the State Administration of Industry and Commerce (SAIC) registration database, which

[1] The analysis in this paper starts in 1994, when the Chinese government reduced its commitment to support state-owned enterprises, opening the door for private firms to enter in large numbers (Zhu, 2012). It ends in 2012, when the first stage of a business registration reform commenced. The central government used firm entry as a performance indicator for local officials from that point onward and this resulted in the appearance of many shell firms in our administrative data (Barwick et al., Forthcoming).

covers the universe of registered firms in China from the 1980's onwards. In contrast, many prior analyses of Chinese firms have relied on a publicly available database of manufacturing firms, with sales above a threshold level (5 million Yuan) and over a shorter 1998-2008 period. The above-scale firms are highly selected, accounting for just seven percent of all private registered firms in 2008. An additional advantage of our administrative data is that they provide a list of key personnel in each firm, with their citizenship ID, which can be used to recover the county of birth. Among these individuals, we designate the firm's principal (legal representative) as the "entrepreneur" for the purpose of our analysis. Based on this classification, firms established by individuals born in rural counties constituted 55 percent of all registered firms in 2012, with these firms (which are usually established outside the birth county) accounting for a comparable share of total registered capital.[2] There were approximately 2000 rural counties in China when market reforms commenced, accounting for 74 percent of its population. The rural-born entrepreneurs, who will typically lack the conventional individual-specific ingredients for business success listed above, are thus an important group to study from both a growth and a distributional perspective. The central thesis of our research is that informal business networks organized around the hometown (birth county) played an instrumental role in supporting the entry of these entrepreneurs into business, at a critical (initial) stage in China's economic development.

The idea that business networks are active and that networks are organized around the birth county in China is not new. Previous research has argued that informal arrangements, providing different forms of support to their members, must have been at work in an economy that was 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 home town (Honig, 1992, 1996; Goodman, 1995).

Building on this past work, we posit that birth county networks allow firms to cooperate, out-source production, and share inputs by harnessing pre-existing social ties. Credit constrained entrepreneurs can out-source different components of their production to firms from their hometown, who are operating in the same production cluster, without substantially sacrificing quality (Long and Zhang, 2011). The additional advantage of the network is that it can expand the scope of relational contracts, which are established in developing economies

[2]The analysis in this paper excludes birth counties with less than one thousand registered firms over all time periods. These counties account for 0.7 percent of all firms in the SAIC registration database. Among the county-born entrepreneurs that are retained for our analysis, 39 percent established their firm in their birth county, 15 percent in their birth prefecture but outside the birth county, 15 percent in their birth province but outside the birth prefecture, and 31 percent outside their birth province.

when formal contracts are difficult to enforce (McMillan and Woodruff, 1999; Macchiavello and Morjaria, 2015, 2021). A firm in a long-term relationship with a buyer or supplier from another community can provide a (credible) referral for another firm in its network who only requires that connection temporarily (Greif, 1993; Munshi, 2011). Although the mutual help that we have described is not observed, we can construct measures of firm performance and network size. Our causal estimates indicate that birth county networks substantially increased the productivity and the revenues of their members, accompanied by increased firm entry into domestic production.

While the discussion thus far paints the birth county networks in an entirely positive light, their role in the next stage of the development process turns out to be more complex. A decade after market reforms commenced, China entered the WTO in 2001 and soon became the largest exporter in the world (Brandt et al., 2017). Given our interest in the transition from domestic production to higher value exporting, we focus on the more productive exporting firms who ship their products directly to foreign buyers.[3] While these firms may be less reliant on sub-contracting than domestic producers, owing to their need to maintain high product quality, they still benefit from a network that provides connections to foreign buyers, and export-specific information about new technologies and opportunities. Our analysis thus allows for the presence of a distinct export network that is restricted to export firms from the birth county. We merge the SAIC registration database with the Customs database, which provides information on all shipments out of China, to compute the number of active exporters and their export revenues at each point in time over the 2002-2012 period. As in the case of domestic production, we provide causal evidence that export networks organized around the birth county were effective in increasing the revenues of their members. However, the additional factor that becomes relevant in the second transition is that the high profitability of domestic production, owing to the domestic network, can discourage entrepreneurs from moving into the new export activity when it became available. We find that this negative domestic network "overhang" dominates the direct positive effect of the export network. Consequently the number of rural-born exporters in 2012 ends up being substantially *lower* on account of the birth county networks.

Atkin and Khandelwal (2020) list a number of barriers to entry into exporting in developing economies. Our analysis uncovers a new friction that has a first-order effect in this important transition. More generally, our unique administrative data, coupled with the compressed nature of the Chinese experience, allows us to uncover novel community-level entry

[3]There are two types of exports in China: production exports and processing exports. Production exports can be further divided into direct exports and indirect exports through intermediaries. As documented in Appendix A, direct exporters are more productive than domestic producers who, in turn, are more productive than indirect exporters and processing exporters.

dynamics that span two major stages in the process of development. Akcigit and Nicholas (2019) advocate for the use of historical micro data, theory, and empirics to study economic growth; our analysis, which we describe below, exemplifies the value of this approach.

We begin in Section 2 by specifying the domain of the network. The productivity-enhancing mutual help that members of a network provide to each other, such as connections and sub-contracting, is inherently local. We thus define the domain of the network by the birth county-destination prefecture; there are 350 prefectures in China and firms from a given birth county will typically locate in multiple destinations. Most of the firms in a birth county-destination prefecture operate in the same or related industries and, hence, we allow for inter-industry spillovers by including all firms in the network. We assume that the mutual help provided by the members of a network is complementary. Hence, firms will benefit from a larger network size, measured by the number of firms from the birth county operating in the same destination prefecture.

The role of the network, as we have described it, matches the conventional characterization of inter-firm spillovers in the agglomeration literature (Combes et al., 2012; Duranton and Puga, 2020; Rosenthal and Strange, 2020). The key difference is that all firms in a prefecture benefit equally from the agglomeration effects, whereas the network effects are restricted to firms from a given birth county. Pre-existing social ties and accompanying social enforcement allow for higher levels of cooperation within the network, which is needed at early stages of economic development to substitute for missing markets. Since firms from many origins co-exist in a prefecture, we will control for agglomeration effects by including prefecture-time effects in the estimating equations. The network effects that we estimate, based on the number of firms from a given birth county in that prefecture, will thus supplement the agglomeration effects.

Section 3 develops a dynamic model of occupational choice that adds a network component and a trade component to the Roy (1951) model. The tension between the domestic network and the export network is an important feature of this model. Successive cohorts of agents choose between a traditional occupation (agriculture or wage labor) and becoming an entrepreneur, serving either the domestic market, the export market, or both. Individual abilities (representing education, wealth, and innate talent) are drawn from an i.i.d. distribution. Placing standard restrictions on the production technology, the returns to ability increase more steeply in business than in the traditional occupation. Consequently, there is an ability threshold above which individuals switch from the traditional occupation to business. In the Melitz (2003) model, there is a higher ability threshold above which domestic producers add an export plant. Our model departs from the Melitz model in a number of ways, one of which is the existence of a scope diseconomy between domestic production and exporting; i.e. a fixed cost of operating both a domestic plant and an export plant. Consequently, there are three ability thresholds in our model: a lower threshold for entry into domestic production, an intermediate threshold for entry into "pure" exporting, and a higher threshold for selection into "mixed" exporting (operating both export and domestic plants). As discussed below, pure exporters are key to the domestic network overhang that dampens entry into exporting, and we observe these exporters in the Chinese data.[4]

An additional feature of our model that distinguishes it from the Melitz model is the presence of birth county networks that boost the productivity of their members, separately in domestic production and exporting. Besides the size of the relevant network, which determines the (mutual) benefit that its members derive, each firm's profits depend on the entrepreneur's ability, and an exogenous market-time effect that incorporates conventional agglomeration effects, product demand, and government support. An increase in domestic network size will increase the profits of domestic producers, shift down the (lower) business entry threshold, and thus increase the propensity of individuals from the birth county to select into business. An increase in the size of the export network will similarly have a positive effect on the export propensity. However, there is a countervailing effect on the export propensity on account of the domestic network. In particular, a larger domestic network increases the profitability of serving the domestic market relative to the export market, which reduces the incentive to enter exporting. This (domestic) network overhang arises because the marginal exporter is a pure exporter who must choose between domestic production and exporting. If this overhang dominates the positive effect of the export network, then the net effect of the networks will be to *reduce* the number of exporters.

We begin the empirical analysis in Section 4 by estimating the relationship between firm performance – revenue or productivity – and the size of the network, measured by the (lagged) stock of firms from the birth county that are established in the prefecture. Domestic performance is measured with data from the SAIC inspection database, which provides revenues and assets for a subset of registered firms over time. Export performance is derived from the Customs database, which provides shipments (by value) for all exporting firms over time. The relevant network sizes can be constructed from the SAIC registration database, which provides information on the location and birth county of all firms, and the Customs database, which includes all exporters and can be merged with the registration database.

Based on the model, firm performance is determined by the entrepreneur's ability and exogenous market-time effects, in addition to the network effects. We account for the former

[4] The presence of pure exporters is not restricted to China and has recently been documented in many developing countries (Lu, Lu and Tao, 2014; de Astarloa et al., 2015; Blum et al., 2020).

by including firm fixed effects and destination-time period effects in the estimating equations. While these covariates account for fixed characteristics and all factors that affect firms in a prefecture equally, regardless of their origin, they do not control for unobserved birth county-destination prefecture shocks. For example, entrepreneurs from a birth county could have preferred access to government connections in a particular prefecture that is evolving over time or could be concentrated in a sector that was growing relatively fast. The resulting increase in productivity and revenues will *pull* firms into that prefecture, with an accompanying increase in network size. The estimated network effects will be evidently biased. We address this possibility by constructing statistical instruments for the *growth* in network size (which becomes the endogenous variable when we first-difference the estimating equation).

The first instrument that we construct for the growth in network size takes advantage of the fact that the birth counties are rural. Agriculture was the dominant activity in these counties as recently as the 1982 population census, with 68 percent of the workforce employed in that sector. Although this statistic declines to 37 percent in the 2000 census, agriculture continues to be a major sector. We thus construct a shift-share instrument for network size, following Imbert et al. (2022), that is based on agricultural income shocks in the birth county that *push* individuals into business. These income shocks are constructed as a weighted average of world crop-price shocks, where the weights reflect the contribution of each crop to birth county agricultural production, as well as a distance adjustment term that distributes the resulting flow of firms across destination prefectures. We draw on the recent literature, particularly Goldsmith-Pinkham, Sorkin and Swift (2020), to implement a series of tests that verify the exogeneity of each component of the shift-share instrument.

Our second instrument is based on the observation that the prototypical birth county-destination prefecture network starts with a single entrant, followed by an exponential increase in the stock of firms over time.[5] If initial entry is restricted to a single individual or small group of individuals, consistent with previous descriptions of accidental business network formation; e.g. Damodaran (2008); Munshi (2011); Kerr and Mandorff (2023), then the time of commencement of the network can be treated as exogenous from the perspective of the birth county as a whole. If subsequent entry is generated by a network multiplier effect, as in our model, then network duration will predict the growth in network size at any point in time and will be a valid instrument. Domestic (export) network duration is a strong predictor of the growth in relevant network size in our data. In addition, *domestic* network duration predicts the growth in *export* network size, with a reversal in sign, as implied by the

[5]We assume that a network has commenced if we observe at least one firm from the birth county in a prefecture for at least three years. The SAIC data provide the registration year and location of each firm. We thus observe the precise time of commencement and the number of initial entrants for each of the 140,000 domestic networks and 7,800 export networks in our data.

domestic network overhang. This instrument is particularly credible because the domestic network typically commences many years before the export network in a prefecture and can thus be plausibly treated as predetermined. Further support for the validity of the duration instruments is provided in Section 4.

Our OLS and 2SLS estimates indicate that firm revenues and productivity are increasing in network size, for both domestic production and exporting. These estimates provide causal evidence of the productivity enhancing effect of birth county networks. Since we use multiple instruments, the benchmark estimating equations are over-identified. Independent estimates of the network effects with each instrument separately turn out to have similar magnitudes, increasing our confidence in their validity. Additional robustness tests, reported in Section 4, verify our definition of the network's domain: (i) it consists of firms from a given birth county operating in a particular prefecture, (ii) the domestic network includes all firms, while the export network consists of exporting firms, and (iii) firms from all industries are included in the network to allow for inter-industry spillovers.

While our analysis focuses on business networks, it complements a well established literature that estimates the effect of exogenous changes in network size on labor market outcomes; e.g. Munshi (2003); Beaman (2012); Tang (2024), with the latter paper focusing on the same Chinese hometown networks. While there is an extant literature on ethnic (migrant) business networks in economics, this literature has largely focused on providing descriptive evidence that these networks are active; e.g. Fafchamps (2000); Rauch (2001); Munshi (2011); Kerr and Mandorff (2023). Our analysis is the first to provide causal evidence that networks of firms improve the outcomes of their members. The additional virtue of our analysis is that it covers both domestic production and exporting, and is based on the universe of (registered) firms in a major developing economy.

We complete the analysis in Section 5 by quantifying the effect of the networks on firm entry in two steps: (i) We estimate the effect of the networks on firm entry, using the same instruments as above, where relevant. This exercise allows us to identify the direct positive effect of the domestic and export networks on the entry of domestic producers and exporters, respectively. It also allows us to identify the negative (overhang) effect of the domestic network on entry into exporting. (ii) We decompose the determinants of firm entry, which consist of an exogenous component, comprising the destination-time period effects and all other unobserved factors, and an endogenous network component. We find that both components contribute approximately equally to the entry of firms into domestic production. In contrast, the positive contribution of the exogenous component and the export network to the entry of export firms is completely offset by the domestic network overhang. As a result, the rate of entry of export firms is roughly constant over time.

The findings in this paper speak to two influential literatures in economics: First, a large body of research, starting with Acemoglu, Johnson and Robinson (2001) points to the long shadow of historical (pre-modern) institutions on the functioning of contemporary legal and political systems, which are seen to be essential for economic growth. As some critics have noted, this view does not adequately explain the remarkable Chinese growth experience since the 1990's, which occurred without secure property rights, rule of law, and protection against government power. Our analysis fills in the missing piece by showing that informal networks that emerge at early stages of economic development can facilitate firm formation and growth in the absence of these formal institutions. Second, a voluminous literature, going back to Galor and Zeira (1993) and Banerjee and Newman (1993), studies how market imperfections constrain occupational mobility in developing economies, resulting in the persistence of inequality. Our analysis indicates that community-based networks can break these occupational traps. At the same time, we find that the domestic networks which support occupational mobility at an initial stage of the development process are restricting further upward mobility at a later stage.

Our model also sheds light on the inefficiencies and the welfare consequences of interventionist policies. As discussed in the concluding section, there is potentially a welfare enhancing role for entry and export subsidies, since self-interested entrepreneurs do not internalize their contribution to the networks. Export subsidies are unambiguously efficiency enhancing, since there is suboptimal entry into that activity. However, the efficiency effects of entry subsidies are more complex, owing to conflicting positive externalities on domestic producers and negative externalities on exporters (due to the domestic network overhang). Evaluating the net effect will require additional research, which we leave for future work.

2 Birth County Networks

2.1 Network Domain

We noted in the introductory section that ethnicity in China is defined by the home town, 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).[6] Chambers of commerce that bring entrepreneurs from the same origin together (*yidi shanghui*) are also commonly found in Chinese cities. At the same time, the help provided by firms to each other, such as connections

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

and information, is inherently local. We thus define the scope of the network by the birth county-destination prefecture in our analysis. Each prefecture consists of an urban center and eight counties on average, and there are approximately 350 prefectures in China. Many government infrastructure and investment initiatives are organized at this administrative level, and buyer and sellers tend to locate in prefecture-level cities, so the birth county-destination prefecture would appear to be the appropriate spatial domain for the networks that we study.

While domestic producers and exporters may manufacture the same goods, the production process and output quality are not the same. As described in Appendix A, 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). 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). As documented in Appendix A, these firms are even less productive than domestic producers. Given our interest in the transition to higher value exporting, we thus define "exporting" in our analysis as *direct product exporting*.

Based on the preceding definition, there were 35 thousand rural-born exporters in 2012 (the end point of our analysis), accounting for 30 percent of such firms at that time. While this may seem like a small number, the direct exporters accounted for 71 percent of total exports (by value) in that year. As documented in Appendix A, (direct) export firms have a higher capital intensity of production than domestic producers, and ship a relatively large share of their product to OECD countries, where the demand for quality and prices are high. Although our administrative data do not report how production is organized, we expect that these exporters are more vertically integrated and less reliant on out-sourcing than domestic producers. Nevertheless, they will continue to benefit from connections to foreign buyers, as well as information about new technologies and business opportunities. Since this help is export-specific, we assume that the export network is restricted to firms engaged in that activity. In contrast the domestic network includes all firms from the birth county who are established in the prefecture.

The preceding definition of the networks distinguishes between activities – domestic production versus exporting – but not between sectors within these activities. As seen in Table 1, Panel A, Column 1, 65 percent of the firms in a given birth county-destination prefecture-time period operate in a single most popular 3-digit Input-Output industry. An additional

18 percent are set up in related upstream-downstream and complementary industries.[7] The preceding statistics are derived from the SAIC registration database, and we can construct corresponding statistics for the export network by combining the SAIC data with the Customs database. As seen in Table 1, Panel A, Column 2, the corresponding statistics for the export network are 74 percent and 10 percent. It follows that most firms from a birth county in a given prefecture at a given point in time were operating in the same or related industries. We allow for spillovers across these industries, and for common factors such as access to credit, by ignoring sectors when constructing the networks in our analysis. Further empirical support for our definition of the domestic and export networks is provided in Section 4.4.

Table 1: Characteristics of Networks

	Domestic network	Export network
	(1)	(2)
Panel A: industry composition within birth county-destination prefecture-time periods		
Percent of firms in the most popular industry	64.5	73.6
Percent firms in related industries	17.8	9.6
Panel B: evolution of birth county-destination prefecture networks over time		
Total number of networks	141,060	7,874
Percent of networks that are multi-firm	71.6	40.7
Percent of firms in multi-firm networks	99.3	90.7
Percent of multi-firm networks that start with one firm	84.8	78.5

Note: statistics are computed using SAIC registration data and Customs data.
The network is defined at the birth county - destination prefecture level and is assumed to commence if we observe at least one firm for at least three years.
Networks that start with a single firm and stay that way are retained in the sample.
The domestic network includes all firms in the birth county-destination prefecture and the export network is restricted to export firms.
The most popular industry is defined as the 3-digit IO code that has the largest share of firms, for a given birth county-destination prefecture-time period.
Related industries are upstream-downstream or share complementary inputs-outputs with the most popular industry, as in Fan and Lang (2000).

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

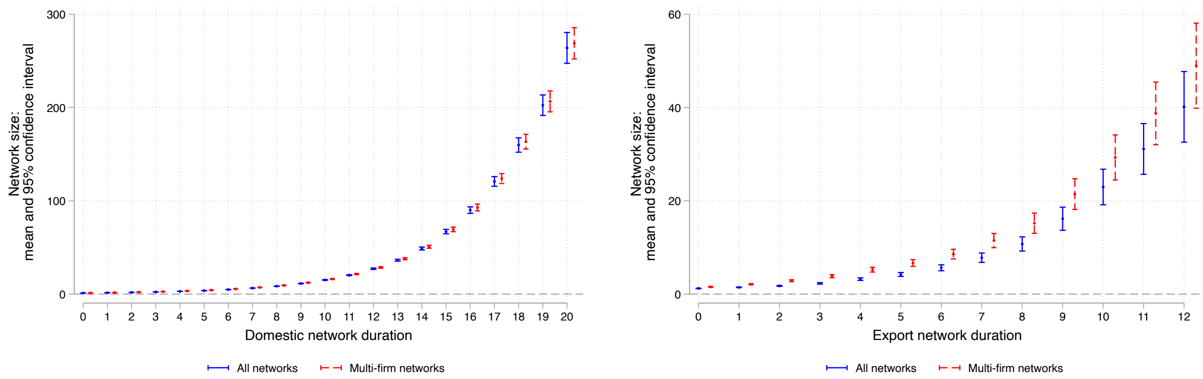
2.2 Network Trajectories

Recall that we define networks at the birth county-destination prefecture level. We assume that a given network has commenced if we observe at least one firm from the birth county in the destination prefecture for three consecutive years.[8] The SAIC data, which extend back to the 1980's, provide the registration year and the location of each firm. We can thus observe the precise point in time at which each network commenced. As seen in Table 1, Panel B there are 140,000 domestic networks and 7,800 export networks in our data. Some of these networks would have started with a single firm and stayed that way. While the term "network" may be somewhat of a misnomer in this case, we retain these singleton networks in the estimation sample to avoid selection bias. Our primary interest, however, is in the multi-firm networks and, as can be seen in the table, most firms belong to such networks. Moreover, most of those networks commenced with a single firm.

Our interpretation of the preceding statistics is that the prototypical firm belongs to a multi-firm network that starts with a single firm. This pioneering entrepreneur presumably receives a fortuitous opportunity in a particular location (prefecture). Once the pioneer's firm is set up, other entrepreneurs from the birth county follow and the network grows in size over time. Figure 1 provides graphical support for the preceding characterization of the network's evolution by plotting network size against network duration (time after commencement). The vertical lines in the figure measure the dispersion in network size (the 95 percent confidence interval) and their midpoints denote the mean. As can be seen, the mean and the dispersion in network size are increasing at an increasing rate with duration, both for domestic and for export networks. The average number of initial entrants is 1.14 for domestic networks and 1.2 for export networks. The dispersion in the number of initial entrants is extremely small, despite the fact that networks commence at very different points in time, which is consistent with our characterization of network formation. The subsequent nonlinear increase in (mean) network size is consistent with a network multiplier effect, which is a key feature of the model that follows in Section 3. Notice that the trajectories for all networks and for multi-firm networks match closely in the figure. We will use network duration to predict the growth in network size when estimating network effects in Sections 4 and 5. While we estimate this relationship for all networks, it is driven by the multi-firm networks.

There were approximately 5 million registered firms and 35 thousand (direct) exporting

[8]When we test for network effects below, we will include the lagged stock of firms from the birth county who are active in the prefecture in the estimating equation. We will first-difference that equation to purge fixed effects, which adds a second lag. To include a birth county-destination prefecture when estimating network effects, at least one firm must therefore be present for three consecutive years.



(a) Domestic Network (b) Export Network

Source: Registration data and Customs data.
Duration is measured by the time (in years) after the network's commencement.
Network size is measured by the number of firms from the birth county in the destination prefecture.

Figure 1: The Trajectory of the Network

firms, drawn from rural origins, in 2012. The enormous difference in the total number of firms does not imply, however, that there is no tension between the domestic and export networks. As seen in Figure 1, average domestic network size is 260, 20 years after commencement. The corresponding statistic for export networks, 12 years after commencement, is 40. In those birth county-destination prefectures where both types of networks co-exist, export firms make up a non-negligible share of all firms.

2.3 Birth County Ties

As documented above, most entrepreneurs belong to multi-firm networks; i.e. there are multiple firms from the birth county in the prefectures where they are located. Restricting attention to such entrepreneurs, who were (in addition) active in 2012, we find that 66 percent of the domestic producers and 46 percent of the exporters were located outside their birth county. As many of these entrepreneurs would have moved a long time ago, a natural question to ask is whether they remain connected to their natal community in some important way.

Table 2 provides descriptive support for the importance of birth county ties for entrepreneurs who are (i) located outside their natal county, (ii) belong to multi-firm networks, and (iii) were active in 2012, the end point of our analysis. In addition to the entrepreneur (legal representative), the SAIC registration database also lists other key personnel in the firm.[9] Columns 1-2 report the fraction of these individuals who are born in the same county

[9]The legal representative, who has the authority to enter into binding obligations on behalf of the company, typically functions as the firm's president, chairman or proprietor. Other listed individuals include directors,

as the legal representative, as well as the counter-factual fraction that is constructed by randomly assigning listed individuals (other than the legal representative) across firms in the prefecture. Focusing on the domestic producers in Column 1, we see that close to half of the listed individuals are born in the same county as the legal representative, which is 50 times more than what would be obtained by random assignment. Qualitatively similar results are obtained in Column 2 with export firms, except that the gap between the observed and counter-factual statistics is not quite as large.

Table 2, Columns 3-4 assess the strength of the birth county ties in a different way, by examining the links between firms in the prefecture. While networks largely rely on informal interactions between socially connected firms, formal links can also be used to complement these interactions and increase cooperation. We denote two firms (located in the same prefecture) as being "linked" if the same individual is listed in both of them. Based on this definition, we see that 50 percent of linked domestic firms are linked to firms from the same birth county. Once again, this is approximately 50 times more than what would be obtained if firms with links were randomly matched in the prefecture. Column 4 reports the corresponding statistics for export firms with qualitatively similar (albeit weaker) results.

Table 2: Birth County Ties

Variable:	fraction of key personnel from the entrepreneur's birth county		fraction of linked firms that are linked to a firm from the same birth county	
Network:	domestic network	export network	domestic network	export network
	(1)	(2)	(3)	(4)
Observed mean	0.487	0.543	0.512	0.787
Counter-factual mean	0.012	0.026	0.014	0.223

Note: statistics are computed using SAIC registration data and Customs data.
The sample is restricted to firms established outside their birth counties that belong to multi-firm networks and were active in 2012.
The legal representative is denoted as the "entrepreneur" in our analysis.
Linked firms have at least one key person in common.
The counter-factual mean is based on the random assignment of key personnel and the random matching of linked firms in the prefectures where they are located.

The evidence presented in Table 2 indicates that entrepreneurs remain connected to their birth county, even when their firms are established elsewhere. Moreover, their firms are disproportionately linked to firms from the same birth county in the prefectures where they are located. We expect the birth county homophily we have uncovered to extend to informal interactions between firms, which, in turn, will further support mutual help and

senior managers, and external "supervisors." Firms with a single listed individual, who will necessarily be the legal representative, are excluded from the analysis in this section.

cooperation. The model of entrepreneurship (occupational choice) that follows will thus incorporate a productivity enhancing role for birth county networks.

3 The Model

3.1 Population and Technology

Since networks are organized at the level of the origin county-destination prefecture, and the dynamics we are interested in occur at this level, the analytical model that we present in this section is based on a single (rural) birth county and a single destination prefecture where businesses are established. When we estimate the model in the section that follows, it will be extended to allow for multiple origins and destinations.

Successive cohorts of agents, indexed by $t' = 1, \ldots, T$ are born in the county. All agents continue to live until the terminal date T. The aggregate measure of agents in each cohort is s and the ability ω of each agent in the cohort is drawn from an i.i.d. log uniform distribution: $\log \omega$ is uniformly distributed on $[A-1, A]$.[10] Cohort t' agents who enter the workforce in period t' choose occupations at each date $t \geq t'$.

There are two possible occupations: a traditional occupation and entrepreneurship. An agent of ability ω earns a stationary payoff ω^σ in the traditional occupation at each date, where $\sigma \in (0, 1)$. If he chooses to become an entrepreneur, he can produce either for the domestic (d) market or the export (e) market, or both. Serving a market $b \in \{d, e\}$ requires investing in a plant specific to that market, with capital size K_{bt} 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 b once he invests in it. The capital irreversibility constraint is $K_{bt} \geq K_{b,t-1}$ for all t.[11]

A plant of size K_{bt} 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 multiplier C_{bt}, which is comprised of an

[10]The parameter A, which represents mean ability, can vary across different origins. It will be subsumed in origin or firm fixed effects in the empirical analysis.

[11]The irreversibility assumption is reasonable in the context of a rapidly growing economy at early stages of economic development. Although there is no exit in our model, all of the results that follow would be retained if we allowed for a uniform and exogenous death rate. The empirical analysis in this paper is thus based on the stock of *surviving* firms.

exogenous market-time effect Q_{bt}, and an endogenously determined birth county-destination prefecture network effect:

$$C_{dt} = Q_{dt} \cdot [n_{t-1}]^{\theta_d}, C_{et} = Q_{et} \cdot [n_{e,t-1}]^{\theta_e} \tag{2}$$

where n_{t-1} measures the stock of firms originating from the birth county and located in the prefecture in period $t-1$, and $n_{e,t-1}$ measures the corresponding stock of export firms. Parameters θ_d, θ_e denote elasticities of TFP with respect to network size for domestic producers and exporters, respectively. The implicit assumption in this formulation is that help at any date is provided to network members by experienced incumbents who have been operating for at least one period already. As discussed in the preceding section, our definition of the network's domain is based on the assumption that spillovers are restricted to firms from the birth county who are operating in a particular prefecture, and that the domestic network includes all firms, whereas the export network is restricted to export firms.[12]

The market-time effect Q_{bt} incorporates conventional agglomeration effects and other exogenous business opportunities associated with product demand, government support, and infrastructure that apply equally to firms from the different origins that are active in the prefecture. This term is increasing over time: $Q_{bt} \geq Q_{b,t-1}$ for each $b = d, e$ and t, which is plausible in the context of China during the period we study. Based on the SAIC data, firms from a given birth county account for only 0.3 percent of firms in the prefectures where they locate, on average. The corresponding statistic for export firms is 4.3 percent. These statistics are based on all entrepreneurs, including those who locate their firms in their county of birth. It is thus reasonable to assume that individual networks do not have market power in the prefectures where they are established and, hence, that Q_{bt} is exogenous.

Capital costs for domestic and export plants are as follows:

$$E_{dt} = rK_{dt}, E_{et} = r(1+I)K_{et} \tag{3}$$

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.[13] An important additional feature of the model is the presence of diseconomies of scope, incurred by *mixed exporters* who produce for both

[12] The analytical results extend to a more general specification where the domestic network is defined as the number of incumbents serving the domestic market, and TFP spillovers for either category of firms depend on the sizes of both networks, provided that the own-network spillovers are stronger than the across-network spillovers. The empirical analysis verifies the more restricted specification (see Table 8).

[13] We could add a labor input to the production function, without changing the results that follow, as long as all firms face a common wage. We omit this factor of production because it is not observed in our administrative data.

the domestic and the export market. This diseconomy of scope, which could be reformulated as a managerial technology with diminishing returns to "span of control," as in Lucas (1978), is represented by a fixed cost β in addition to plant costs (3). Hence, the total cost of a mixed exporter equals $E_{dt} + E_{et} + \beta$. This will result in the presence of *pure exporters*, who specialize in that activity.[14]

Given the irreversibility of market entry decisions, network sizes cannot shrink: $n_t \geq n_{t-1}$, $n_{et} \geq n_{e,t-1}$. With regard to initial conditions, we make the simplifying assumption that opportunities to enter the domestic and export market both exist at the initial date $t = 1$, with an exogenous number of incumbents in each sector (n_0 firms, n_{e0} of whom are exporters) at date 0. Later we shall discuss the consequences of exporting opportunities starting at same later date $\hat{t} > 1$, so that agents only have the option to enter the domestic market between dates 1 and $\hat{t} - 1$.

3.2 Occupational Choice in Equilibrium

To simplify the exposition, we assume that agents are myopic and that network sizes at past dates are observable by all agents. As shown in Appendix B.2, the results that follow extend to the case where agents are forward looking but discount future profits at a high enough rate. Consider date t, with given productivity multiplier $C_{bt}, b \in \{d, e\}$. An entrepreneur of ability ω who was active in previous periods inherits plant sizes $K_{b,t-1}$ and selects current plant sizes $K_{bt}, b \in \{d, e\}$ to maximize

$$[C_{dt}\omega^{1-\alpha}K_{dt}^{\alpha} - rK_{dt}] + [C_{et}\omega^{\delta(1-\alpha)}K_{et}^{\alpha} - r(1+I)K_{et}] - \beta\mathbb{I}(K_{dt}K_{et}) \tag{4}$$

subject to the irreversibility constraints

$$K_{bt} \geq K_{b,t-1}, b \in \{d, e\} \tag{5}$$

where C_{bt} is given by (2), $\mathbb{I}(x)$ denotes an indicator function which takes the value 1 if $x > 0$ and 0 otherwise, and past plant size is set equal to zero for any entrepreneur that has not entered the corresponding market previously.

Recall that market-time effects, Q_{bt}, are assumed to be increasing over time and that network sizes are non-decreasing. This implies that the productivity multiplier $C_{bt}, b \in \{d, e\}$, is increasing over time and, hence, that optimal plant sizes must increase over time for incumbents. It follows that the irreversibility constraint is non-binding. Maximizing

[14] Lu, Lu and Tao (2014) also use differences in fixed costs to motivate the coexistence of domestic producers, pure exporters, and mixed exporters.

profit, as expressed in equation (4), with respect to current plant size in each market and then substituting back in the profit function, the equilibrium profit (conditional on entry) for an entrepreneur with ability ω in period t can then be derived for each occupation $W \in \{O, D, E, M\}$, where O refers to the traditional (other) occupation, D is domestic production, E is pure exporting, and M is mixed exporting:

$$\begin{aligned}
\Pi_{Ot}(\omega) &= \omega^{\sigma} \\
\Pi_{Dt}(\omega) &= \omega[\frac{1}{\zeta}]C_{dt}^{\frac{1}{1-\alpha}} \\
\Pi_{Et}(\omega) &= \omega^{\delta}[\frac{1}{\zeta\gamma}]C_{et}^{\frac{1}{1-\alpha}} \\
\Pi_{Mt}(\omega) &= \Pi_{Dt}(\omega) + \Pi_{Et}(\omega) - \beta
\end{aligned} \tag{6}$$

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

The above profits are generated by optimal choices on the intensive margin, for a given occupational choice W on the extensive margin. We now turn to equilibrium (extensive form) occupational choices. Observe from (6) that the return to ability is increasing as we progress from the traditional occupation (Π_{Ot}) to domestic production (Π_{Dt}) to exporting (Π_{Et}, Π_{Mt}). At the same time, the entrepreneur must face increasing costs as he moves up the occupational ladder: he must bear a cost of capital, r, if he selects domestic production; there is an incremental cost, I, if he opens an export plant; and then there are the diseconomies of scope, β, that accompany mixed exporting. It follows that there will be positive selection on ability in equilibrium, moving up the occupational ladder, as described below:

Proposition 1 *Parametric restrictions specified in Appendix B.1 ensure that for any cohort t' at date $t \geq t'$ there are three interior ability thresholds:*

$$A - 1 < \log \omega_{dt}^{*} < \log \omega_{et'}^{*} < \log \omega_{mt}^{*} < A \tag{7}$$

and a unique Nash equilibrium in which:

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

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

(c) those between $\omega_{et'}^{*}$ and ω_{mt}^{*} specialize in exports (E)

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

The proof of the proposition is in Appendix B.1. Property (7) ensures that there is a positive share of agents in all four occupations, for every cohort t' and date $t \geq t'$. Moreover, the threshold $\omega^*_{et'}$ for transition between domestic production and pure exporting for cohort t' remains unchanged at every subsequent date $t > t'$, i.e., some pure exporters in cohort t' continue to remain pure exporters subsequently.[15] As a result, the number of exporters in any cohort does not change over time. However, this number will vary across different cohorts, depending on the evolution of market-time effects and network sizes in the domestic and export markets, respectively. Aggregate changes in the number of exporters are thus driven by the arrival of new cohorts.[16]

In contrast with entry into exporting, 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. The ω^*_{mt}, ω^*_{dt} thresholds apply to all older cohorts in the same way.

3.3 Firm Entry

Based on Proposition 1, individuals with ability $\log \omega \in [\log \omega^*_{dt}, A]$ become entrepreneurs. Deriving the expression for ω^*_{dt} from (6), by setting $\Pi_{Ot}(\omega^*_{dt}) = \Pi_{Dt}(\omega^*_{dt})$, and unpacking C_{dt}:

$$n_t = ts[A - \log \omega^*_{dt}] = ts[A - \frac{\log \zeta}{1-\sigma} + \frac{q_{dt} + \theta_d \log n_{t-1}}{(1-\sigma)(1-\alpha)}] \tag{8}$$

where q_{dt} denotes $\log Q_{dt}$. Growth in network size over time is therefore driven by three sources: arrival of newer cohorts (the ts term), market growth (rising q_{dt}) and growth in the log of lagged network size (n_{t-1}). In the sections that follow, we will identify and quantify the role of the lagged network size effect.

Based on Proposition 1, individuals from cohort t' with ability $\log \omega \in [\log \omega^*_{et'}, A]$ become exporters. As noted, there is no further entry into exporting from the t' cohort after that

[15] This is a consequence of the irreversibility constraints, which prevent agents switching from specialization in exporting to domestic production or vice versa.

[16] The transition from domestic production to exporting does not arise in the current simple version of the model where both networks have been assumed to start at the same time. In the next section, we explain that if export opportunities arrive after the domestic network has started, then high ability domestic producers who did not have access to the export network when they entered will become mixed exporters, as in Melitz (2003).

period. Thus, the stock of exporters at any period t is just the sum of exporters supplied by all preceding cohorts. The marginal pure exporter in cohort t', with ability $\omega^*_{et'}$, is indifferent between domestic production and pure exporting. Following the same steps as above, we set $\Pi_{Dt'}(\omega^*_{et'}) = \Pi_{Et'}(\omega^*_{et'})$ to derive $\omega^*_{et'}$ from (6) and then unpack $C_{dt'}$, $C_{et'}$ to obtain:

$$n_{et} = ts[A - \frac{\log\gamma}{\delta-1}] + \frac{s}{(\delta-1)(1-\alpha)}\sum_{t'=1}^{t}[q_{et'} - q_{dt'} + \theta_e \log n_{e,t'-1} - \theta_d \log n_{t'-1}] \qquad (9)$$

As observed in the preceding equation, $\omega^*_{et'}$, which pins down the number of exporters supplied by cohort t' is determined by market-time effects $(q_{et'}, q_{dt'})$ and network sizes $(n_{e,t'-1}, n_{t'-1})$, in exporting versus domestic production. In particular, an increase in domestic network size, $n_{t'-1}$, increases $\omega^*_{et'}$ and, thus, results in a decline in the number of exporters. This (domestic) network overhang, which we identify and quantify in the sections that follow, arises because the marginal exporter is a pure exporter who must choose between domestic production and exporting. Pure exporters have been observed in many developing countries and we document their presence in China, by matching the economic censuses to the Customs database, in Appendix B.3. Pure exporters comprise around 15 percent of all exporters and their revenues lie between domestic-firm revenues and mixed-exporter revenues, as implied by the model. Although the number of pure exporters may not be substantial, they are critical to the analysis. If the marginal exporter were a mixed exporter, instead, then the domestic network would not negatively impact 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 (2003) model, in which the entire overhead production cost is accounted for in domestic profits and, hence, a firm will export if its additional revenues exceed the additional costs. This implies that a demand shock on the domestic market will have no bearing on the firm's export decision. However, the nonseparability 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. 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.

4 Testing the Model

4.1 Estimating Equations

To map the analytical model to the data, we extend it in the following ways:

1. We allow for multiple birth counties and multiple destination prefectures, indexed by j and k, respectively. We do this in a very simple way, by assuming that an exogenous fraction of the agents from any origin birth county j have the opportunity to become entrepreneurs at a given destination prefecture k. We then apply the model to the dynamics of that particular birth county-destination prefecture pair.

2. For a given birth county-destination prefecture pair, we allow the domestic network to start exogenously at time t_{djk} and for the export network to start exogenously at a later date $t_{ejk} \geq t_{djk}$.

3. We add a time varying TFP component, U_{jt}, to the payoff in the traditional occupation in the birth county, which is now specified as $U_{jt}\omega^{\sigma}$. Denote $u_{jt} \equiv \log U_{jt}$.

4. We introduce an unobserved productivity term that benefits firms from the birth county in a specific prefecture. The productivity multiplier is thus specified as $C_{djkt} = V_{djkt}Q_{dkt}[n_{jk,t-1}]^{\theta_d}$, $C_{ejkt} = V_{ejkt}Q_{ekt}[n_{ejk,t-1}]^{\theta_e}$. Denote $v_{djkt} \equiv \log V_{djkt}$, $v_{ejkt} \equiv \log V_{ejkt}$.

Before estimating the effect of the birth county networks on firm entry, we first need to establish that these networks are active. If mutual help is complementary, as we assume, then firms will benefit from a larger network. This implies that a firm's *performance* – revenue or productivity – will be increasing in the *number* of firms from its birth county that are established in the same prefecture. In the analysis that follows, we derive the estimating equations that can be used to implement this test, discuss the biases that arise when these equations are estimated, and propose statistical instruments that could be constructed to address these biases.

Domestic production: Based on the model, the revenue obtained by a domestic producer with ability ω, $R_{djkt} = C_{djkt}\omega^{1-\alpha}K_{djkt}^{\alpha}$. Taking logs, substituting the value of the profit maximizing capital investment, and unpacking C_{djkt}:

$$\log R_{djkt} = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r}\right) + \frac{q_{dkt}}{1-\alpha} + \frac{\theta_d \log n_{jk,t-1}}{1-\alpha} + \frac{[(1-\alpha)^2+1]}{1-\alpha}\log\omega + \frac{v_{djkt}}{1-\alpha} \qquad (10)$$

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,

$$\log P_{djkt} = q_{dkt} + \theta_d \log n_{jk,t-1} + (1-\alpha)\log\omega + v_{djkt} \qquad (11)$$

Leaving aside the constant, each of the structural equations derived above consists of four terms: a market-time term, a network term, an ability term, and an error term. The SAIC inspection database, which we use to estimate these equations, provides firm-level information over time. We will thus include firm fixed effects in the equations that we estimate to collect the ability term. Since firms from a given birth county are established in multiple destination prefectures and firms from many origin counties are established in a given prefecture, it is possible to empirically disentangle network effects from market-time effects, with the latter being subsumed in the destination-time period effects that we also include in the estimating equations. Conditional on the firm fixed effects and the destination-time period effects, consistent estimates of the network effects will be obtained if network size, $n_{jk,t-1}$, is uncorrelated with the structural error v_{djkt}. The entry equation that we derive next will allow us to systematically examine this orthogonality condition and to construct suitable instruments in the event that it is not satisfied.

We define the entrepreneurial propensity by the number of firms divided by the number of potential entrepreneurs: $\frac{n_t}{ts}$ in equation (8). Based on that equation, and using s_{jt} to denote the number of potential entrepreneurs from birth county j, the fraction who establish firms in prefecture k is specified as follows:

$$\frac{n_{jkt}}{s_{jt}} = A_{jk} + \frac{q_{dkt}}{(1-\sigma)(1-\alpha)} + \theta_d \frac{\log n_{jk,t-1}}{(1-\sigma)(1-\alpha)} + \frac{v_{djkt}}{(1-\sigma)(1-\alpha)} - \frac{u_{jkt}}{1-\sigma} \tag{12}$$

By moving the number of potential entrepreneurs, s_{jt}, to the denominator of the left hand side of the estimating equation, we are left with a specification that broadly matches the revenue and productivity equations derived above. There are five terms in this equation: a fixed birth county-destination prefecture term, which more flexibly incorporates the mean ability A parameter in the model, a market-time term, a network term, and two structural error terms. Notice that the TFP term, u_{jt}, is now specified at the birth county-destination prefecture-time period level, as u_{jkt}. As observed in equation (12), an increase in TFP in the traditional occupation, which is the outside option to business, has a negative effect on the stock of firms. This effect is exogenously distributed across destinations, in the same way that a fixed fraction of agents from the birth county are assumed to have the opportunity to become entrepreneurs in a given destination prefecture.[17]

Notice that the productivity term, v_{djkt}, appears in the error term of equations (10)-(12). If we lag equation (12) by one period, then $v_{djk,t-1}$ will determine $n_{jk,t-1}$ and, hence, $\log n_{jk,t-1}$. The estimates in equations (10)-(11) will evidently be biased if v_{djkt} is serially

[17]The right hand side of equation (12) should, more correctly, be multiplied by this fixed fraction. We omit this term from the estimating equation to simplify the exposition, since it has no bearing on our interpretation of the estimates that follow or the quantitative analysis in Section 5.

correlated. This bias arises because the revenue in any birth county-destination prefecture determines firm entry and this entry, in turn, feeds back into revenues (with a lag) through the change in network size.

When we estimate equations (10)-(12), we will first-difference them to purge fixed effects. The endogenous variable then becomes the (lagged) growth in network size, $\log n_{jk,t-1} - \log n_{jk,t-2}$, and $v_{djk,t-1}$ also appears in the error term (with a minus sign). Following the same reasoning as above, the estimated network effects will be biased, but this is now true even if v_{djkt} is serially uncorrelated (in which case the estimates will be biased downward).[18] In addition, when we first-difference equation (12), $n_{jk,t-1}$ appears on both sides of the estimating equation, biasing the network effect even further downward if network sizes are measured with error.

The first instrument that we construct for the growth in domestic network size in the first-differenced equations (10) and (11) is based on the observation that TFP shocks to the payoff in the traditional occupation, $u_{jkt} - u_{jk,t-1}$, will determine firm entry, $n_{jkt} - n_{jk,t-1}$, as seen in equation (12). These shocks will push potential entrepreneurs into business and are thus plausibly uncorrelated with the unobserved productivity shocks in the destination prefecture, $v_{djkt} - v_{djk,t-1}$, that pull them into that occupation. Our second instrument is based on the network multiplier effect, which deterministically brings firms from birth county j into destination prefecture k, independently of other time varying factors, q_{dkt}, v_{djkt}, u_{jkt} in equation (12), once the network has formed exogenously in that prefecture. Recall from Figure 1 that the number of firms in the birth county-destination prefecture network grows nonlinearly with its duration, consistent with a multiplier effect. The instrument that we construct for the contemporaneous growth rate of the domestic network is thus simply its duration, $t - t_{djk}$. A detailed discussion on the validity of both instruments is postponed to Section 4.3. While we have two potential instruments when estimating the firm performance equations (10) and (11), notice that only the second – domestic network duration – instrument is valid when we estimate the entrepreneurial propensity equation (12) because u_{jkt} appears in the residual of that equation.

Exporting: The expression for export revenue, corresponding to the domestic revenue

[18] This negative bias is conceptually related to the well known Nickell bias, which arises when estimating dynamic panel models with fixed effects.

equation (10), is obtained as:[19]

$$\log R_{ejkt} = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r(1+I)}\right) + \frac{q_{ekt}}{1-\alpha} + \frac{\theta_e \log n_{ejk,t-1}}{1-\alpha} + \frac{\delta[(1-\alpha)^2+1]}{1-\alpha}\log\omega + \frac{v_{ejkt}}{1-\alpha} \tag{13}$$

The Customs database, which we use to estimate the preceding equation, provides firm-level export revenues over time. We can thus include firm fixed effects when estimating this equation to account for the ability term. As with equation (10), we can also include destination-time period effects to account for the market-time term. It follows that consistent estimates of the network effects will be obtained if network size, $n_{ejk,t-1}$, is uncorrelated with the structural error, v_{ejkt}. As with the domestic revenue equation, we systematically examine this condition by constructing the accompanying export propensity equation. Based on equation (9), the number of "fresh" exporters, n_{fjkt}, who establish their firms after the export network commences in period t_{ejk}, divided by the number of potential entrepreneurs, s_{jt}, is specified as follows:

$$\begin{aligned}\frac{n_{fjkt}}{s_{jt}} = A_{jk} &+ \sum_{t'=t_{ejk}+1}^{t} \frac{q_{ekt'} - q_{dkt'}}{(t-t_{ejk})(\delta-1)(1-\alpha)} + \theta_e \sum_{t'=t_{ejk}+1}^{t} \frac{\log n_{ejk,t'-1}}{(t-t_{ejk})(\delta-1)(1-\alpha)} \\ &- \theta_d \sum_{t'=t_{ejk}+1}^{t} \frac{\log n_{jk,t'-1}}{(t-t_{ejk})(\delta-1)(1-\alpha)} + \sum_{t'=t_{ejk}+1}^{t} \frac{v_{ejkt'}}{(t-t_{ejk})(\delta-1)(1-\alpha)} \end{aligned} \tag{14}$$

There are five terms in this equation: a fixed birth county-destination prefecture term, a market-time term, an export network term, a domestic network overhang term, and an error term. In contrast with the structural equations we have derived thus far, notice that the network terms include the history of relevant network sizes, rather than a single lag.

Recall that our analytical model made the simplifying assumption that the domestic network and the export network start at the same time. If this were true, then Proposition 1 implies that domestic producers never transition to (mixed) exporting. Once we extend the model to allow the export network to start at a later date than the domestic network, then high ability domestic producers who entered a prefecture before the export network was established; i.e. between periods t_{djk} and t_{ejk}, will become mixed exporters after period t_{ejk} if their export profits exceed β, as in Melitz (2003). This condition is more likely to be satisfied as the export network expands, with an accompanying increase in the productivity

[19] We do not specify an equation for export productivity because export-specific assets, which are needed to construct the productivity statistic, are not observed. Most export firms also produce for the domestic market. While the SAIC inspection data provide assets for each firm, they do not separate assets by the type of activity. In contrast, we can measure productivity for domestic producers because they are engaged in a single activity.

multiplier C_{ejkt}, bringing in more mixed exporters over time. Incorporating this extension to the model, and omitting the constant term for simplicity, the share of incumbent domestic producers from birth county j who become mixed exporters in prefecture k is specified as follows:

$$\frac{n_{mjkt}}{n_{jkt_{ejk}}} = A_{jk} + \frac{q_{ekt}}{\delta(1-\alpha)} + \theta_m \frac{\log n_{ejk,t-1}}{\delta(1-\alpha)} + \frac{v_{ejkt}}{\delta(1-\alpha)} \tag{15}$$

Henceforth, we will call these firms "incumbent exporters," to distinguish them from the "fresh exporters" described above, who enter after period t_{ejk} and export immediately. Notice that the denominator on the left hand side of the preceding equation is the stock of domestic firms in period t_{ejk} when the export network is established, since this is the pool from which the incumbent exporters are drawn. Among the fresh exporters, some pure exporters will also later become mixed exporters, as in our model, but their numbers will be determined by the size of the domestic network and not the export network (since they are inframarginal). These firms are included in n_{fjkt} on the left hand side of equation (14) and thus there is no double-counting: the stock of export firms, $n_{ejkt} = n_{fjkt} + n_{mjkt}$.

n_{fjkt} is positively correlated with v_{ejkt} in equation (14) and n_{mjkt} is positively correlated with v_{ejkt} in equation (15). It follows that n_{ejkt} is positively correlated with v_{ejkt}. Following the same argument as above, with the analysis of domestic production in equations (10)-(12), the estimates of the export network effects will be biased. The first instrument that we construct for the growth in export network size, $\log n_{ejk,t-1} - \log n_{ejk,t-2}$, once equations (13)-(15) have been first-differenced, is the export network duration, $t - t_{ejk}$. Recall from Figure 1 that the stock of firms in the birth county-destination prefecture export network grows nonlinearly with its duration, consistent with a multiplier effect. The export network duration thus determines the growth in export network size at any subsequent point in time. However, additional instruments are now available because the domestic network overhang term restricts entry into exporting in equation (14). In particular, any variable that determines the growth in this term, which incorporates the history of domestic network sizes, will also be a valid instrument for the growth in export network size (with a switch in the sign). Extending our discussion on the identification of the domestic network effect, we can thus use the history of TFP shocks to the traditional occupation in the birth county; i.e. the average up to period $t-1$, and domestic network duration, $t - t_{djk}$, as additional instruments for the growth in export network size.[20] A detailed discussion on the validity of

[20] As discussed above, the TFP shock to the traditional occupation in the birth county can be used as an instrument for the growth in domestic network size in equations (10)-(11). By extension, the history of TFP shocks determines the growth of the domestic network term in the fresh exporter propensity equation. Notice that if the domestic productivity shocks, v_{djkt}, and the export productivity shocks, v_{ejkt}, are assumed to be orthogonal, then the domestic network term in this equation can be treated as exogenously determined. We are not willing to make this assumption. Hence, the history of TFP shocks in the birth county, the domestic

the instruments that we use for export network size is postponed to Section 4.3.

4.2 Identifying Network Effects

When networks are active, a firm will perform better when more firms from its birth county are present in the same prefecture. As specified in equations (10) - (11) and (13), this implies that the firm's performance – revenue or productivity – will be increasing in the size of its network, conditional on destination-time period effects and firm fixed effects.

While the SAIC registration database provides the location and sector of each firm, it does not include information on its performance. To measure the performance of domestic producers, we thus turn to the SAIC inspection database, which provides revenues and assets (which can be used to construct productivity, as shown in Appendix C.1) for a subset of registered firms over time.[21] Recall that our analysis of exporters is restricted to those relatively productive firms who ship their products directly to buyers abroad. Revenues for these exporters are recorded, by shipment, in the Customs database. However, assets specific to exporting activity are unavailable for these firms, since most exporters are also engaged in domestic production, and thus measures of export productivity cannot be constructed. This is not a limitation *per se* because a firm's productivity is an affine transform of its revenue, as derived in the previous section. To measure the size of the domestic network, we return to the SAIC registration database, which allows us to construct the (lagged) stock of firms from birth county j located in prefecture k in period $t-1$. The corresponding statistic for export firms can be constructed by merging the SAIC registration database with the Customs database.[22]

Although we include a rich set of covariates in the estimating equations, the estimated network effects could still be biased on account of the birth county-destination prefecture productivity shocks. In the previous section, we proposed two types of instruments to address these biases.

The first (shift-share) instrument that we construct is based on the idea that TFP shocks

network duration, and the export network duration will serve as instruments for the two network terms in equation (14).

[21] The inspection database has reasonable coverage for 20 (out of 31) provinces from 1998 onwards and, hence, the sample that we use for the analysis spans the 1998-2012 period with this restricted set of provinces. It is possible that selection into this sample is non-random, but the firm fixed effects that we include in all the estimating equations will account for any resulting bias. Extensions to the analysis, discussed in Section 4.3, will go further and allow for heterogeneity in experience effects across firms, which could potentially arise due to non-random selection.

[22] As noted, most export firms are also engaged in domestic production and, hence, they do not necessarily send shipments abroad in each year. We thus designate a firm as being an export firm in a given year if it has appeared in the Customs database in the past and continues to be active; i.e. it remains in the SAIC registration database.

to non-business activities in the rural birth county will push potential entrepreneurs into business, independently of unobserved pull factors. Following Imbert et al. (2022), we construct the shift-share instrument 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 11 major crops that account for 96 percent of cultivated area in China. (ii) For a given birth county, we weight each crop's price shock by a fixed factor that reflects its contribution to local agricultural production (by value) to construct a composite agricultural income shock in each year. (iii) We assume that the decision to establish a firm and, hence, firm entry in a given year is based on the average of the income shocks in that year and the preceding two years. (iv) The entering firms are then "distributed" across destination prefectures by dividing the county-level income shocks by distance (plus one). This adjustment is motivated by the standard gravity model, but does not require the estimation of any auxiliary parameters.[23] Further details of variable construction are provided in Appendix C.2.

Our second instrument, which is simply the duration of the domestic network or the export network, is motivated by Figure 1 and the descriptive statistics reported in Section 2: recall that most networks start with a single firm, and many destination prefectures subsequently draw in firms from the birth county at an increasing rate over time. This description of the representative network's evolution aligns with our model and the common narrative in the literature on business network formation in developing and advanced economies, which is that a fortuitous confluence of circumstances typically jump starts a network, with a (non-linear) network multiplier effect subsequently bringing in additional firms from the ethnic (migrant) community. When we first-difference the firm performance equation to purge firm fixed effects, the endogenous variable becomes the growth in network size and this is consequently predicted by the network's duration. A discussion on the validity of this instrument, and the shift-share instrument, is postponed to the section that follows.

Table 3 reports first-stage estimates corresponding to the first-differenced equations (10) - (11) and (13). The dependent variable in Column 1 is the growth in domestic network size: $\log n_{jk,t-1} - \log n_{jk,t-2}$. Note that first-differencing purges firm fixed effects, but the destination-time period effects are retained as covariates in the first-stage equation. We see in Column 1 that the coefficient on the birth county income shocks is negative and

[23] We could, in principle, estimate a gravity equation that would provide us with a "migration" elasticity with respect to distance between the birth county and any given destination prefecture. However, the dependent variable in the gravity equation is the share of firms from the birth county in each destination prefecture, which is endogenous to the unobserved productivity shocks. This implies that the estimated elasticity will also be correlated with these shocks. Our distance adjustment effectively sets the elasticity to be minus one, as described in Appendix C.2. This reduces the (predictive) power of the instrument, but maintains its validity.

Table 3: First-Stage Estimates of the Firm Performance Equations

Dependent variable:	growth in log domestic network size	growth in log export network size
	(1)	(2)
Birth county income shocks	-0.316***	0.501
	(0.096)	(0.773)
Domestic network duration	-0.003***	0.006***
	(0.000)	(0.001)
Export network duration	–	-0.012***
		(0.002)
Destination-time period effects	Yes	Yes
Observations	5,340,649	128,313

Note: Network size is constructed from SAIC registration data and Customs data.
Growth in network size is measured by $\log n_{jk,t-1} - \log n_{jk,t-2}$ for the domestic network and $\log n_{ejk,t-1} - \log n_{ejk,t-2}$ for the export network.
Income shocks are measured in a single period in Column 1 and as the average over the history of the network in Column 2.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

significant, indicating that negative TFP shocks to the traditional occupation (the outside option) are pushing potential entrepreneurs into business. The coefficient on the domestic network duration is also negative and significant. This is because the dependent variable in Table 3 is measured by the growth of log network size. If we measured the growth of the network in levels rather than logs, then the association with network duration would be positive and significant, as observed in Appendix Table C1 and consistent with the pattern in Figure 1a.[24]

Turning to Column 2, the dependent variable is now the growth in export network size; $\log n_{ejk,t-1} - \log n_{ejk,t-2}$, and we see that the coefficient on export network duration is negative and significant, matching the sign of the coefficient on domestic network duration in Column 1.[25] Notice, however, that the latter coefficient and the coefficient on the birth county income shocks switch signs from Column 1 to Column 2. This switching can be interpreted through the lens of our model as a consequence of the domestic network overhang; exogenous

[24]While the size of the network is increasing in its duration, this is not necessarily true for its growth rate. As observed in Appendix Table C1, the change in the stock of firms, $n_t - n_{t-1}$, is increasing in the network's duration, as in Figure 1a. However, the change in the log stock of firms is decreasing in duration, matching what we observe in Table 3.

[25]In contrast, the change in the stock of export firms, $n_{et} - n_{e,t-1}$, is increasing in export network duration in Appendix Table C1, as in Figure 1b.

factors that increase the size of the domestic network, dampen entry into exporting. While the coefficient on the birth county income shocks has the expected sign in Column 2, it is imprecisely estimated.[26] We will thus use export network duration and domestic network duration as instruments for the growth in export network size in the analysis that follows.

Table 4: Second-Stage Estimates of the Firm Performance Equations

Estimation:	OLS			2SLS		
Dependent variable:	log domestic revenue	log domestic TFP	log export revenue	log domestic revenue	log domestic TFP	log export revenue
	(1)	(2)	(3)	(4)	(5)	(6)
Log network Size	0.458***	1.216***	0.619***	1.340***	3.272***	1.346***
	(0.018)	(0.056)	(0.026)	(0.091)	(0.239)	(0.135)
Destination-time period effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	86.11	86.11	48.69
Hansen J	–	–	–	2.583	0.574	3.765
Observations	5,340,649	5,340,649	128,313	5,340,649	5,340,649	128,313

Note: Network size is constructed from SAIC registration data and Customs data.
Revenue and TFP are constructed from SAIC inspection data and Customs data.
Firm fixed effects are purged by first-differencing prior to estimation.
The modified network variable is thus measured by the growth in its size: $\log n_{jk,t-1} - \log n_{jk,t-2}$ for the domestic network and $\log n_{ejk,t-1} - \log n_{ejk,t-2}$ for the export network.
Instruments for the growth in domestic network size: birth county income shocks, domestic network duration.
Instruments for the growth in export network size: export network duration, domestic network duration.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table 4 reports the second-stage revenue and productivity equations (10) - (11) and (13), with OLS estimates in Columns 1-3 and 2SLS estimates in Columns 4-6.[27] The network size effect is positive and significant without exception, with the point estimates increasing in magnitude when we instrument for network size. The increase in the point estimates is consistent with the discussion in Section 4.1, which tells us that the OLS estimates will be biased downward when we first-difference the estimating equation if the unobserved productivity term is serially uncorrelated. The Kleibergen-Paap F statistic indicates that the

[26]The income shock is measured in a single period in Column 1 and as the average over the history of the network in Column 2. Recall from Section 4.1 that the history of income shocks determines the growth in the domestic network term in the fresh exporter propensity equation, which, in turn, determines the growth in export network size through the overhang effect.

[27]We discard the top one percentile and the bottom one percentile of the first-differenced dependent variable when estimating all of the firm performance equations to remove outliers.

instruments have sufficient power. Notice that we pass the Hansen J over-identification test with all outcomes (the 5 percent critical value is 3.84). This increases our confidence in the validity of the individual instruments, which we subject to closer scrutiny in the section that follows.

4.3 Validating the Statistical Instruments

We used two types of instruments to identify network effects above: a shift-share instrument, leveraging exogenous agricultural income shocks in the birth county, and network durations, separately for domestic production and exporting. In this section, we provide additional support for the validity of each of these instruments.

We begin by estimating the revenue equations, for domestic production and exporting, separately with each instrument. If treatment effects are heterogeneous, then the excluded instrument will have a direct effect on the outcome and thus belongs in the estimating equation (Mogstad, Torgovitsky and Walters, 2021). The coefficients on the excluded instruments are statistically significant in Table 5, with one exception, which indicates that there is indeed heterogeneity in the treatment effects. This heterogeneity will help us interpret some of the results that we report below. However, it cannot cause the estimates of the network effects to diverge by too much, since we passed the tests of the over-identifying restrictions, based implicitly on the assumption that treatment effects are homogeneous, in Table 4. As expected, the point estimates with each instrument are similar in magnitude, for a given outcome, in Table 5.

Shift-Share Instrument: We next examine the instrument based on income shocks in the birth county, using the estimates in Table 5, Column 1 as the reference point. In recent years, shift-share instruments have received much attention in the economics literature. We follow this literature and implement a series of robustness tests in Appendix C.3 that validate each component of the shift-share instrument.

1. Agricultural price shocks: One way in which agricultural price shocks could directly impact firm performance is if they affect the local economy more broadly and the firm is located in the birth county itself. A second way in which agricultural price shocks could affect a firm's performance is if it is operating in that sector. Finally, a third way in which agricultural price shocks could directly affect business is through the wealth channel. If own (family) wealth is used to finance business, as in Song, Storesletten and Zilibotti (2011), then a negative price shock will curtail the operations of entrepreneurs from agricultural families. This is true regardless of the location in which they are active and will result in a decline in their revenues. Appendix Table C2 shows that the results are retained when the

Table 5: Second-Stage Estimates of the Firm Performance Equations by Instrument

Instrument:	birth county income shocks	domestic network duration	export network duration	domestic network duration
Dependent variable:	log domestic revenue		log export revenue	
	(1)	(2)	(3)	(4)
Log network size	1.681***	1.302***	0.971***	1.343***
	(0.279)	(0.093)	(0.216)	(0.135)
Domestic network duration	0.001	–	0.002**	–
	(0.001)		(0.001)	
Birth county income shocks	–	-0.120*	–	–
		(0.072)		
Export network duration	–	–	–	0.004*
				(0.002)
Destination-time period effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F	10.80	166.1	23.71	89.36
Observations	5,340,649	5,340,649	128,313	128,313

Note: Network size is constructed from SAIC registration data and Customs data.
Revenue is constructed from SAIC inspection data and Customs data.
Firm fixed effects are purged by first-differencing prior to estimation.
The modified network variable is thus measured by the growth in its size.
Instruments for the growth in domestic network size: birth county income shocks or domestic network duration.
Instruments for the growth in export network size: export network duration or domestic network duration.
The excluded instrument is included as a covariate in each case.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

sample is restricted to firms operating outside the birth county or in non-agricultural sectors. They are also robust to including the agricultural income shocks directly in the estimating equation.

2. Crop shares: While the direct effect of the crop shares is subsumed in the firm fixed effects, we consider the possibility that the interaction of these shares with time determines firm revenues. As Goldsmith-Pinkham, Sorkin and Swift (2020) note, these interaction effects must also be considered when examining the validity of any shift-share instrument.[28] To do this, we build on Goldsmith-Pinkham, Sorkin and Swift's insight that if the crop shares are

[28]For example, suppose that (historical) cultivation of a particular crop is associated with an entrepreneurial culture or a greater willingness to bear risk in the local population. If these traits have a differential effect on firm performance over time with economic development, then our instrument would violate the exclusion restriction. Alternatively, if counties growing particular crops industrialize relatively fast due to the nature of the agricultural production technology, then entrepreneurs born in those counties will have preferred access to capital (to the extent that firms are self-financing). This would undermine the validity of the instrument once again.

exogenous, then the shift-share instrument that we construct is "equivalent" to using the shares associated with each crop, interacted with time effects, as independent instruments for network size. 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 from other crops. Appendix Table C3 shows that the network effects estimated with each crop are positive, statistically significant, and similar in magnitude to each other and to the benchmark estimates with the shift-share instrument in Table 5, Column 1.

3. Distance adjustment: Distance is a fixed characteristic and, hence, its direct effect on firm performance is subsumed in the firm fixed effect. However, its interaction with time must also be considered when examining the validity of the shift-share instrument, as above. Suppose that firms located at a greater distance from their rural origin are established in faster-growing prefectures. Distance interacted with time will then determine firm performance, but this does not undermine our identification strategy because destination-time period effects are included in the estimating equation. The threat to identification with this component of the shift-share instrument is that particular types of individuals may choose to move far away and the outcomes for those types may vary differentially with experience or at different stages of economic development. To address the preceding concern, we include distance interacted with time effects in the estimating equation (see Appendix Table C2) and verify that the estimated network effects are unchanged.

Network Duration Instruments: Our characterization of the firm entry trajectory described in Figure 1 is that a shock, which is restricted to a single individual or a small group of individuals, jump starts the birth county-destination prefecture network. The number of firms subsequently grows at an increasing rate on account of a network multiplier effect. This implies that the time of commencement can be treated as exogenously determined from the perspective of the birth county as a whole and that network duration will predict the growth in the number of firms at any point in time. The threat to identification with the duration instruments is that initial entry is determined, instead, by an unobserved birth county-destination prefecture factor that boosts firm revenues; v_{djkt}, v_{ejkt} in Section 4.1. If this factor is persistent, then our duration instrument will predict its value at any subsequent point in time, violating the exclusion restriction.

In general, if a birth county-destination prefecture level factor starts the process, then we would expect to see a large number of initial entrants. This is at odds with the trajectories reported in Figure 1. To reconcile the alternative mechanism with that figure, we need to introduce additional pull and push factors, which are possibly growing at an increasing rate over time, and a moving cost. There will then be a point in time at which locating in destination prefecture k just becomes viable for firms from birth county j. The number of firms will consequently start at an extremely low level and then grow, in response to the revenue-boosting factor and other push and pull factors, potentially matching the dynamics in Figure 1. There are many moving parts to this alternative mechanism, and we do not have empirical support for any of them. In contrast, our preferred characterization of the firm entry dynamics is supported by numerous accounts of business network formation. Nevertheless, we proceed to independently validate the duration instruments below, based on the consistency in the estimated network effects in Table 5.

With domestic revenue as the outcome, the shift-share instrument in Table 5, Column 1 is particularly credible because it is leveraging exogenous shocks to the traditional occupation in the *origin* birth county that serves as the outside option to business. With export revenue as the outcome, *domestic* network duration is a particularly credible instrument in Column 4 because it determines *export* network size through the indirect domestic network overhang channel. The domestic network is established long before the export network; in our data, this network starts, on average, 11 years earlier than the export network in those birth county-prefectures where both networks co-exist. The conditions that gave rise to the domestic network are unlikely to be related to those that start the export network. The fact that domestic production and exporting are different activities, with distinct networks (as verified below), gives us additional confidence in the validity of the domestic network duration instrument. Notice that the point estimates in Table 5, Columns 2 and 3 are similar in magnitude to our most credible estimates in Columns 1 and 4, respectively. This consistency, despite the fact that our instruments are leveraging independent sources of variation, and our resulting ability to pass the over-identification test with each outcome, gives us additional confidence in the validity of the entire set of instruments.

We complete this section by comparing and contrasting the duration instruments with the identification strategy that is conventionally adopted in the dynamic panel literature. The canonical dynamic panel model includes the lagged dependent variable and a fixed effect as covariates in the estimating equation. When this equation is first-differenced, it induces a correlation between the growth in the lagged dependent variable on the right hand side and the residual term, exactly as described in Section 4.1. If the error term is serially uncorrelated, then the twice lagged dependent variable can be used as an instrument. If the error term is serially correlated, but dampens sufficiently fast, then lags further back in time can be used as instruments (Arellano and Bond, 1991; Blundell and Bond, 1998). However, the lags that are used will typically be recent because most panel datasets are short and because longer lags of the dependent variable will lack predictive power. Our estimating equations, particularly the propensity equations, are closely related to the canonical dynamic panel equation and face the same source of bias. However, a unique feature of our data is that we observe the precise point in time when the dynamic process commences in each birth county-destination prefecture. We can thus exploit the network multiplier effect to construct an alternative, more robust, instrument that is based on the network's duration, rather than on recent lagged values of the dependent variable.

4.4 Verifying the Network's Domain

Our definition of the network's domain is based on the following assumptions: (i) it is restricted to firms from a given birth county operating in a particular prefecture, (ii) in those prefectures where domestic producers and exporters from the birth county co-exist, there are two networks: a domestic network consisting of all firms and an export network restricted to export firms, and (iii) all firms (without regard to industry) are included in the network to account for inter-industry spillovers. The analysis that follows tests each of these assumptions.

When we specify that the network in a prefecture is restricted to firms from the same birth county, this does not imply that other cross-firm spillovers are absent. Recall that the destination-time period effects that we include in all the estimating equations incorporate conventional agglomeration effects. The implicit assumption underlying this specification of the agglomeration effects is that spillovers from a given birth county network benefit all firms from other origins in the prefecture equally. Firms from the birth county itself receive a further boost that is reflected in the estimated network effect. This characterization of inter-firm spillovers implies that a network from any other origin should have no effect on a firm's revenues, conditional on the destination-time period effects.

We test the preceding implication in Table 6 by including the birth county network and the nearest neighbor's network in the estimating equation. The nearest neighbor is defined as the county that is closest to the birth county among all the counties that are represented in the prefecture in a given time period. As can be seen, the size of the nearest neighbor's network has no bearing on the firm's revenue, for both domestic production and exporting. This result is obtained with and without instrumenting for network size, where the instruments for the nearest neighbor's network size are constructed in exactly the same way as for the birth county network. If the agglomeration effects were not uniform or if the network's domain was more expansive and included neighboring counties, then this result would not have been obtained.

Based on our description of the networks in Section 2, most firms in a birth county-destination prefecture will be established in related industries. We allow for spillovers across these industries by including all firms in the network, regardless of the industry in which

Table 6: Estimates of the Firm Performance Equation: Allowing for Nearest-Neighbor Effects

Estimation:	OLS		2SLS	
Dependent variable:	log domestic revenue	log export revenue	log domestic revenue	log export revenue
	(1)	(2)	(3)	(4)
Log network size	0.450***	0.619***	1.299***	1.251***
	(0.017)	(0.026)	(0.120)	(0.171)
Log nearest-neighbor network size	0.034***	0.009	0.065	0.029
	(0.009)	(0.018)	(0.109)	(0.146)
Destination-time period effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	29.34	21.75
Observations	5,340,649	128,032	5,340,649	128,032

Note: Network size is constructed from SAIC registration data and Customs data.
Revenue is constructed from SAIC inspection data and Customs data.
The nearest neighbor is the county that is located closest to the birth county among all the counties that are represented in a given destination-time period.
Firm fixed effects are purged by first-differencing prior to estimation.
Instruments in Column 3: birth county income shocks, domestic network duration, nearest neighbor's income shocks, nearest neighbor's domestic network duration.
Instruments in Column 4: domestic network duration, export network duration, nearest neighbor's domestic network duration, nearest neighbor's export network duration.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

they operate. We verify that cross-industry spillovers, which motivate this more expansive definition of the network, do exist in Table 7 by including industry-specific network size as an additional covariate. The instrument for the industry-specific network size is simply the industry-specific network duration. As can be seen, particularly with the more credible instrumental variable estimates, the coefficients on overall network size and industry-specific network size are positive and statistically significant (with one exception). These results indicate that the industry-specific network does give firms an additional boost, as we might expect. At the same time, cross-industry effects, measured by the coefficient on network size, are also substantial and, thus, cannot be ignored. Notice that the revenue of the domestic firms is more dependent on the cross-industry effects. This finding is consistent with the argument put forward in Section 2 that domestic firms will rely more on out-sourcing than export firms. The latter will use their network for connections to foreign buyers and for information about new technologies and business opportunities. This type of help is export-

Table 7: Estimates of the Firm Performance Equation: Allowing for Industry-Specific Networks

Estimation:	OLS		2SLS	
Dependent variable:	log domestic revenue	log export revenue	log domestic revenue	log export revenue
	(1)	(2)	(3)	(4)
Log network size	0.076***	0.040	0.656***	0.293
	(0.016)	(0.037)	(0.201)	(0.221)
Log industry-specific network size	0.385***	0.646***	0.864***	1.008***
	(0.007)	(0.020)	(0.281)	(0.152)
Destination-time period effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	11.14	68.09
Observations	5,261,006	119,614	5,261,006	119,526

Note: Network size is constructed from SAIC registration data and Customs data.
Revenue is constructed from SAIC inspection data and Customs data.
Industries are defined at the 3-digit level from the NBS Input-Output Table (2007).
Firm fixed effects are purged by first-differencing prior to estimation.
Instruments in Column 3: birth county income shocks, domestic network duration, industry-specific domestic network duration.
Instruments in Column 4: domestic network duration, export network duration, industry-specific domestic network duration, industry-specific export network duration.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

specific *and* industry-specific.

We used the preceding distinction between domestic firms and export firms to posit in Section 2 that export firms will access an export-specific network, while the domestic network will consist of all firms, in a given birth county-destination prefecture. To test this hypothesis, the estimating equations in Table 8 include both domestic network size and export network size. The OLS estimates in Columns 1-2 are consistent with our definition of the network's domain: domestic revenues are determined exclusively by the domestic network and export revenues are determined by the export network alone. The instrumental variable estimates with domestic revenue as the outcome in Column 3 are broadly consistent with the corresponding OLS estimates in Column 1. However, the OLS and 2SLS estimates in Columns 2 and 4, with export revenue as the outcome, are very different; the coefficient on domestic network size, in particular, becomes negative, large (in absolute magnitude), and statistically significant when we instrument for network sizes.

The standard interpretation when OLS and 2SLS estimates differ substantially is that

Table 8: Estimates of the Firm Performance Equations: Allowing for Cross-Network Effects

Estimation:	OLS		2SLS	
Dependent variable	log domestic revenue	log export revenue	log domestic revenue	log export revenue
	(1)	(2)	(3)	(4)
Log domestic network size	0.535***	-0.002	1.573***	-0.587**
	(0.039)	(0.042)	(0.071)	(0.277)
Log export network size	-0.004	0.619***	-0.080	1.165***
	(0.007)	(0.026)	(0.131)	(0.156)
Destination-time period effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	16.43	16
Observations	3,462,895	128,313	3,462,895	128,313

Note: Network size is constructed from SAIC registration data and Customs data.
Revenue is constructed from SAIC inspection data and Customs data.
Firm fixed effects are purged by first-differencing prior to estimation.
Instruments in Columns 3-4: birth county income shocks, domestic network duration, export network duration.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

there is a weak instrument problem, but this is not the case here because the Kleibergen-Paap F statistic is above 15. Our explanation for the divergence in Columns 2 and 4 is that the OLS and 2SLS estimates of the export revenue equation are not comparable, on account of the heterogeneous treatment effects we have uncovered and the domestic network overhang that is implied by our model. Notice that the specification in Table 5, Column 3 is the same as the specification in Table 8, Column 4, except that domestic network duration, which appears as a covariate with a positive coefficient in the former table is replaced by (instrumented) domestic network size in the current table. We know from Table 3, Column 1 that the association between domestic network size and domestic network duration is negative, once we first-difference the estimating equation, which is why the sign of the coefficient on domestic network size is now negative. Making this argument more precise, the product of the first-stage coefficient in Table 3, -0.003, and the domestic network size coefficient in Table 8, -0.6, is equal to the "reduced form" domestic duration coefficient in Table 5, which is 0.002.

The intuition underlying the preceding explanation is that once we include domestic network size in the estimating equation, the coefficient on export network size can be interpreted as a local average treatment effect (associated with the export network duration instrument).

Since treatment effects are heterogenous, this leaves room for the domestic network duration instrument to affect the export revenue through its independent effect on export network size. An alternative interpretation of the estimates in Column 4 is that a larger domestic network directly reduces export revenues, perhaps by crowding out inputs or connections. However, if this were true, then we would also expect to observe a negative and significant coefficient on domestic network size with the OLS estimates in Column 2. It is difficult to credibly argue that bias in these estimates would exactly offset the "true" negative coefficient. Notice also that this is the only specification in Tables 6 - 8 where the OLS and 2SLS estimates diverge so substantially, and heterogeneous treatment effects together with the domestic network overhang provide a simple explanation for this divergence.

5 Quantitative Analysis

5.1 Firm Entry

The evidence presented thus far indicates that domestic networks increase domestic revenues and export networks increase export revenues. There is also empirical support, in Table 3 and Table 8, for a domestic network overhang that discourages entry into exporting. To quantify the contribution of the networks to firm entry, however, it is necessary to estimate the propensity equations.

We begin with the entrepreneurial propensity equation (12) and the incumbent exporter propensity equation (15) because the right hand side of these equations has the same covariates as the revenue equations that we estimated in Section 4.2. The only difference is that the propensity equations are specified at the birth county-destination prefecture-time period level; hence, firm fixed effects are replaced by birth county-destination prefecture effects. When we first-difference the propensity equations to purge the birth county-destination prefecture effects, the destination-time period effects are retained and the network terms are measured by the growth in network size, as with the revenue equations. As discussed in Section 4.1, domestic network duration can be used as an instrument for the growth in domestic network size in the entrepreneurial propensity equation. However, the birth county income shocks, which were also used as instruments in the domestic revenue equation, are no longer valid since they directly determine entry into business. As with the export revenue equation, we use export network duration and domestic network duration (via the overhang effect) as instruments for the growth in export network size in the incumbent exporter propensity equation.

Entrepreneurial propensity is measured by the number of firms divided by the number of potential entrepreneurs, n_{jkt}/s_{jt}. Appendix D.1 describes how the number of potential entrepreneurs is computed.[29] When we estimate the first-differenced entrepreneurial propensity equation, we replace s_{jt}, $s_{j,t-1}$ in the denominator on the left hand side by their average, which is reasonable since the number of potential entrepreneurs is a slow-moving variable. The advantage of this approximation is that the numerator on the left hand side of the first-differenced equation then becomes the number of entering firms, $n_{jkt} - n_{jk,t-1}$. This will allow us to quantify the contribution of the birth county networks to firm entry in the section that follows.

Incumbent exporter propensity is measured by the number of firms who were engaged in domestic production before the export network was established and subsequently added an export plant (became mixed exporters), divided by the number of domestic producers who were active when the export network was established. When we first-difference this equation, the numerator on the left hand side becomes the number of entering mixed exporters, and this will allow us to also quantify the contribution of the birth county networks to the number of these entrants below. We see that the coefficient on domestic network size in Table 9, Column 1, with entrepreneurial propensity as the dependent variable and the coefficient on export network size in Column 2, with incumbent exporter propensity as the dependent variable, are both positive and significant, as implied by the model. These results hold up when we instrument for network sizes in Columns 3-4.[30]

Notice that the number of observations in Column 1 is an order of magnitude larger than in Column 2. This is not an artifact of the data since we have a complete count of all registered firms from the SAIC registration database and all direct export firms from the Customs database. The sample in Column 1 covers all time periods after each domestic network commences, up until 2012. In contrast, the sample in Column 2 covers the time periods after each export network is established. On average each birth county sets up domestic networks in 88 prefectures and export networks in five prefectures. In addition, domestic networks commence nine years earlier than export networks on average. This explains why the number of network-time periods in Column 1 is 40 times larger than in Column 2.

Notice also that the estimated network effects in Columns 3-4, where we have instrumented, are an order of magnitude larger than the OLS estimates in Columns 1-2. As

[29]Based on the characteristics reported for a sample of entrepreneurs (legal representatives) in the registration database, the number of potential entrepreneurs in a given period is specified as the number of men aged 25-44, with at least high school education, who were born in the county. This statistic 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 2000-2012 period.

[30]When estimating all of the entry equations, we discard the top one percentile and the bottom one percentile of the first-differenced dependent variable to remove outliers.

Table 9: Propensity Equation Estimates

Method:	OLS		2SLS		OLS	2SLS
Dependent variable	entrepreneurial propensity	incumbent exporter propensity	entrepreneurial propensity	incumbent exporter propensity	fresh exporter propensity	
	(1)	(2)	(3)	(4)	(5)	(6)
Log network size	0.011***	0.071***	2.420***	0.470***	–	–
	(0.000)	(0.007)	(0.133)	(0.029)		
Average log export network size	–	–	–	–	0.019***	0.071***
					(0.001)	(0.008)
Average log export network size	–	–	–	–	-0.002*	-0.314***
					(0.001)	(0.061)
Destination-time period effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth county-prefecture effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	253.4	516.8	–	10.71
Observations	957,529	22,582	957,529	22,582	22,572	22,572

Note: Propensity and network size, measured at the birth county-destination prefecture-time period level, are constructed from SAIC registration data and Customs data.
Network size is measured by the lagged stock of all firms with entrepreneurial propensity as the dependent variable and by the lagged stock of export firms with incumbent exporter propensity as the dependent variable.
Average network size is computed over the network's history with fresh exporter propensity as the dependent variable.
Birth county-prefecture fixed effects are purged by first-differencing prior to estimation and the modified network variables are thus measured by the growth in their size.
Instrument for the growth in domestic network size in column (3): domestic network duration.
Instruments for the growth in export network size in column (4): export network duration, domestic network duration.
Instruments for the growth in average export network size and average domestic network size in column (6): birth county income shocks, export network duration, domestic network duration, export network duration interacted with its initial entry, domestic network duration interacted with its initial entry. Income shocks are measured as the average over the history of the network.
All coefficients in the table are multiplied by 100.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

discussed in Section 4.1, downward bias in the OLS estimates arises on account of the correlation between lagged network size and unobserved productivity shocks, and because the lagged dependent variable appears on both sides of the estimating equation when we first-difference. The revenue equations are subject to the first source of bias, but not the second. This explains why the difference between the 2SLS and OLS estimates in Table 4 is not as large as in Table 9, despite the fact that the structure of the estimating equations and the instruments that we construct for network size are the same.

One might worry that the large difference between the OLS and 2SLS estimates is due to a weak-instrument problem. However, this does not appear to be the case, given the size of the Kleibergen-Paap F statistics. Nevertheless, as an independent check on the 2SLS estimates, we will compare the effect of the networks on firm entry and firm revenue in Section 5.2. In our model, firm revenues determine firm entry and, hence, we expect these effects to be comparable. This is indeed what we will find. Since have rigorously validated the revenue equations in the previous section, this consistency gives us additional confidence in the estimates reported in Table 9, Column 3-4.

We next turn to the fresh exporter propensity equation (14). The dependent variable in this equation is measured by the number of exporters who established their firms after the export network was established in the prefecture, divided by the number of potential entrepreneurs. When we first-difference this equation to purge the birth county-destination prefecture effects, we replace s_{jt}, $s_{j,t-1}$ with their average in the denominator on the left hand side, as we did for the entrepreneurial propensity. The numerator then becomes the number of entering fresh exporters. Note that the right hand side of equation (14) has a different structure from the equations we have estimated thus far. In particular, the network terms are constructed as the averages of network sizes, over the history of the network, rather than as a lagged stock in a single period. As discussed in Section 4.1, we can use the history of income shocks in the birth county, domestic network duration, and export network duration as instruments for the growth in the domestic network term and the export network term in the first-differenced equation.

Since there are now two endogenous network terms, and these terms are constructed differently than before, we report the first-stage estimates in Appendix D.2. While a detailed discussion of the first-stage results is provided in the appendix, the main takeaway is that the domestic network duration instruments – the birth county income shocks and domestic network duration – lack the statistical power to shift the domestic network term sufficiently. This limitation is rectified when we add two more instruments: the interaction of domestic network duration and export network duration with their respective initial levels of entry. Although we have not used initial entry to construct our instruments thus far, we have assumed that it is exogenously determined, from the perspective of the birth county as a whole, when motivating the duration instruments. Over-identification tests, discussed in Appendix D.3, provide statistical support for the exogeneity of the additional instruments. We will thus use five instruments when estimating the fresh exporter propensity equation: birth county income shocks, domestic and export network durations, and the interactions of the durations with initial entry.

As implied by the model, we see that the coefficient on the export network term is positive and significant, while the coefficient on the domestic network term is negative and significant in Table 9, Columns 5-6. This is true for the OLS estimates and the 2SLS estimates. The negative coefficient on the domestic network term is indicative of an overhang effect, which will reduce the number of fresh exporters, who account for 70 percent of all exporters in our data.

The estimated network coefficients, with domestic revenue and export revenue as outcomes, have very similar magnitudes in Table 4. This implies, from equation (14), that the coefficients on the network terms in the fresh exporter propensity equation should have similar magnitudes. This is not what we observe, however, on account of the heterogeneous treatment effects that are generated by our instruments. Since the domestic network term is included as covariate in the fresh exporter propensity equation, the coefficient on the export network term can be interpreted as a local average treatment effect that is associated with the export network duration instruments. As in Table 8, Column 4, this leaves room for the domestic network duration instruments to have a distinct effect on export entry through their independent effect on export revenue.

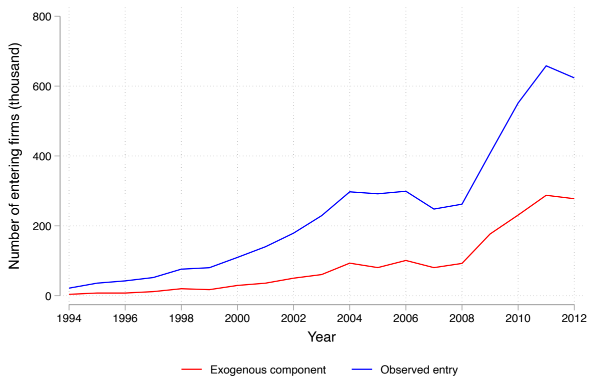
Based on the preceding discussion, the coefficient on the domestic network term will incorporate two effects: (i) the domestic network overhang effect on export entry, as specified in the model, and (ii) the negative effect of the domestic network on export revenue and, hence, export entry, which is not in the model but arises on account of the heterogeneous treatment effects (coupled with the domestic network overhang). This explains why the coefficient on the domestic network term is substantially larger (in absolute magnitude) than the coefficient on the export network term in Table 9, Column 6. When we quantify the contribution of the domestic network to export entry in the section that follows, this will incorporate both effects described above.

5.2 Decomposition Analysis

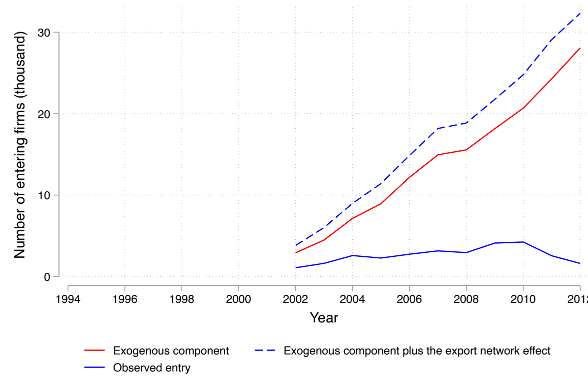
Based on the first-differenced propensity equations, the determinants of firm entry in our model can be partitioned into two components: an exogenous component, which includes the destination-time period effects and all other unobserved factors, and an endogenous network component. Our instrumental variable estimates of the network effects allow us to quantify the contribution of the network component to firm entry at each point in time. This, in turn, allows us to back out the contribution of the (residual) exogenous component to firm entry.

The red line in Figure 2a plots the contribution of the exogenous factors to firm entry. As can be seen, this contribution is increasing over time, reflecting improved opportunities in business and (possibly) increasing government support. The blue line in the figure plots the observed entry of firms in each year. The gap between the two lines measures the contribution of the networks, and this is also increasing over time. Based on our estimates, the birth county networks account for about half of the observed entry in 2012.

We can implement a similar decomposition exercise with the first-differenced domestic revenue equation to quantify the contribution of the birth county networks to that outcome. Based on our estimates, if the networks were absent in 2012, then average firm revenues in that year would have been 24 percent smaller.[31] This effect is of a similar order of magnitude as the entry effects that we have estimated, which is as expected since entry is determined by revenues in our model. The revenue estimates have been subjected to a number of robustness tests and, hence, this consistency gives us additional confidence in our estimated entry effects.



(a) All Firms



(b) Exporters

Figure 2: Decomposition Analysis

Source: SAIC registration data and Customs data.

The red line in Figure 2b plots the contribution of the exogenous factors to the entry of export firms, combining incumbent exporters and fresh exporters. As can be seen, this contribution is increasing over time, presumably due to improved export opportunities and increasing government support. The gap between the red line and the dashed blue line measures the contribution of the export networks to entry, once again combining the incumbent exporters and fresh exporters. While this contribution is positive, it is small relative to the contribution of the domestic networks in Figure 2a. This is not because the export networks are less effective; looking back at Table 4, the network size coefficient is very similar in magnitude with domestic revenue and export revenue as the outcomes. The very different contributions of the networks to firm entry arise because the number of domestic firms is growing much faster than the number of export firms, for reasons described below. This

[31] This quantification exercise is implemented in two steps: First, we compute the effect of removing the contemporaneous network on the dependent variable in the first-differenced revenue equation. Second, we back out the resulting effect on current revenue, treating lagged revenue as predetermined.

will also have consequences for firm revenues. Our estimates of the export revenue equation indicate that average export revenues in 2012 would have declined by just 10 percent if the export networks were absent. Recall that the corresponding counterfactual statistic for average domestic revenues was 24 percent.

The remaining component of the export entry is the domestic network term representing the overhang effect, which applies to fresh exporters alone. The contribution of this term to overall export entry is measured by the gap between the dashed blue line and the solid blue line (observed entry) in Figure 2b. As can be seen, this gap is increasing over time, matching the increase in domestic network size that is implied by Figure 2a. The negative domestic network effect completely offsets the positive contribution of the exogenous factors and the export network to the entry of export firms, resulting in a relatively constant number of entrants over time. The disproportionate contribution of the domestic network arises because that network is growing relatively fast. The resulting decline in the growth rate of the export network feeds back into this effect, locking the rural-born entrepreneurs into low-value domestic production.

6 Conclusion

This research provides a network-based explanation for the enormous increase in the number of entrepreneurs in China, following the economic reforms of the early 1990's. This explanation is based on the idea that networks of firms provided mutual support to their members, filling the gap in an environment where many markets were missing or incomplete. Our estimates indicate that hometown (birth county) networks doubled the number of entering rural-born entrepreneurs in 2012, the end point of our analysis. Although the existence of community-based business networks has been documented historically and in contemporary industry studies, this constitutes the first economy-wide evidence to date of the important role played by these informal institutions.

While the domestic networks that we identify may have facilitated mobility in the initial transition, they slowed the growth of newly emerging export networks and, as a result, the transition to the next stage of economic development. The export networks also facilitate mobility, but if the domestic network overhang is sufficiently large, then the entry rate of exporters in equilibrium could be even lower than the counter-factual rate in an economy without networks, and this is what we observe. Based on our estimates, the exogenous factors in our model would have increased the number of entering exporters over time, but this is offset by the domestic network effect, resulting in a relatively constant rate of entry.

Self-interested entrepreneurs do not internalize the effect of their entry on the performance of other firms (through the change in network size) and, hence, there is a role for policy. Export subsidies, which have no consequence for domestic profits, are unambiguously efficiency enhancing. In contrast, entry subsidies must balance two opposing effects: their positive effect on domestic profits due to a larger domestic network and the negative effect on export profits due to a smaller export network (on account of the domestic network overhang). If the latter effect is sufficiently large, it may even be optimal to tax entry. Adding to the complexity, if the second transition is anticipated, domestic policies during the first transition would need to take account of their future consequences for exporting. Although a complete characterization of dynamic optimal subsidies is left to future research, we note that industrial policy could have large positive impacts in economies where networks are active.

The organic process of economic development that we describe in this paper, in which networks emerge at each stage to facilitate the occupational mobility of their members, and pre-existing networks slow down the growth of networks at subsequent stages, may not be specific to China or to business activities. Nevertheless, the analysis in this paper will only be relevant in populations where community networks are already active or have the potential to be activated and this will, in general, depend on the underlying social structure. A natural question to ask is which social structures are more conducive to network formation and growth. One way to answer this question would be to examine heterogeneity in social structure across our Chinese counties, with its consequences for network performance and occupational mobility. Such heterogeneity would have further implications for industrial policy, with optimal subsidies now varying across space. We plan to examine this extension of the current analysis in future research.

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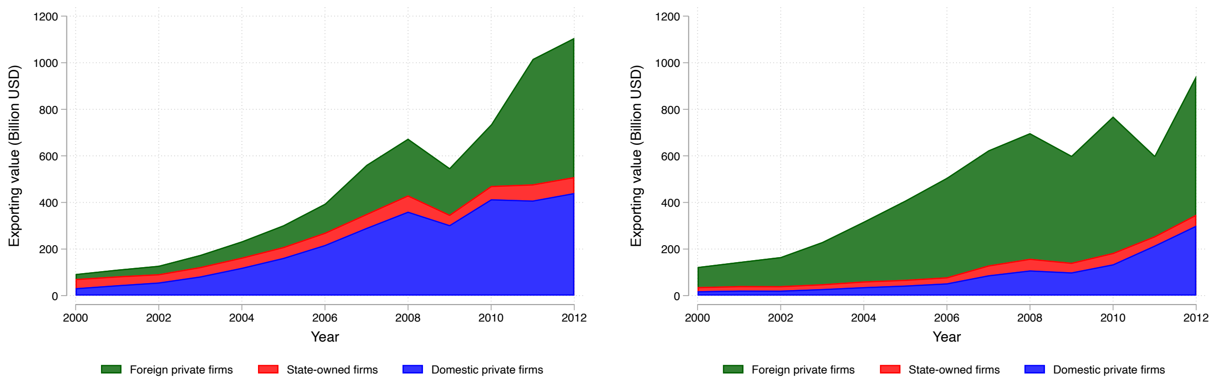
Supplemental Appendix A: Export Accounting

There are two types of exports in China: production exports and processing exports. 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, we thus restrict attention to production exports. The Customs database, which indicates the type of export for each shipment over the 2000-2012 period, can be merged with the SAIC registration database, which provides the ownership structure of each supplying firm. The merged data, reported in Figure A1, indicate that private domestically owned firms are largely involved in production exports in any case, whereas processing exports are dominated by foreign owned firms.



(a) Production Export

(b) Processing Export

Figure A1: Production and Processing Export, By Ownership

Source: Customs data.

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

Table A1: Unit Price and Destination of Exported Goods

Dependent variable:	price per unit	OECD destination
	(1)	(2)
Trading firms	-60.001***	-0.066***
	(14.115)	(0.000)
Constant	175.177***	0.454***
	(11.649)	(0.000)
Goods-year fixed effects	Yes	Yes
Observations	10,838,870	10,838,870

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%.

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 1998-2008 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 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.

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

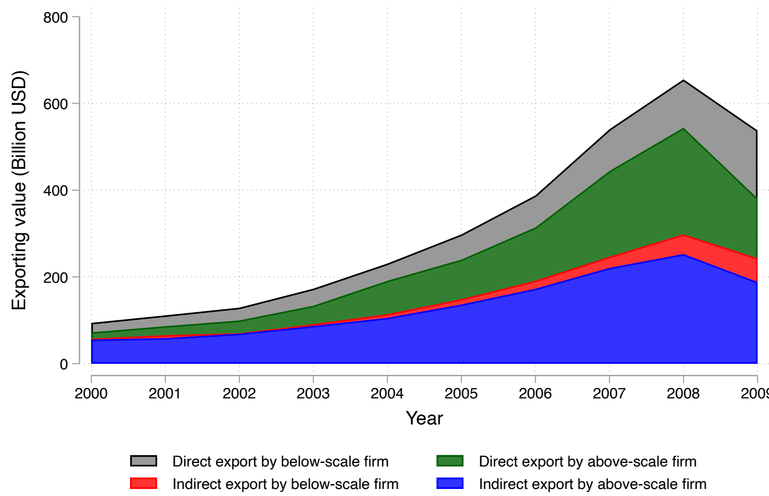


Figure A2: Export Accounting

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

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.

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.

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	0.018*	0.076***
	(0.010)	(0.015)
Indirect export share	-0.320***	-0.287***
	(0.005)	(0.011)
Constant	16.769***	11.784***
	(0.111)	(0.038)
Industry-year fixed effects	Yes	Yes
Observations	682,483	693,290

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

Supplemental Appendix B: The Model

1. Proposition 1

Recall that log ability ω is uniformly distributed with constant density 1 on support $[a, a+1]$ with $a \equiv A - 1$.

The following parameter restrictions ensure existence of a unique equilibrium featuring positive shares of different occupations at each date for every cohort:

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

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

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

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

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

Proof of Proposition 1:

To prove the Proposition, we show that ability thresholds are interior and ordered, as in (7), given the parameter restrictions (16-19).

We begin by showing that $\log \omega_{dt}^* > a$ if (16) is satisfied. From (6):

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

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

Next, we show that $\log \omega_{et'}^* > \log \omega_{dt}^*$, for all $t \geq t'$, if (17) is satisfied. From (6):

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

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

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

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

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

2. Extending the model to allow for forward looking behavior

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

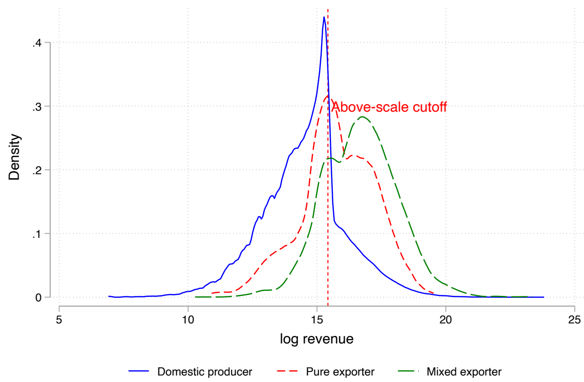
Table B1: Composition of Firms

Year	2004		2008	
Type:	number	log revenue	number	log revenue
Domestic producer	243,302	14.477	486,729	14.871
Pure exporter	615	15.763	2,180	15.592
Mixed exporter	4,396	16.544	10,933	16.440

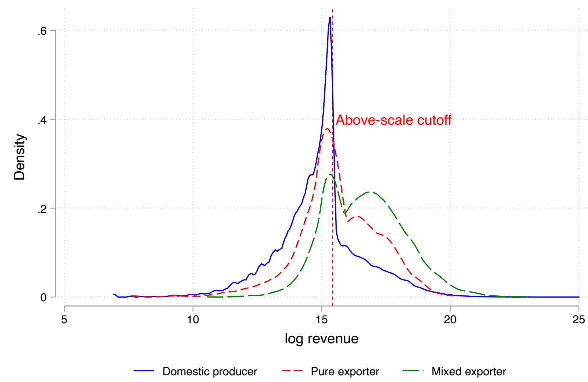
Source: Economic Census (2004,2008) and Customs data.

Data restricted to manufacturing firms. Revenue measured in Yuan.

Table B1 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, which is also documented by Lu, Lu and Tao (2014) using the Above Scale database, matches the ordering of firms in our model with respect to revenues (and ability). Figure B1 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.



(a) 2004



(b) 2008

Figure B1: Revenue Distribution

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

The vertical line in Figure B1 marks the 5 million Yuan cutoff above which firms are selected into the Above Scale database, which is maintained by the National Bureau of Statistics and has been used in many previous studies. Above Scale firms are subjected to increased government oversight, which is presumably why there is bunching just below the threshold (especially for domestic firms). Firms in the Above Scale database are evidently highly selected, which is why we prefer the economic censuses and the SAIC databases for our analyses. The SAIC inspection database, which we use for the analysis of network effects, also provides firm revenues. However, this is only for a sample of firms.

Supplemental Appendix C: Testing the Model

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

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

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

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

Taking logs,

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

β at the one-digit sector level and η can be obtained from Hsieh and Klenow. The last term on the right hand side of the preceding equation is common to all firms in a destination-time period and, hence, is subsumed in the destination-time period effects.

2. Growth in network size with respect to duration: Based on Figure 1, we expect that the change in the stock of firms from one period to the next will be increasing in network duration. This is what we observe in Columns 1-2 below. However, the sign of this association is reversed when the stock is measured in logs, as seen in Columns 3-4. This is in line with what we observe in Table 3.

Table C1: Change in the Stock of Firms and Network Duration

Dependent variable:	change in the stock of firms		change in the log stock of firms	
Network:	domestic	export	domestic	export
	(1)	(2)	(3)	(4)
Duration	1.719***	0.049***	-0.003***	-0.015***
	(0.055)	(0.010)	(0.000)	(0.001)
Birth county-destination fixed effects	Yes	Yes	Yes	Yes
Observations	1,144,111	45,087	1,144,111	45,087

Note: Network size is constructed from SAIC registration data and Customs data.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

3. Constructing the shift-share instrument: This instrument predicts the entry of firms from birth county j into prefecture k in time period t based on agricultural income shocks at the origin. It 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 11 crops that account for 96 percent of cultivated area in China. 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., 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: The decision to establish a firm is a major decision that is unlikely to be determined by a single income shock. We thus assume that firm entry in year t from county j is determined by the average of the income shocks in that year and the preceding two years:

$$AS_{jt} = \frac{1}{3} \sum_{\tau=t-2}^{t} S_{j\tau}.$$

Step 4: The entering firms from birth county j are then "distributed" across destination prefectures, k, by dividing the county-level average income shock by distance, d_{jk}, plus one. 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. The standard gravity equation in the New Economic Geography literature; e.g. Tombe and Zhu (2019) is specified as follows:

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

To construct the shift-share instrument, we set the "migration" elasticity, κ, to be equal to minus one, instead of estimating it from the preceding equation:

$$IV = \frac{AS_{jt}}{(d_{jk}+1)}.$$

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

4. Validating the shift-share instrument: In this section, we assess whether each component of the shift-share instrument satisfies the exclusion restriction. Estimates with the benchmark specification, using the shift-share instrument and with the full sample of firms are reported in Table C2, Column 1.

(a) Agricultural price shocks: One way in which agricultural price shocks could directly impact firm performance 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 Table C2, Column 2. As can be seen, the network size coefficient continues to be positive and significant, although it is smaller in size than the benchmark coefficient estimate in Column 1.

A second way in which agricultural price shocks could affect a firm's performance 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. The estimates reported in Table C2, Column 3 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. We account for this in Table C2, Column 4 by including the uninteracted agricultural income shock in the birth county as a covariate in the estimating equation. The income shock has a positive and significant direct effect on firm revenue, whereas our first-stage estimates in Table 3 indicate that it has a negative effect on firm entry and, with it, network size. These effects work in opposite directions and, hence, by ignoring a potential wealth effect in the benchmark specification, we are (if anything) reporting conservative estimates of the network size effect.

Table C2: Robustness Check for Shift-Share IV

Sample:	all	outside birth county	excluding agricultural processing	all	all
Dependent variable:	log domestic revenue				
	(1)	(2)	(3)	(4)	(5)
Log network size	1.455***	0.622***	1.437***	1.621***	1.412***
	(0.121)	(0.178)	(0.119)	(0.100)	(0.119)
Agriculture income shock	–	–	–	0.386**	–
				(0.154)	
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Destination-time period effects	Yes	Yes	Yes	Yes	Yes
Distance-time effects	No	No	No	No	Yes
Kleibergen-Paap F	48.01	46.24	48.38	70.95	41.59
Observations	5,340,649	3,342,116	5,225,613	5,340,649	5,340,649

Note: Network size is constructed from SAIC registration data.
Revenue is constructed from SAIC inspection data.
Firm fixed effects are purged by first-differencing prior to estimation.
The modified network variable is thus measured by the growth in (domestic) network size.
Instrument for the growth in network size: birth county income shocks.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

(b) Distance adjustment: Distance is a fixed characteristic and, hence, its direct effect on firm performance is subsumed in the firm fixed effect. However, Goldsmith-Pinkham, Sorkin and Swift (2020) note that its interaction with time, and the interaction of the "share" with time more generally, must also be considered when examining the validity of the shift-share instrument. As observed in Table C2, Column 5 the results are robust to including distance interacted with time effects in the estimating equation.

(c) Crop shares: The crop shares, like the distance multiplier, are fixed characteristics and, hence, their direct effect on firm performance is subsumed in the firm fixed effect. As with distance, however, we must consider the possibility that the interaction of the shares with time directly determines firm revenues when examining the validity of the shift-share instrument.

Table C3: Testing the Exogeneity of the Crop Shares: Shift-Share IV

Crop used to construct IV:	maize	potato	repeseed	rice	wheat	soybean	sorghum
Dependent variable:	log domestic revenue						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log network size	1.864***	2.115***	1.180***	1.717***	1.311***	1.420***	2.035***
	(0.154)	(0.174)	(0.134)	(0.093)	(0.123)	(0.102)	(0.313)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-time period effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	9.302	9.620	8.772	14.49	4.887	6.043	1.533
Share	0.328	0.115	0.123	0.065	0.099	0.120	0.013
Weight	0.432	0.140	0.121	0.099	0.091	0.073	0.044
Observations	5,340,649	5,340,649	5,340,649	5,340,649	5,340,649	5,340,649	5,340,649

Note: Network size is constructed from SAIC registration data and Customs data.
Revenue is constructed from SAIC inspection data.
Firm fixed effects are purged by first-differencing prior to estimation.
The modified network variable is thus measured by the growth in (domestic) network size.
Instrument for the growth in network size: crop share interacted with time effects.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

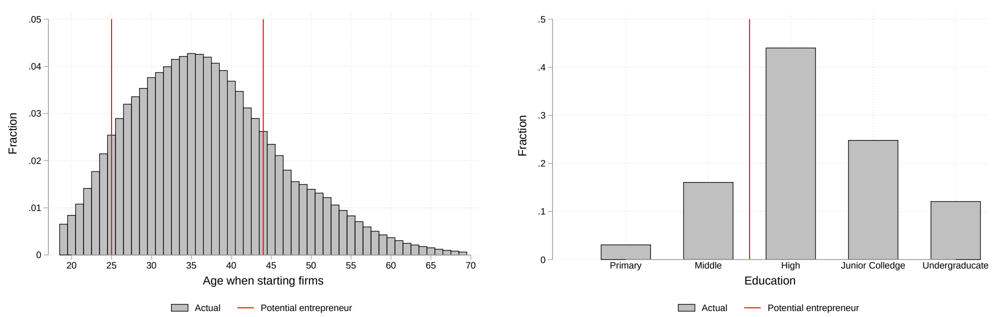
To address the preceding concerns, we take advantage of the fact that if the crop shares are exogenous, then the shift-share instrument that we construct is "equivalent" to using the shares associated with each crop, interacted with time effects, as independent instruments for network size (Goldsmith-Pinkham, Sorkin and Swift, 2020). It follows that if the share for any crop violates the exclusion restriction, then the instrumental variable estimates obtained with that crop would differ from the estimates obtained with other crops. Table C3 reports results with domestic revenue as the dependent variable, using the share for each crop interacted with time effects (and the distance adjustment) as instruments for network size. We report estimates with all 7 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, potato, repeseed, and rice have the largest weights, together accounting for 79.2 percent of the variation in the instrument and 63.1 percent 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 C2, Column

1. This indicates that no crop has a separate and independent effect on firm performance, validating the exogeneity of the corresponding shares.

Supplemental Appendix D: Quantitative Analysis

1. Computing the number of potential entrepreneurs: The SAIC registration database provides the gender, age, and education for a subset of legal representatives. Among those individuals who report their gender, 79 percent are men. In addition, we see in Appendix Figure D1 that most (male) entrepreneurs in the registration database have at least high school education and that most were aged 25-44 when their firm was established. The number of potential entrepreneurs from a given county is thus specified to be the number of men aged 25-44, with at least high school education, who were born in that county. This statistic 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 2000-2012 period. Large-scale internal migration only commenced in China in the 1990's and, hence, the gender, age, and education distribution of county residents in the 1990 census can be used, without modification. However, the 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.

Figure D1: Education and Age Distribution of Male Entrepreneurs



(a) Age

(b) Education

Source: SAIC registration database.

2. First-stage estimates of the fresh exporter propensity equation: As discussed in Section 4.1, income shocks in the birth county, domestic network duration, and export network duration can be used as instruments for the change in the domestic network term and the export network term when we first-difference the fresh exporter propensity equation. These first-stage estimates are reported in Table D1, Columns 1-2.

The F statistic testing the joint significance of the instruments is greater than 400 in Column 2, where the change in the export network term is the dependent variable. However, it is less than 10, the conventional threshold for joint significance, in Column 1 (with the

Table D1: First-Stage Estimates of the Fresh Exporter Propensity Equation

Dependent variable:	change in domestic network term (1)	change in export network term (2)	change in domestic network term (3)	change in export network term (4)
Export network duration	0.001***	-0.003***	0.002***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Domestic network duration	-0.000	0.005***	0.000	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Birth county income shock	-0.453***	0.259	-0.364**	0.239
	(0.171)	(0.327)	(0.168)	(0.324)
Export network duration * initial entry	–	–	-0.027***	-0.035***
			(0.006)	(0.006)
Domestic network duration * initial entry	–	–	-0.003***	0.008***
			(0.001)	(0.003)
Destination-time period effects	Yes	Yes	Yes	Yes
F-test stat.	9.678	413.6	11.15	257.5
Observations	22,572	22,572	22,572	22,572

Note: Network size is constructed from SAIC registration data and Customs data.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

change in the domestic network term as the dependent variable). This is despite the fact that export network duration, one of our instruments, appears in the denominator of both dependent variables, giving rise to a mechanical correlation. To increase statistical power, we thus add two instruments – the interactions of domestic network duration and export network duration with their initial levels of entry – in Columns 3-4. The network duration interactions are precisely estimated and the F statistics are now above 10 in both columns. The five variables in Columns 3-4 are thus used as instruments when estimating the fresh exporter propensity equation. As observed in Table 9, Column 6, the Kleibergen-Paap F statistic with the five instruments is greater than 10 (the conventional threshold above which the instruments are assumed to have sufficient power).

3. Testing the exogeneity of the additional instruments: To test the exogeneity of the additional instruments, we need to start with an equation where we have sufficient confidence in the estimates with the benchmark set of instruments; i.e. without the interactions. We cannot use the fresh exporter equation for this purpose since we know from Table D1, Columns 1-2 that this equation is under-powered with the benchmark set of three instruments. We thus re-estimate the export revenue equation in Table 8, Column 4 with all five instruments. This equation has two key features in common with the fresh exporter propensity equation in Table 9, Column 6: (i) There is an export network term and a domestic network term, both of which need to be instrumented. (ii) The structural error in both equations includes the birth county-destination prefecture productivity term, v_{ejkt}, which is the potential source of bias. The difference between these equations is that the network terms are constructed as the average of network sizes over the history of the network in the fresh exporter propensity equation and as the lagged stock (in a single period) in the export revenue equation. As a result, the birth county income shock instrument in Table 9, Column 6 is constructed as the average shock over the history of the network, whereas it is restricted to the lagged shock in Table 8, Column 4. Since the additional instruments that we are considering are associated with the network duration variables, this difference is unlikely to be relevant. It follows that if we can verify the exogeneity of the additional instruments with the export revenue equation, then we can infer (with reasonable confidence) that this will apply to the fresh exporter propensity equation. As seen in Table D2, the point estimates with the five instruments are very similar to the corresponding estimates with three instruments. This is corroborated by a formal over-identification test, where the "difference in Sargan" or C statistic is 0.63 (p-value 0.73), verifying the exogeneity of the additional instruments.

Table D2: Firm Performance Equations with Cross-Network Effects and Additional Instruments

Dependent variable:	log export revenue	
	(1)	(2)
Log domestic network Size	-0.587**	-0.704***
	(0.277)	(0.205)
Log export network Size	1.165***	1.115***
	(0.156)	(0.120)
Destination-time period effects	Yes	Yes
Firm fixed effects	Yes	Yes
Kleibergen-Paap F	16	19.74
C-test stat.	–	0.632
P-value for C-test	–	0.729
Observations	128,313	128,313

Note: Network size is constructed from SAIC registration data and Customs data.
Revenue is constructed from Customs data.
Firm fixed effects are purged by first-differencing prior to estimation.
Instruments in Column 1: birth county income shock, domestic network duration, export network duration.
Instruments in Column 2: birth county income shock, domestic network duration, export network duration, domestic network duration interacted with its initial entry, export network duration interacted with its initial entry.
C-test statistics examines the exogeneity of the additional instruments, which are the domestic network duration interacted with its initial entry and the export network duration interacted with its initial entry.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.