COMMUNITY NETWORKS, ENTREPRENEURSHIP AND THE PROCESS OF ECONOMIC DEVELOPMENT

By

Ruochen Dai, Dilip Mookherjee, Kaivan Munshi

and Xiaobo Zhang

September 2024

COWLES FOUNDATION DISCUSSION PAPER NO. 2406

COWLES FOUNDATION FOR RESEARCH IN ECONOMICS

YALE UNIVERSITY
Box 208281
New Haven, Connecticut 06520-8281

http://cowles.yale.edu/

Community Networks, Entrepreneurship and the Process of Economic Development*

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

September 7, 2024

Abstract

This research 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 market imperfections 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 were effective at increasing the revenues of their members, both in domestic production and exporting. While this substantially increased the number of domestic producers in the first stage, the incumbent domestic networks created a disincentive to enter exporting in the second stage that dominated the 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 facilitate the occupational mobility of their members, and pre-existing networks slow down the growth of the networks that follow.

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

*We are grateful to numerous seminar and conference participants and many colleagues for their constructive comments. Research support from the Economic Development and Institutions (EDI) RA4 program, Cambridge-INET, National Natural Science Foundation of China (project number 71874008, 71441008, 71873121, 72192844, and 72203252) and the Agence Nationale de la Recherche (ANR) under the EUR Project ANR-17-EURE-0010 is gratefully acknowledged. We are responsible for any errors that may remain.

†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, which emerge in response to market imperfections, 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 dominated the positive effect of newly emerging export networks. This tension highlights the complex dynamics of the development process in economies where overlapping networks, supporting occupational mobility at different stages, are active.

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 focussed 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, the received literature does not tell us how millions of entrepreneurs were able to establish and grow their businesses at early stages of the economic reforms, when many markets were missing or incomplete.

Our analysis, which aims to fill the preceding gap in the literature, is based in large part on the State Administration of Industry and Commerce (SAIC) registration database, which covers the universe of registered firms in China from the 1980's onwards. A unique feature of these 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 or 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

[1] The analysis in this paper extends from 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 local government officials were incentivized to increase the number of registered firms, undermining the quality of the administrative data that we use in our analysis.

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, and thus these individuals, almost all of whom would be first-generation businessmen, are an important group to study from a growth and a distributional perspective. The central thesis of our research is that networks organized around the hometown (birth county) played an instrumental role in supporting the entry of the rural-born entrepreneurs into business, at a critical (initial) stage in China's economic development.

The idea that business networks are active in China and that networks are organized around the birth county 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 native place (Honig, 1992, 1996; Goodman, 1995). Building on this past work, we posit that birth county networks allow firms to cooperate and share inputs and information by harnessing pre-existing social ties. For example, a longstanding literature describes how firms respond to the difficulty in enforcing formal contracts in developing economies by establishing relational contracts (McMillan and Woodruff, 1999; Macchiavello and Morjaria, 2015, 2021). Community networks can expand the scope of such bilateral arrangements; a firm in a long-term relationship with a buyer or supplier can provide a (credible) referral for another firm from its network who only requires that connection temporarily (Greif, 1993, 1994). Members of a network can also provide information about new technologies and business opportunities to each other. Our estimates indicate that birth county networks were active and important; in their absence, the number of rural-born entrepreneurs would have been substantially lower in 2012, the end point of our analysis.

The preceding finding speaks to two influential literatures in economics: First, a large body of research, starting with Acemoglu, Johnson and Robinson (2001), documents the long shadow of historical institutions on the trajectory of economic development. Our complementary analysis examines the informal institutions that emerge endogenously at early stages of development in response to market imperfections, showing that they also have important consequences for an economy's subsequent trajectory. 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.

While the analysis thus far paints the birth county networks in an entirely positive light, their role in the second transition to exporting turns out to be more nuanced. A decade after privatization

[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% established their firm in their birth county, 15% in their birth prefecture but outside the birth county, 15% in their birth province but outside the birth prefecture, and 31% outside their birth province.

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, the analysis in this paper focuses on relatively productive exporting firms who ship their products directly to foreign buyers.[3] The SAIC registration database can be merged with the Customs database, which provides information on all shipments out of China. Based on these data, we find that the rural-born entrepreneurs were less visible in the second transition, with their firms accounting for 30 percent of the 170,000 "direct" exporting firms and an even smaller share of direct exports by volume in 2012. There are many, potentially co-existing, explanations for this relatively weak performance. For example, rural-born entrepreneurs may lack the ability, the resources, or the government connections that are need to be successful in exporting. In our analysis, we attempt to identify a role for the network channel once again. Our results indicate that export networks providing mutual help to entrepreneurs from the same birth county were also active. However, the additional factor that becomes relevant in the second transition is that the previously established domestic network can discourage entrepreneurs from moving into the new export activity when it became available. We find that the negative domestic network "overhang" dominates the positive effect of the export network on entry into that activity. Our estimates indicate that the number of rural-born exporters in 2012 would have been substantially *higher* in the absence of the birth county networks.

As reviewed in Munshi (2014), previous research in developing and advanced economies has shown that community-based networks that have been in place for many generations can restrict the occupational (and spatial) mobility of their members when economies restructure. Our unique administrative data, coupled with the compressed nature of the Chinese development experience, allows us to go further and document the positive and the negative role played by the *same* (domestic) network at different stages of the development process. Akcigit and Nicholas (2019) advocate for the use of historical micro data, theory, and empirics to study economic growth, and our analysis, which we describe step by step below, exemplifies the value of this approach.

The productivity enhancing mutual help that members of a network provide to each other is inherently local, as also documented in the agglomeration literature in which firms benefit from inter-firm spillovers, but without relying on pre-existing social ties; e.g. Combes et al. (2012); Duranton and Puga (2020); Rosenthal and Strange (2020). We thus specify the domain of the network by the birth county-destination prefecture in our analysis; there are 350 prefectures in China and firms from a given birth county will typically locate in multiple destinations. Restricting attention to firms that are established outside the birth county, we use SAIC registration data in Section 2 to document the importance of birth county ties. In particular, we find that key personnel (senior managers, directors, shareholders) in these firms are 50 times more likely to be born in the same county as the legal representative than would be the case with random assignment. In addition, firms are 50 times more likely to be (formally) linked to firms from the same birth county

[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.

than would be the case with random matching.[4] While these statistics emphasize the importance of the birth county, a more stringent test that networks are active is that these informal arrangements should improve the performance of their members. The model that we describe next will allow us to derive such a test.

The dynamic model of occupational choice that we develop in Section 3 adds a network component and a trade component to the Roy (1951) model. In our model, successive cohorts of agents choose between a traditional occupation and becoming an entrepreneur (serving the domestic market, the export market, or both markets). Placing standard restrictions on the production technology, the returns to ability increase more steeply in business (domestic production) than the traditional occupation (agriculture, wage labor). This implies that there is an ability threshold above which individuals select into domestic production. In the Melitz (2003) model, there is a higher threshold above which individuals select into exporting. Our model departs from the Melitz model in a number of ways, the most important of which is a scope diseconomy (a fixed cost of setting up a domestic plant and an export plant) that results in the presence of "pure" exporters who specialize in that activity, and who are needed to explain why the domestic network can discourage entry into exporting.[5] It follows that there are three ability thresholds in our model: a lower threshold above which individuals select into domestic production, an intermediate threshold above which individuals select into pure exporting, and a higher threshold above which individuals select into "mixed" exporting (operating export and domestic plants).

In our model, a firm's profits, separately in domestic production and exporting, are determined by the entrepreneur's ability, an exogenous market-time effect that incorporates conventional agglomeration effects, product demand, and government support, as well as an endogenous birth county network effect. If the mutual support that members of a network provide to each other is complementary, then firms will benefit from a larger network. It follows that an increase in domestic network size will increase firm profits, shift down the lower 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, by shifting down the intermediate threshold. However, there is now a countervailing effect on this threshold on account of the domestic network. In particular, an increase in the size of this network, which increases domestic profits, will shift the intermediate threshold up, reducing the export propensity. This (domestic) network "overhang" arises because the marginal exporter is a pure exporter who must choose between domestic production and exporting. If the domestic network overhang dominates the positive effect of the export network, then the net effect of the networks will be to *reduce* the number of exporters.

Before estimating the effect of the birth county networks on firm entry, we first need to establish

[4]While networks largely rely on informal interactions, formal links between firms can also be used to complement these interactions and increase cooperation. We denote two firms, located in the same prefecture, as being "linked" if one or more key personnel are listed in both of them.

[5]The presence of such exporters has recently been documented in many developing countries (Lu, Lu and Tao, 2014; de Astarloa et al., 2015; Blum et al., 2020). Combining the Customs database with the economic censuses, we show that they also exist in China.

that these networks are active. We thus 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 these terms by including firm fixed effects and prefecture-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, and we address this possibility by constructing statistical instruments for network size.

The first instrument that we construct for 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 continue to be a major sector and 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. In addition, we draw on the recent literature, particularly Goldsmith-Pinkham, Sorkin and Swift (2020), to implement a series of tests that validate each component of the shift-share instrument.

Our second instrument is based on an implication of the dynamic model, which is that once a birth county network forms in a particular prefecture, there will be a deterministic relationship between its duration and its contemporaneous growth rate. The SAIC data, which extend back to the 1980's, provide the registration year and the location of each firm. We thus observe the precise point in time at which each of the 140,000 domestic networks and 7,800 export networks in our data commenced, which, in turn, allows us to compute their durations in any subsequent year.[6] It is common practice in the migration literature, going back to Card (2001), to assume that initial settlement from an origin in a particular destination is exogenously determined. When constructing our instrument, we make the weaker assumption that the *timing* of network formation is exogenous.

[6]A network is said to have commenced if we observe at least one firm from a birth county in a particular prefecture for two consecutive years. We place no restrictions on when networks commence, although in practice most of them began after 1994.

This assumption is supported by anecdotal evidence that there is typically an accidental aspect to business network formation (Damodaran, 2008; Kerr and Mandorff, 2023). Lending credence to this claim, almost all the networks in our data start with a single firm, which suggests that initial entry is idiosyncratic and not a response to origin-level opportunities in the prefecture. Once we first-difference the revenue equations to purge firm fixed effects, the instruments need to predict changes (growth) in network size, and we see that both domestic and export network duration have sufficient power to do this.

Our OLS and our 2SLS estimates indicate that firm revenues and productivity are increasing in network size. These estimates provide direct evidence that birth county networks are active, and are obtained for both domestic production and exporting. While our analysis focuses on business networks, it complements a well established literature that documents the positive effect of migrant labor networks on the outcomes of their members. One line of research shows that job referrals increase wages, controlling for unobserved heterogeneity with fixed effects; e.g. Heath (2018); Barwick et al. (2023). An alternative approach, which is related to our research design, has been to estimate 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 focussed on providing descriptive evidence that these networks are active; e.g. Fafchamps (2000); Rauch (2001); Munshi (2011); Kerr and Mandorff (2023). Our analysis is the first to provide causal evidence that networks of firms can improve the outcomes of their members. The additional virtue of our analysis is that it covers both domestic production and exporting, and is based on the universe of (registered) firms in a major developing economy.

We complete the tests of the model in Section 4 by estimating the effect of the birth county networks on firm entry. Based on the model, the entrepreneurial propensity, measured as the number of firms divided by the number of potential entrepreneurs, is increasing in (lagged) domestic network size. The export propensity, measured analogously, is increasing in the lagged average of the export network size and decreasing in the lagged average of the domestic network size, with the averages constructed over the entire history of each network. Birth county-destination prefecture effects and prefecture-time period effects are included as covariates, and once the propensity equations are first-differenced to purge the fixed effects, we are left with the growth in network sizes as the endogenous variables. The income shocks in the birth county can no longer be used as instruments because they determine firm entry directly, but the network durations continue to be valid.[7] Based on our estimates, the domestic network has a positive and statistically significant effect on firm entry. The export network also has a positive and statistically significant effect on the entry of export firms, but this is offset by the negative and statistically significant domestic network overhang. Based on the quantitative analysis in Section 5, the number of domestic pro-

[7]To estimate the export propensity equation, we add an instrument – the interaction of network duration with initial entry – to give us sufficient statistical power. Lagged levels are typically used as instruments to predict growth rates in the endogenous variable when estimating dynamic panel models in first differences (Arellano and Bond, 1991; Blundell and Bond, 1998). We make the weaker assumption that the *initial* entry level is exogenous and our over-identification tests provide statistical support for this assumption.

ducers would have been 23 percent lower and the number of exporters would have been 76 percent higher if the birth county networks were absent.

Entrepreneurs do not internalize their contribution to the networks and, hence, there is a role for entry and export subsidies. While export subsidies are unambiguously efficiency enhancing, the entry subsidies must be attentive to their negative effect on export profits, due to the domestic network overhang, underscoring both the value and the difficulty of designing industrial policy in economies where networks are active. As discussed in the concluding section, the networks that we describe in this paper are not restricted to China or to business. However, their importance in other developing economies will depend on their social structure, and this will vary across regions of the world.

2 Descriptive Evidence

In a conventional analysis of agglomeration effects, firm performance would be determined by the number of firms in the prefecture, regardless of their ethnicity. The prefecture-time period effects that we include in all the estimating equations will subsume these agglomeration effects, which benefit all firms equally. Supplementing these effects, we posit that community-based business networks will also be relevant in developing economies. This is because higher levels of cooperation (mutual help) are needed at early stages of economic development when many markets are missing or incomplete. Entrepreneurs will thus harness pre-existing social ties, and the social enforcement that they provide, within narrower networks of firms, while continuing to benefit from conventional agglomeration effects in the locations where they are established.

We noted in the introductory section that ethnicity in China is defined by the native place, and it is well documented that *laoxiang* or "native-place fellows" help each other in different ways (Ma and Xiang, 1998; Zhang and Xie, 2013).[8] 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 and information, is inherently local, as also assumed in the agglomeration literature. We thus define the scope of the network by the birth county-destination prefecture in our analysis.[9]

Table 1 uses the preceding definition of the network to provide descriptive support for the importance of birth county ties, restricting attention to firms that are located *outside* the entrepreneur's natal county and were active in 2012, the end point of our analysis. In addition to the entrepreneur

[8] 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.

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

or legal representative, the SAIC registration database also lists other key personnel in the firm.[10] Column 1 reports the fraction of these individuals who are born in the same county 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. 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. Column 2 uses shareholders rather than listed individuals to measure ties to the birth county, as in Bai et al. (2020), with very similar results.

Table 1, Column 3 assesses 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 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 uses shareholders rather than listed individuals to construct links, without changing the results.

Table 1: 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	
Type of personnel:	listed individuals	shareholders	listed individuals	shareholders
	(1)	(2)	(3)	(4)
Mean	0.488	0.476	0.499	0.436
Counter-factual mean	0.013	0.012	0.014	0.013

Note: the statistics are computed using SAIC registration data.
The sample is restricted to firms established outside their birth counties and 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 this section indicates that entrepreneurs remain connected to their birth counties, 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, and we expect this homophily to extend to informal interactions between firms. The model of entrepreneurship (occupational choice) that follows will build on these findings to incorporate a

[10] 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, 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.

productivity enhancing role for birth county networks.

3 The Model

3.1 Population and Technology

For expositional convenience, 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. Successive cohorts of agents indexed by $t' = 1, \dots, T$ 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 $[A-1, A]$.

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

Capital costs for domestic and export plants are as follows:

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

where r includes interest and material costs of equipment, and $I > 0$ is the incremental cost of operating an export plant, arising from the need to vertically integrate production or to conform to international quality standards.[12] An important additional feature of the model is the presence of diseconomies of scope, incurred by *mixed exporters* who produce for both the domestic and the

[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.

[12] 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.

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 (2). 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 and who are needed to explain why the domestic networks can discourage entry into exporting.[13]

We now turn to the productivity multiplier term, C_{bt}, which is comprised of an exogenous market-time effect, Q_{bt}, and the endogenously determined birth county-destination prefecture network, where n_{t-1} measures the stock of firms located in the prefecture in period $t-1$; i.e. prior to period t and $n_{e,t-1}$ measures the corresponding stock of export firms:

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

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

The market-time effect 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 a developing economy. The network component of the productivity multiplier is specific to an origin birth county and is based on the assumption that the mutual help that the incumbent (experienced) members of a network provide is complementary, which, in turn, implies that firms will benefit from a larger network. Notice that the domestic network is specified to include the (lagged) stock of all firms, whereas the export network is restricted to exporting firms. The implicit assumption, as in Fernandes and Tang (2014), is that the information and connections needed for exporting are specific to that activity, and we will provide empirical support for this assumption in the section that follows.

Our definition of the network does not distinguish between sectors. The SAIC registration data indicate that 62 percent of the firms in a given birth county-destination prefecture operate in two, most popular, 3-digit Input-Output industries on average. An additional 22 percent are set up in upstream-downstream and complementary industries.[14] Combining the SAIC data with the Customs database, the corresponding statistics for export firms are 74 percent and 17 percent. This tells us that most firms from a birth county will operate in the same or related sectors in the prefectures where they are established. In addition, many forms of mutual help, such as government connections, will cross sectoral lines and, hence, our more expansive definition of the network's scope seems reasonable. Notice also that other birth county networks do not affect the firm's productivity. The implicit assumption is that networks do not have the market power to

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

[14]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).

compete or collude strategically. Based on the SAIC data, firms from a given birth county account for 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.

Although the export network starts after the domestic network in practice, we assume for the analysis in this section that independent and exogenous entry shocks bring n_0 firms, n_{e0} of whom are exporters, into the market in the initial period 0. The number of firms in both networks will subsequently evolve endogenously over time. Given the irreversibility of market entry decisions, network sizes cannot shrink: $n_t \geq n_{t-1}$, $n_{et} \geq n_{e,t-1}$.

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

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

subject to the irreversibility constraints

$$K_{bt} \geq K_{b,t-1}, b \in \{d, e\} \tag{4}$$

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

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 profit, as expressed in equation (3), 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:

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

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

The above profits are generated by optimal choices on the intensive margin, for a given occupational choice W on the extensive margin. We now turn to equilibrium (extensive form) occupational choices. Observe from (5) that the return to ability is increasing as we progress from the traditional occupation (Π_{Ot}) to domestic production (Π_{Dt}) to exporting (Π_{Et}, Π_{Mt}). At the same time, the entrepreneur must face increasing costs as he moves up the occupational ladder: he must bear a cost of capital, r, if he selects domestic production, there is an incremental cost, I, if he opens an export plant, and then there are the diseconomies of scope that accompany mixed exporting. It follows that there will be positive selection on ability in equilibrium, moving up the occupational ladder, as specified below:

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

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

and a unique Nash equilibrium involving the following strategies:

(a) those with ability below ω^*_{dt} stay in the traditional occupation (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. The condition $\log \omega^*_{et'} < \log \omega^*_{mt}$ for all t in (6) maintains the ordering of the three ability thresholds for any cohort t' at each point in time. This ensures that some pure exporters in cohort t' stay that way, which implies that the additional profit from operating a domestic plant never exceeds β for them. If mixed exporting is never feasible for the marginal pure exporter, then this will also be true for the domestic producers in the cohort, who have ability less than $\omega^*_{et'}$. 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.[15]

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. These changes affect all older cohorts in the same way.

Our objective in this section is to show how networks can both support and restrict firm entry, depending on the circumstances. We are particularly interested in the role of the domestic networks in this regard and so we next proceed to derive expressions for the total number of firms and the number of exporting firms.

Based on Proposition 1, individuals with ability $\omega \in [\omega^*_{dt}, A]$ become entrepreneurs. Deriving the expression for ω^*_{dt} from (5), by setting $\Pi_{Ot}(\omega^*_{dt}) = \Pi_{Dt}(\omega^*_{dt})$, and unpacking C_{dt}:

$$n_t = ts[A - \omega^*_{dt}] = ts[A - \frac{\log \zeta}{1-\sigma} + \frac{q_{dt} + \theta_d \log n_{t-1}}{(1-\sigma)(1-\alpha)}] \tag{7}$$

The initial, exogenous, entry of firms in period 0, n_0, generates subsequent entry through a dynamic network multiplier effect. Solving equation (7) recursively, it is straightforward to verify that the number of firms is increasing over time, $dn_t/dt > 0$, independently of the market-time effect q_{dt}, when networks are active. In the sections that follow, we will identify and quantify this positive (domestic) network effect on the number of firms.

Based on Proposition 1, individuals from cohort t' with ability $\omega \in [\omega^*_{et'}, A]$ become exporters. As noted, there is no further entry into exporting from the t' cohort after that period. Thus, the stock of exporters at any period t is just the sum of exporters supplied by all preceding cohorts. The marginal pure exporter in cohort t', with ability $\omega^*_{et'}$, is indifferent between domestic production and pure exporting. Following the same steps as above, we set $\Pi_{Dt'}(\omega^*_{et'}) = \Pi_{Et'}(\omega^*_{et'})$ to derive $\omega^*_{et'}$ from (5) and then unpack $C_{dt'}$, $C_{et'}$ to obtain:

$$n_{et} = ts[A - \frac{\log \gamma}{\delta - 1}] + \frac{s}{(\delta-1)(1-\alpha)} \sum_{t'=1}^{t} [q_{et'} - q_{dt'} + \theta_e \log n_{e,t'-1} - \theta_d \log n_{t'-1}] \tag{8}$$

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

[15] The transition from domestic production to exporting does not arise in our model, as it is currently formulated, because both networks start at the same time. If the export network starts after the domestic network, as specified in the next section, then high ability domestic producers who did not have access to the export network when they entered will become mixed exporters when export opportunities become available, as in Melitz (2003).

"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.[16] 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, and while the focus of these recent papers is on the intensive margin, they could in principle generate the same tradeoff at the extensive margin between domestic production and exporting as in our model.

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.

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

3. We add a stochastic term to the payoff in the traditional occupation, which is now specified as $U_{jkt}\omega^{\sigma}$. Denote $u_{jkt} \equiv \log U_{jkt}$.

4. We add a birth county-destination prefecture specific term to the productivity multiplier, which is now 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 $v_{djkt} \equiv \log V_{djkt}$, $v_{ejkt} \equiv \log V_{ejkt}$.

[16] The condition $\log \omega^*_{et'} < \log \omega^*_{mt}$ for all t in (6) is critical to this result. If the inequality were reversed in later time periods, then all firms who started as pure exporters, as well as some domestic producers, would become mixed exporters. The marginal exporter in the cohort would no longer be a pure exporter and the negative domestic network overhang would no longer apply. A strong implication of our model, which we verify in the section that follows, is that exporters must commence that activity as soon as their firms are established; i.e. there are no subsequent transitions from domestic production to (mixed) exporting.

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, then firms will benefit from a larger network, as we assume in the model. 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.

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

$$\log R_{djkt} = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r}\right) + \frac{q_{dkt}}{1-\alpha} + \frac{\theta_d \log n_{jk,t-1}}{1-\alpha} + \frac{[(1-\alpha)^2+1]}{1-\alpha}\log\omega + \frac{v_{djkt}}{1-\alpha} \tag{9}$$

The corresponding expression for export revenue is obtained as:

$$\log R_{ejkt} = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r(1+I)}\right) + \frac{q_{ekt}}{1-\alpha} + \frac{\theta_e \log n_{ejk,t-1}}{1-\alpha} + \frac{\delta[(1-\alpha)^2+1]}{1-\alpha}\log\omega + \frac{v_{ejkt}}{1-\alpha} \tag{10}$$

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,

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

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.[17] The SAIC inspection database and the Customs database that we use to estimate these equations provide 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 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 prefecture-time period effects that we also include in the estimating equations. Conditional on the firm fixed effects and the prefecture-time period effects, consistent estimates of the network effects will be obtained if network sizes, $n_{jk,t-1}$, $n_{ejk,t-1}$ are uncorrelated with the structural errors; v_{djkt}, v_{ejkt}. The entry equations that we derive next will allow us to systematically examine these orthogonality conditions and to construct suitable instruments in the event that these conditions are 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 (7). Based on that equation, and incorporating the extensions

[17] 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. The analysis of productivity is thus restricted to domestic producers who are engaged in a single activity, which is why we do not specify an equation for export productivity.

to the model that we listed above, the fraction of potential entrepreneurs from birth county j, s_{jt}, who establish firms in prefecture k is specified as follows:

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

In the analytical model, there is a single destination prefecture and, hence, potential new entrepreneurs can be partitioned by ability into distinct activities. With multiple destinations, however, the same individual could possibly be willing to establish his firm in more than one prefecture. To avoid such double-counting, we assume that each potential entrepreneur receives a business opportunity in a single prefecture. If there is an equal probability of receiving that referral from all prefectures, then the right hand side of the propensity equation will be multiplied by a constant and the estimation proceeds without modification. However, we implicitly add destination-level heterogeneity to the analytical model when we first-difference the propensity equation to purge the fixed effect. This equation is estimated at the birth county-destination prefecture-time period level and, hence, the fixed term, A_{jk}, is defined (by construction) at the birth county-destination prefecture level.

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, a market-time term, a network term, and two structural error terms. n_{jkt} is positively correlated with v_{djkt} in equation (12) and, going back one period, this implies that $n_{jk,t-1}$ is positively correlated with $v_{djk,t-1}$. If we first-difference equations (9) and (11) to purge firm fixed effects, then $v_{djk,t-1}$ will appear in the residual of the modified equation, biasing the network effect downward. The bias in equation (12) is even more obvious. If we first-difference that equation to purge A_{jk}, then $n_{jk,t-1}$ will appear on both sides of the modified equation, biasing the network effect downward if network sizes are measured with error. In addition, $v_{djkt} - v_{djk,t-1}$, $u_{jkt} - u_{jk,t-1}$ will be correlated with the (lagged) growth in network size, $\log n_{jk,t-1} - \log n_{jk,t-2}$, biasing the estimated network effects even further.[18]

The first instrument that we construct for the growth in domestic network size, in the first-differenced equations (9) and (11), is based on the observation that income shocks in the birth county, u_{jkt}, will exogenously determine firm entry, as seen in equation (12). The observed component of these shocks, which we use to construct the instrument, will "push" potential entrepreneurs into business and is thus plausibly uncorrelated with the unobserved productivity shocks in the destination prefecture, v_{djkt}, 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 desti-

[18]The negative bias that we have just described is conceptually related to the well known Nickel bias, which arises when estimating dynamic panel models with fixed effects. The preceding discussion implicitly assumes that the structural errors are serially uncorrelated, as in the dynamic panel literature. If we relax that assumption, then $n_{jk,t-1}$ will be positively correlated with v_{djkt}, through $v_{djk,t-1}$, biasing the estimated network effects upward. However, we do not expect this indirect channel to dominate the direct effect of the correlation between $n_{jk,t-1}$ and $v_{djk,t-1}$.

nation prefecture k, independently of the shocks, q_{dkt}, v_{djkt}, u_{jkt} in equation (12), once the network has formed in that prefecture. The instrument that we construct for the growth rate of the network is simply the network duration, $t-t_{djk}$. The identifying assumption with this instrument (discussed in the section that follows) is that the shocks that jump-start the birth county-destination prefecture networks are accidental one-off events. While we thus have two potential instruments when estimating equations (9) and (11), notice that only the second – network duration – instrument is valid when we estimate equation (12) because u_{jkt} appears in the residual of that equation.

We next subject the export revenue equation (10) to similar scrutiny by constructing the accompanying export propensity equations. Based on equation (8), and incorporating the extensions to the model that we listed above, the number of "fresh" exporters who establish their firms after the export network is established, n_{fjkt}, divided by the number of potential entrepreneurs, s_{jt}, is specified as follows:

$$\frac{n_{fjkt}}{s_{jt}} = A_{jk} + \sum_{t'=t_{ejk}+1}^{t} \frac{[q_{ekt'} - q_{dkt'}] + [\theta_e \log n_{ejk,t'-1} - \theta_d \log n_{jk,t'-1}] + v_{ejkt'}}{(t-t_{ejk})(\delta-1)(1-\alpha)} \tag{13}$$

In our analytical model, the domestic network and the export network start at the same time. It follows, from Proposition 1, that domestic producers then never transition to (mixed) exporting. Once we allow the export network to start after the domestic network, 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 if their export profits exceed β. This condition is more likely to be satisfied as the export network expands, with an accompanying increase in the productivity multiplier C_{ejkt}, bringing in more mixed exporters over time. Based on the model, and incorporating the extensions listed above, the share of incumbent domestic producers from birth county j who become mixed exporters in prefecture k is specified as follows:

$$\frac{n_{mjkt}}{n_{jkt_{ejk}}} = A_{jk} + \frac{q_{ekt}}{\delta(1-\alpha)} + \theta_m \frac{\log n_{ejk,t-1}}{\delta(1-\alpha)} + \frac{v_{ejkt}}{\delta(1-\alpha)} \tag{14}$$

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 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 (13) 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 (13) and n_{mjkt} is positively correlated with v_{ejkt} in equation (14). It follows that $n_{ejk,t-1}$ is positively correlated with $v_{ejk,t-1}$. The estimated network effect will thus be biased downward when we first-difference equation (10). The first instrument that we construct for the growth in export network size, once equation (10) has been differenced, is the export network duration, $t-t_{ejk}$. While this corresponds to the use of domestic network duration as an instrument for the growth in domestic network size above, additional instruments are now available because the domestic network overhang term restricts entry into exporting in equation (13). In particular, any variable that determines the growth in this term will also be a valid instrument for the growth in export network size.[19] Following our discussion on the identification of the domestic network effect, we can thus use the history of the income shocks in the birth county $u_{jkt'}$; i.e. the average up to period $t-1$, and domestic network duration, $t-t_{djk}$, as additional instruments.

When estimating the export revenue equation (10) in the section that follows, we will see that the history of income shocks in the birth county does not have sufficient statistical power to identify the export network effect (indirectly through the domestic network overhang channel). We will thus use the export network duration and the domestic network duration as instruments in that equation. We will also use these variables as instruments when estimating equation (14) because the structure of the two equations, and the bias that arises when we estimate them, are the same.

The estimates in equation (13) will be biased even without differencing because the history of productivity shocks, $v_{ejkt'}$, $t' = t_{ejk}+1, ...t$, appears in the structural error term. Although export network duration and domestic network duration can also be used, in principle, as instruments in equation (13), the estimation is more challenging. To begin with, notice that export network duration, $t-t_{ejk}$, enters the denominator of the export network term and the domestic network term on the right hand side of that equation. It follows that this instrument will mechanically predict the change in these terms, once we first-difference the propensity equation to purge A_{jk}. This is not a problem *per se* if export network duration also shifts the numerator of the export network term, but the additional challenge when estimating this equation is that the network terms are constructed as averages of network sizes. These are slowly changing statistics and we will see below that domestic network duration does not have sufficient statistical power, by itself, to shift the domestic network term. When estimating equation (13), we will thus include domestic network duration and export network duration, interacted with the respective initial entry levels, as additional instruments. When constructing these instruments, we treat initial entry at the point of inception of the network as exogenously determined, providing statistical support for this assumption in the section that follows.

4.2 Firm Performance

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 (9) - (11), this implies that the firm's performance – revenue or productivity – will be increasing in the size of its network, conditional on prefecture-time 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

[19]The domestic network term determines n_{fjkt} in equation (13) and, hence, $\log n_{ejkt}$. The growth (change) in this term will thus determine $\log n_{ejk,t-1} - n_{ejk,t-2}$.

to construct productivity, as shown in Appendix C.1) for a subset of registered firms over time.[20] 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.[21]

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 income shocks 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, with further details of variable construction provided in Appendix C.2.

Our second instrument, which is simply the duration of the domestic network or the export network, is based on the idea that there is a deterministic aspect to network growth on account of the dynamic multiplier effect. 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 predicted by the network's duration. A discussion on the validity of both instruments is postponed until later in this section.

Table 2 reports first-stage estimates corresponding to the first-differenced equations (9) - (11). The dependent variable in Column 1 is the growth in domestic network size: $\log n_{jk,t-1} - \log n_{jk,t-2}$.

[20] 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 will go further and allow for heterogeneity in experience effects across firms, which could potentially arise due to non-random selection.

[21] 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.

Note that first-differencing purges firm fixed effects, but the prefecture-time 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 significant, indicating that this instrument is pushing potential entrepreneurs into business, as expected. The coefficient on the domestic network duration is also negative and significant. While the size of a network is increasing in its duration, $\frac{dn_t}{dt} > 0$ in equation (7), this is not necessarily true for its growth rate (the sign of $\frac{d^2 n_t}{dt^2}$ is ambiguous). 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. 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, which dampens entry into exporting. While the coefficient on the birth county income shocks has the expected sign in Column 2, it is imprecisely estimated.[22] 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 2: First-Stage Estimates of the Firm Performance Equations

Dependent variable:	growth in domestic network size	growth in export network size
	(1)	(2)
Birth county income shocks	-0.343***	0.516
	(0.094)	(0.770)
Domestic network duration	-0.004***	0.006***
	(0.000)	(0.001)
Export network duration		-0.012***
		(0.002)
Prefecture-time effects	Yes	Yes
Observations	5,211,514	126,971

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.
Instruments include birth county income shocks, domestic network duration, and export network duration.
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%.

Table 3 reports the second-stage revenue and productivity equations (9) - (11), with OLS estimates in Columns 1-3 and 2SLS estimates in Columns 4-6.[23] The network size effect is positive and

[22]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.

[23]We discard the top one percentile and the bottom one percentile of the first-differenced dependent variable when

significant without exception, with the point estimates increasing in magnitude as expected when we instrument for network size. The Kleibergen-Paap F statistic indicates that the instruments have sufficient power and we will provide further support for their validity below. While we just pass the Hansen J over-identification test with domestic revenue as the outcome, we just fail with export revenue as the outcome (the 5 percent critical value is 3.84). A standard interpretation of the latter finding is that there are heterogeneous treatment effects: different sub-populations of firms enter in response to different treatments (instruments) and these sub-populations generate distinct network effects. We subject this interpretation to further scrutiny by estimating the revenue equations one instrument at a time.

Table 4 reports the estimated revenue equations, for domestic production and exporting, separately with each instrument. The excluded instruments are added as covariates in each case, as required when treatment effects are heterogeneous (Mogstad, Torgovitsky and Walters, 2021). The coefficients on the excluded instruments are statistically significant in Table 4 in all columns, which indicates that treatment effects are heterogeneous. At the same time, the tests of the over-identifying restrictions were marginally (in)significant with the two outcomes in Table 3. While the estimated network effects do vary by instrument for each outcome in Table 4, they are consequently of comparable magnitude.

Table 3: 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	0.504***	1.339***	0.630***	1.194***	2.932***	1.353***
	(0.023)	(0.072)	(0.029)	(0.073)	(0.194)	(0.141)
Prefecture-time effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	118.2	118.2	42.80
Hansen J	–	–	–	3.558	1.178	4.760
Observations	5,211,514	5,211,514	126,971	5,211,514	5,211,514	126,971

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%.

The shift-share instrument in Table 4, Column 1 with domestic revenue as the outcome is

estimating all of the firm performance equations to remove outliers. In addition, we drop the less than five percent of observations where the (lagged) growth in network size, on the right hand side of the estimating equation, is negative.

particularly credible because it is leveraging exogenous shocks to activities in the *origin* birth county that serve as the outside options to business. In recent years, shift-share instruments have received much attention in the economics literature. We build on this literature, drawing particularly on Goldsmith-Pinkham, Sorkin and Swift (2020), to implement a series of robustness tests in Appendix C.3 that validate each component of the shift-share instrument. This exercise, by extension, increases our confidence in the domestic network duration instrument because it is based on a completely different source of variation – the timing of network formation in the *destination* prefecture – but, nevertheless, generates network effects in Column 2 that are similar in magnitude to the estimates in Column 1.

Table 4: 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	1.560***	1.157***	0.954***	1.363***
	(0.234)	(0.075)	(0.213)	(0.142)
Domestic network duration	0.002*	–	0.002**	–
	(0.001)		(0.001)	
Birth county income shocks	–	-0.138**	–	–
		(0.070)		
Export network duration	–	–	–	0.005**
				(0.002)
Prefecture-time effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F	13.30	224.4	27.12	82.31
Observations	5,211,514	5,211,514	126,971	126,971

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%.

The idea behind the network duration instruments, which is consistent with the common narrative in the literature on business network formation in developing and advanced economies; e.g. Damodaran (2008); Kerr and Mandorff (2023) is that a fortuitous confluence of circumstances typically jump-starts a network by bringing in one or more firms from a birth county into a particular prefecture. Once the network has formed, more firms enter over time on account of the dynamic multiplier effect that is implied by our model. In practice, we assume that a network has "formed" if one or more firms from the birth county are located in a particular prefecture for two consecutive years. Since our data cover the universe of registered firms, going back to the 1980's, the year of inception and, hence, the duration at each subsequent point in time, is available for each network. The threat to identification when network duration is used as an instrument is that the initial shock is not idiosyncratic and one-off but, instead, is birth county-destination prefecture specific and persistent (serially correlated). Network duration will then be correlated with contemporaneous entry shocks, which continue to draw firms into the prefecture, violating the exclusion restriction. We respond to this concern in two ways:

First, we note that 89 percent of the 140,000 domestic networks and 91 percent of the 7,800 export networks in our data started with a single firm. Although 33 percent of those domestic firms and 65 percent of those export firms remain as a "singleton" network, the rest bring in more firms from the birth county into the prefecture where they are established over time.[24] Among all the multi-firm networks in our data, it follows that 84 percent of the domestic networks and 78 percent of the export networks were started by a *single* firm. If initial entry was a response to an origin-level advantage, then this would typically have brought in multiple firms from the birth county into the prefecture at the outset, which is at odds with what we observe.[25]

Second, the concern we have raised is less relevant when *domestic* network duration is used as an instrument for *export* network size because the domestic network is established long before export opportunities become available. In our data, the domestic network starts, on average, 11 years earlier than the export network in a given birth county-destination prefecture. Even if the initial shock that started the domestic network was persistent, it is unlikely to have been relevant when exporting commenced. 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. Although we cannot make a similar case for the export network duration instrument, the comparability of the estimated export network size effects in Table 4, Columns 3-4, separately for the two instruments, gives us confidence in its validity.

The estimated network effects are positive and significant, without exception, in Tables 3 and 4. This allows us to infer that networks are active, both in domestic production and exporting. In addition, the switch in the sign of the domestic network duration coefficient from Column 1 to Column 2 in Table 2 provides indirect support for the domestic network overhang, which is a key feature of our model. We complete the analysis in this section by verifying the robustness of the core revenue results in the following ways:

(i) Both the shift-share instrument and the network duration instruments are most credible when they are applied to networks established outside the birth county. Agricultural income shocks, for

[24] We retain the singleton networks in our analysis because the subsequent entry of firms into the prefecture is an endogenous outcome and we would not want to select the sample on the basis of such an outcome. Among the prefectures that do receive additional firms over time, the inflow is almost always (weakly) positive; just 4.5 percent of domestic network-years and 1.5 percent of export network-years in our data have negative growth rates in network size.

[25] An alternative explanation for why a single initial entrant can spawn a large network is based on uncertainty in the (fixed) payoff from business. As more firms enter, this uncertainty is gradually resolved, bringing in more (risk averse) entrepreneurs over time. However, this social learning mechanism cannot explain why firm revenues and productivity increase with the size of the network, net of firm fixed effects (which take account of differential selection by ability).

example, could directly affect firm revenues in the birth county through general equilibrium (price) effects. The initial shocks that start the networks are also more likely to be accidental outside the birth county, with the pioneering migrants who set up these networks being exposed to fortuitous opportunities. We thus verify in Appendix C.4 that the core results are retained when the sample is restricted to the majority (62.8 percent) of firms that are established outside their birth county.

(ii) The assumption in our model is that entrepreneurial ability is a fixed trait, which does not vary with experience. Heterogeneity in this trait is captured by firm fixed effects in the preceding empirical analysis. We now allow for the possibility that experience effects vary by community, possibly due to underlying heterogeneity in ability as in Banerjee and Munshi (2004), by including the interaction of the firm's experience with a birth county effect in the revenue equation. Once the revenue equation is first-differenced to purge the firm fixed effects, we are left with birth county effects as additional covariates in this augmented specification of the estimating equation. The results with this specification, reported in Appendix C.4, are very similar to the benchmark estimates in Table 3, Columns 4 and 6.

(iii) A key assumption in the model, which gives rise to the network overhang, is that domestic producers benefit from the domestic network, which includes the (lagged) stock of all firms, while exporters benefit from a distinct network that is restricted to the (lagged) stock of exporting firms. To test this assumption, the estimating equations in Table 5 include both domestic network size and the export network size, in addition to firm fixed effects and prefecture-time effects. The OLS estimates in Columns 1-2 are consistent with the assumptions of the model: 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 there is a weak instrument problem, but this is not the case here because the Kleibergen-Paap F statistic is above 20. 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 the model. Notice that the specification in Table 4, Column 3 is the same as the specification in Table 5, Column 4, except that domestic network duration, which appears as a covariate with a positive coefficient in the former table is replaced by domestic network size (instrumented by domestic network duration) in the current table. We know from Table 2, Column 1 that the association between domestic network size and domestic network duration is negative, which is why the sign of the coefficient on domestic network size is now negative. The intuition underlying this mechanical 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

Table 5: Estimates of the Firm Performance Equations with Cross-Network Effects

Method:	OLS		2SLS		
Dependent variable	log domestic revenue	log export revenue	log domestic revenue	log export revenue	log export revenue
	(1)	(2)	(3)	(4)	(5)
Log domestic network size	0.613***	0.002	1.543***	-0.624**	-0.755***
	(0.037)	(0.042)	(0.065)	(0.271)	(0.202)
Log export network size	-0.002	0.630***	-0.000	1.182***	1.124***
	(0.007)	(0.028)	(0.130)	(0.162)	(0.124)
Prefecture-time effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	22.74	21.59	20.82
Observations	3,388,312	126,971	3,388,312	126,971	126,971

Note: Network size is constructed from SAIC registration data and Customs data.
Firm fixed effects are purged by first-differencing prior to estimation.
Instruments in columns (3)-(4): domestic network duration, export network duration.
Instruments in column (5): domestic network duration, export network duration, and their interactions with initial entry.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

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, although we will need to wait till the next section to identify the mediating domestic network overhang effect directly. 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. In contrast, our interpretation of the OLS estimates is that they represent average (rather than local) effects; conditional on export network size, the domestic network has no effect on export revenues, as assumed in the model.

As discussed in Section 4.1, we will need to include an additional set of instruments when estimating the fresh exporter propensity equation. The augmented set of instruments will include domestic network duration, export network duration, and the interaction of these variables with the respective levels of initial entry. Since the network duration instruments, on their own, lack sufficient statistical power, the fresh exporter equation is effectively just identified. To test the exogeneity of the additional instruments, we thus estimate the export revenue equation with all four instruments in Table 5, Column 5. This equation has two key features in common with the fresh exporter propensity equation that we estimate in the section that follows: (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. If we can verify the exogeneity of the additional instruments with the export revenue equation, then we can infer that this will apply to the fresh exporter propensity equation. As seen in Column 5, the point estimates with the four instruments are very similar to the corresponding estimates with two instruments in Column 4. This is corroborated by a formal over-identification test, where the "difference in Sargan"" or C statistic is 1.05 (p-value 0.59), verifying the exogeneity of the additional instruments.

4.3 Firm Entry

We now test the implications of the model for firm entry by estimating the propensity equations at the level of the birth county-destination prefecture-year in Table 6. We begin with the entrepreneurial propensity equation (12) and the incumbent exporter propensity equation (14) because the right hand side of these equations has the same structure as the revenue equations that we estimated in Section 4.2; the only difference is that 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 prefecture-time effects are retained, but the network terms are now measured by the growth in network size. As discussed in Section 4.1, domestic network duration can be used as an instrument for the growth in domestic network size and that variable, together with the export network duration, can be used as instruments for the growth in export network size.[26]

Entrepreneurial propensity, which is the dependent variable in Table 6, Column 1 is measured by the number of firms divided by the number of potential entrepreneurs.[27] The incumbent exporter propensity, which is the dependent variable in Column 2, is measured by the number of exporters who were initially engaged in domestic production and subsequently added exporting when the opportunity became available, divided by the number of domestic producers who were active when the export network commenced. We see that the coefficient on domestic network size in Column 1 and the coefficient on export network size in Column 2 are both positive and significant, as implied by the model. These results hold up when we instrument for network sizes in Columns 3-4.[28]

Notice that the number of observations in Column 1 is an order of magnitude larger than in

[26]We used the same instruments to estimate the revenue equations, except that birth county income shocks, which were used as instruments in the domestic revenue equation, cannot be used as instruments in the entrepreneurial propensity equation because they determine firm entry directly.

[27]The SAIC registration database provides the gender and age for a subset of legal representatives. Among those individuals who report their gender, 79 percent are men. Among those that report their age, 89 percent are aged 25-55. The number of potential entrepreneurs in 1994, the first year of the propensity estimation, is thus measured by the number of 25-45 year old men residing in the birth county. In each subsequent year, we add a cohort of 25 year old men, which implies that the age distribution spans the 25-62 range in 2012 (the last year of the analysis). The male age distribution in each county is derived in each year using a one percent sample from the most recent population census: the 1990 census for the 1994-1999 period and the 2000 census for the 2000-2012 period. Large-scale internal migration only commenced in China in the 1990's and, hence, the age distribution of county residents in the 1990 census can be used, without modification. However, the age distribution obtained from the 2000 census, and used for the years that follow, is adjusted to account for in-migration and out-migration over the preceding five years.

[28]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. In addition, we drop the less than 5 percent of observations where the (lagged) network growth, on the right hand side of the estimating equation, is negative.

Table 6: 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	0.012***	0.001***	1.903***	0.005***	–	–
	(0.000)	(0.000)	(0.076)	(0.000)		
Average log export network size	–	–	–	–	0.023***	0.083***
					(0.001)	(0.010)
Average log domestic network size	–	–	–	–	-0.003**	-0.397***
					(0.001)	(0.068)
Prefecture-time effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth county-prefecture effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	465.2	521.2	–	18.17
Observations	913,802	22,272	913,802	22,272	22,573	22,573

Note: Network size is 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.
Birth county-prefecture fixed effects are purged by first-differencing prior to estimation.
The modified network variables are thus measured by the growth in their size.
Instrument for the growth in domestic network size: domestic network duration.
Instruments for the growth in export network size: export network duration, domestic network duration.
Instruments for the growth in average export network size and average domestic network size: export network duration, domestic network duration, and their interactions with initial entry.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

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. Each birth county sets up domestic networks in 88 prefectures and export networks in five prefectures, on average. In addition, domestic networks commence 11 years earlier than export networks on average within birth county-destination prefectures. 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 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 3 is not as large as in Table 6, despite the fact that the structure of the estimating equations and the instruments that we construct for network size are the same.

We next turn to the pure exporter propensity equation (13), which has a different structure from the equations we have estimated thus far. In particular, the estimating equation includes an export network term and a domestic network term. Moreover, 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. Nevertheless, as discussed in Section 4.1, the same biases that arise when estimating the incumbent exporter propensity equation apply here as well. We can thus use the same instruments – domestic network duration and export network duration – to address these biases.

Since there are now two endogenous network terms, and these terms are constructed differently than before, we report the first-stage estimates in Appendix C.5. While a detailed discussion of the first-stage results is provided in the appendix, the main takeaway is that the domestic network duration instrument lacks 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. We will thus use four instruments when estimating the fresh exporter propensity equation; recall that the tests of the over-identifying restrictions in Table 5 provided statistical support for the exogeneity of the additional instruments.

Fresh exporter propensity, which is the dependent variable in Table 6, Columns 5-6 is measured by the number of exporters who established their firms after the export network commenced in the prefecture, divided by the number of potential entrepreneurs. 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. This is true for the OLS estimates in Column 5 and the 2SLS estimates in Column 6. 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.

An important assumption of our model is that fresh exporters will commence that activity as soon as their firms are established; i.e. there are no subsequent transitions to mixed exporting by lower ability domestic producers in any cohort. If that were not the case, then the marginal exporter in that cohort would no longer be a pure exporter and the domestic network overhang would no longer apply. Since we have uncovered a domestic network overhang in Columns 5-6, we expect that our modeling assumption will be satisfied in most cohorts. Linking the Customs data to the SAIC registration data, we find that 65 percent of the fresh exporters began that activity within two years of registering their firm, with an increase in this statistic to 75 percent if we allow for a lag of three years. These statistics are broadly consistent with our modeling assumption, once we allow for delays in raising capital, starting production, and finding buyers and suppliers in practice after a firm is registered.[29]

Comparing the 2SLS estimates in Column 6 with the OLS estimates in Column 5, we see that the 2SLS coefficients are larger in (absolute) magnitude than the OLS coefficients, in line with the estimates in columns 1-4. However, the coefficient on the export network term does not increase by

[29] We account for these delays when classifying firms as fresh exporters versus incumbent exporters by setting the cutoff registration year that distinguishes between them as one year prior to the commencement of the birth county-destination prefecture network.

quite as much as it did before. This is because the network terms in the fresh exporter propensity equation are averages and, hence, the lagged dependent variable on the right hand side does not receive as much weight and, by extension, does not generate as much bias, as it did when we estimated the other equations. At the same time, we see that the 2SLS coefficient on the domestic network term is substantially larger (in absolute magnitude) than the OLS coefficient. As in Table 5 with export revenue as the dependent variable, we interpret this finding as a consequence of the heterogeneous treatment effects that we previously uncovered.

With heterogeneous treatment effects, the coefficient on the export network term in Table 6, Column 6 can be interpreted as a local average treatment effect (associated with the export network duration instruments). The coefficient on the domestic network term, will then incorporate two effects: (i) the distinct export network effect, associated with the domestic network duration instruments, which is decreasing in the size of the domestic network term, and (ii) the domestic network overhang, as implied by the model. The latter effect is responsible for the negative and statistically significant coefficient on the domestic network term in Column 5, while the substantial increase in the (absolute) magnitude of this coefficient when we instrument in Column 6 is explained by the bias in the OLS estimates and the additional heterogeneous treatment effect channel. Although the interpretation of the instrumental variable estimates is now more complex, they remain unbiased and can be used to quantify the role of the networks in the section that follows.

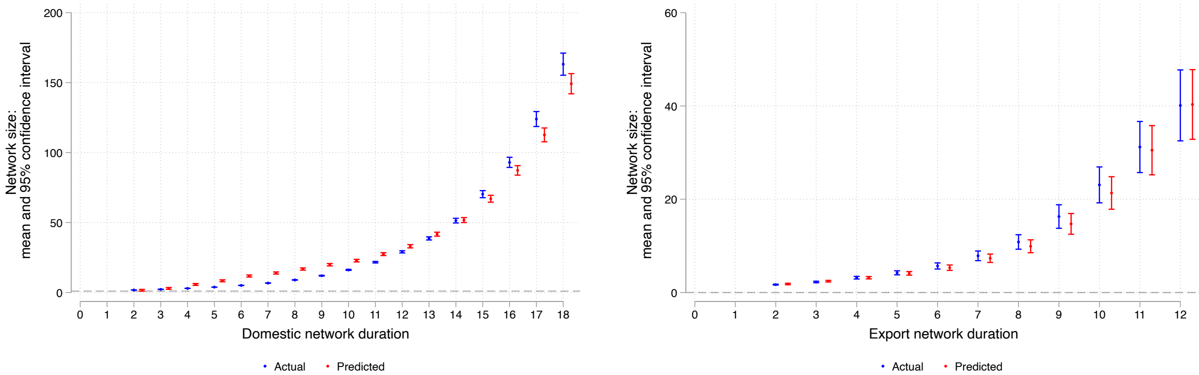
5 Quantitative Analysis

5.1 Model Fit

Our objective in this research is to identify and quantify the contribution of birth county networks to the entry of firms in China. The analysis thus far has shown that these networks are active and that they can have a positive and a negative effect on firm entry, depending on the circumstances. We now build on these qualitative findings to estimate the magnitude of the network effects.

In our model, three additive terms determine firm entry: a fixed birth county-destination prefecture term, a prefecture-time period term, and a network term. Our instrumental variable estimates of the network effects will be used to isolate the contribution of the network term in the section that follows. However, a precondition for this contribution to be sizeable is that the model as a whole; i.e. the three terms together should explain a substantial share of the variation in firm entry. We thus begin the quantitative analysis by evaluating the fit of the model; i.e. its ability to explain observed variation in firm entry.

When we estimate the parameters of the propensity equations (12)-(14), we minimize the difference between actual and predicted propensity or, equivalently, firm entry at the birth county-destination prefecture-time period level. Since we are matching on a very large number of moments, it is difficult to visualize model fit based on all of them. What we do, instead, is to construct and compare a smaller number of entry statistics. In particular, we compute the mean and the 95 percent confidence interval, based on the distribution of firm stocks or network sizes across birth county-destination prefectures at each network duration, in the data and as predicted by the model in Figure 1.



(a) All Firms

(b) Exporters

Figure 1: Number of Firms by Network Duration

Source: SAIC registration database and Customs database

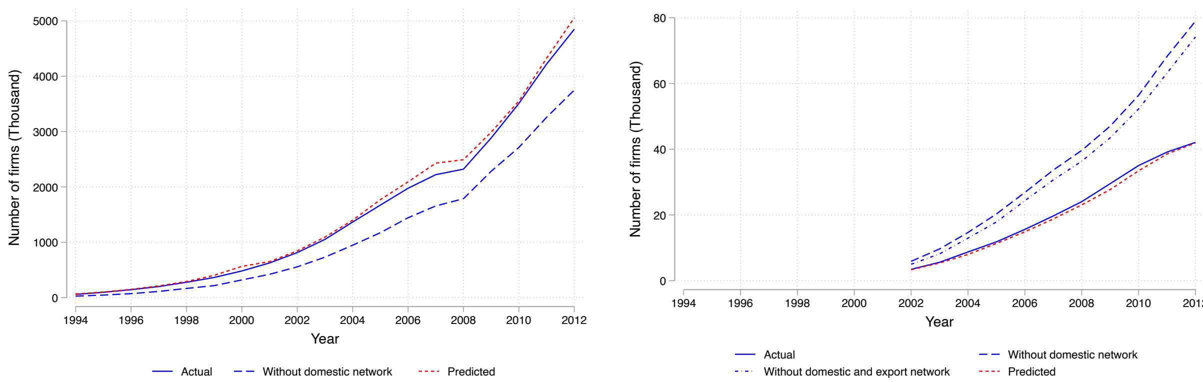
The estimation of the entrepreneurial propensity equation runs from 1994 to 2012. However, the domestic networks could have started much earlier and, as seen in Figure 1a, domestic network durations extend up to 33 periods. Network sizes and the dispersion in these sizes are increasing with network duration in the figure. Based on the model, this could be due to the network multiplier effect or prefecture-time effects (since network durations are mechanically increasing with time). Despite our model's parsimonious structure, it fits the data very well: the actual and predicted statistics match closely at each duration. This is true for the mean and the dispersion in network size. This is also true for export network sizes in Figure 1b. The Customs data, which we combine with the SAIC registration data to compute the stock of export firms in each birth county-destination prefecture are only available from 2000 onwards. We thus need to assume that the earliest export networks commenced in that year, which reduces the range of export network durations. Nevertheless, the model fits the data quite closely again.[30]

5.2 Decomposition Analysis

Based on the preceding analysis, much of the variation in firm entry at each network duration can be explained by the model. This is telling us that the residual component of the propensity equations is relatively small, but these results do not decompose the role of the birth county-destination prefecture effects, the prefecture-time effects, and the network effects. We now proceed to examine firm entry at each point in time, rather than by network duration, and to quantify the contribution of the birth county networks to this entry.

[30]The export propensity equation has the lagged stock of export firms on the right hand side. Since we first-difference this equation to purge the birth county-destination prefecture effects, the earliest year for which we can predict the number of firms is 2002. This is why network durations range from two to 12 in Figure 1b. In contrast, network durations start from one in Figure 1a.

Figure 2a plots the total number of firms and the number of firms predicted by the model from 1994 to 2012. Starting with almost no private firms with rural origins in 1994, we see that there were close to 5 million firms in 2012. Based on the results from the previous section, we expect the three components of the model to explain much of this variation, and the predicted number of firms is indeed very close to the actual number of firms at each point in time. However, when we remove the network term, but retain the residual component of the entrepreneurial propensity equation, we see that the number of firms drops substantially. Based on our estimates, the total number of firms in 2012 would decline by 23 percent in the absence of the birth county networks. This statistic is derived from a decomposition exercise that leaves the prefecture-time period effects unchanged. In practice, the decline in the number of firms could generate an increase in the product price, which, in turn, would feed back to firm entry. Although our estimates of the network effects on firm entry may thus be an upper bound, we expect that these effects would be substantial even if they were corrected for general equilibrium effects.



(a) All Firms (b) Exporters

Figure 2: Decomposition Analysis

Source: SAIC registration database and Customs database

Figure 2b reports the total number of export firms, the number of export firms predicted by the model, and the estimated change in the number of export firms on account of the networks from 2002 to 2012. Once again, the model fits the data very well at each point in time, which tells us that much of the variation in the number of export firms can be explained by its three components. However, the decomposition exercise isolating the network effect is now more complicated on account of the domestic network overhang. When we shut down the domestic network effect, we see that there is a substantial increase in the number of exporters. This increase is dampened when we simultaneously shut down the export network effect, which encourage the entry of export firms, but the net effect of the networks is still to *reduce* the number of exporters.

Based on our estimates, the number of export firms in 2012 would have increased by 76 percent if the birth county networks were absent. Although we have not adjusted for the general equilibrium effects discussed above, this might still seem like an unusually large number at first glance. Recall, however, that there were approximately 5 million firms with rural origins, of which just over 40,000 were exporters, in 2012 in our data. This would have resulted in an enormous difference in network size, which would have been reinforced by the substantially larger coefficient on domestic network size than on export network size in the fresh exporter propensity equation that we estimated in Section 4.3. Networks that emerge at earlier stages of economic development will have a head start and will typically face lower barriers to entry. The resulting size advantage could potentially reduce subsequent entry at later stages, relative to a counter-factual scenario in which networks are absent, as we observe in China and might expect in other developing economies where overlapping networks are active.

6 Conclusion

Despite its well documented inefficiencies, the Chinese economy grew at an unprecedented rate in the first two decades after the economic reforms of the 1990's. Our analysis provides a (partial) explanation for these apparently contradictory facts, based on the idea that networks of firms provided mutual help to each other in an economy where markets functioned imperfectly. Our estimates indicate that hometown (birth county) networks contributed substantially to the increase in the number of rural-born entrepreneurs, whose firms accounted for 55 percent of registered firms in China 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 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. Entrepreneurs do not internalize the effect of their entry on network performance and, hence, there is a role for policy. Export subsidies (which have no consequence for domestic profits) are unambiguously efficiency enhancing. In contrast, entry subsidies must balance two opposing effects: their positive effect on domestic profits due to a larger domestic network and the negative effect on export profits due to a smaller export network (on account of the domestic network overhang). If the latter effect is sufficiently large, it may even be optimal to tax entry. Adding to the complexity, if the second transition is anticipated, then domestic policies during the first transition would need to take account of their future consequences for exporting. Although a complete characterization of dynamic optimal subsidies is left to future research, we note that industrial policy could have large positive impacts in economies where networks (with their dynamic multiplier effects) are active.

The organic process of economic development that we describe in this paper, in which networks emerge at each stage to facilitate the occupational mobility of their members, and pre-existing networks slow down the growth of the networks that follow, is not specific to China or to business. As reviewed in Munshi (2014), there are many examples of working-class communities, who historically benefited from mobility-enhancing labor networks, subsequently getting locked into traditional industrial occupations. At the same time, the analysis in this paper will only be relevant in populations where community networks are already active or have the potential to be activated and this will, in general, depend on the underlying social structure. Contemporary and historical accounts of the role played by community networks have been based, almost without exception, on European and Asian populations. One explanation for this regional focus is that Eurasian populations have a cooperative culture that is conducive to the formation of community networks. Alternatively, high population densities in Eurasia and the resulting spatial proximity may have given rise to more frequent social interactions, which, in turn, support higher levels of social enforcement and cooperation among self-interested individuals. In other, more sparsely populated regions of the world, such as sub-Saharan Africa, community-based networks may function less effectively and, thus, will play a less prominent role during the process of development. While the political economy of African development has been studied extensively, and differences in the complexity of Eurasian and African societies have been previously noted (Diamond, 1997), this particular aspect of African society has received less attention and may be responsible (in part) for the observed variation in the economic trajectory across these regions.

References

Acemoglu, Daron, Simon Johnson, and James A Robinson. 2001. "The colonial origins of comparative development: An empirical investigation." *American Economic Review*, 91(5): 1369–1401.

Ahn, JaeBin, Amit K Khandelwal, and Shang-Jin Wei. 2011. "The role of intermediaries in facilitating trade." *Journal of International Economics*, 84(1): 73–85.

Akcigit, Ufuk, and Tom Nicholas. 2019. "History, microdata, and endogenous growth." *Annual Review of Economics*, 11: 615–633.

Allen, F, J Qian, and M Qian. 2005. "Law, finance, and economic growth in China." *Journal of Financial Economics*, 77(1): 57–116.

Almunia, Miguel, Pol Antràs, David Lopez-Rodriguez, and Eduardo Morales. 2021. "Venting out: Exports during a domestic slump." *American Economic Review*, 111(11): 3611–62.

Arellano, Manuel, and Stephen Bond. 1991. "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *The Review of Economic Studies*, 58(2): 277–297.

Atkin, David, and Amit K Khandelwal. 2020. "How distortions alter the impacts of international trade in developing countries." *Annual Review of Economics*, 12: 213–238.

Bai, Chong-En, Chang-Tai Hsieh, Zheng Song, and Xin Wang. 2020. "Special deals from special investors."

Banerjee, Abhijit, and Kaivan Munshi. 2004. "How efficiently is capital allocated? Evidence from the knitted garment industry in Tirupur." *Review of Economic Studies*, 71(1): 19–42.

Banerjee, Abhijit V, and Andrew F Newman. 1993. "Occupational choice and the process of development." *Journal of Political Economy*, 101(2): 274–298.

Barwick, Panle Jia, Yanyan Liu, Eleonora Patacchini, and Qi Wu. 2023. "Information, mobile communication, and referral effects." *American Economic Review*, 113(5): 1170–1207.

Beaman, Lori A. 2012. "Social networks and the dynamics of labour market outcomes: Evidence from refugees resettled in the US." *The Review of Economic Studies*, 79(1): 128–161.

Blum, Bernardo S, Sebastian Claro, Ignatius Horstmann, and Trevor Tombe. 2020. "The DNA of new exporters: Spin-offs and FDI at the extensive margin of trade." *American Economic Review: Insights*, 2(3): 397–408.

Blundell, Richard, and Stephen Bond. 1998. "Initial conditions and moment restrictions in dynamic panel data models." *Journal of Econometrics*, 87(1): 115–143.

Brandt, Loren, and Xiaodong Zhu. 2010. "Accounting for China's growth."

Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang. 2012. "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing." *Journal of Development Economics*, 97(2): 339–351.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang. 2017. "WTO accession and performance of Chinese manufacturing firms." *American Economic Review*, 107(9): 2784–2820.

Card, David. 2001. "Immigrant inflows, native outflows, and the local labor market impacts of higher immigration." *Journal of Labor Economics*, 19(1): 22–64.

Combes, Pierre-Philippe, Gilles Duranton, Laurent Gobillon, Diego Puga, and Sebastien Roux. 2012. "The Productivity Advantages of Large Cities: Distinguishing Agglomeration from Firm Selection." *Econometrica*, 80(6): 2543–2594.

Dai, Mi, Madhura Maitra, and Miaojie Yu. 2016. "Unexceptional exporter performance in China? The role of processing trade." *Journal of Development Economics*, 121: 177–189.

Damodaran, Harish. 2008. *India's new capitalists: Caste, business, and industry in a modern nation.* Permanent Black.

de Astarloa, Bernardo Díaz, Jonathan Eaton, Kala Krishna, Bee Aw Roberts, Andrés Rodríguez-Clare, and James Tybout. 2015. "Born to export: Understanding export growth in Bangladesh's apparel and textiles industry." Working paper.

Diamond, Jared. 1997. *Guns, germs and steel: The fates of human societies.* New York:W. W. Norton,.

Duranton, Gilles, and Diego Puga. 2020. "The economics of urban density." *Journal of Economic Perspectives*, 34(3): 3–26.

Fafchamps, Marcel. 2000. "Ethnicity and credit in African manufacturing." *Journal of Development Economics*, 61(1): 205–235.

Fan, Haichao, Yu Liu, Larry D Qiu, and Xiaoxue Zhao. 2020. "Export to elude." *Journal of International Economics*, 127: 103366.

Fan, Joseph PH, and Larry HP Lang. 2000. "The measurement of relatedness: An application to corporate diversification." *The Journal of Business*, 73(4): 629–660.

Fernandes, Ana P, and Heiwai Tang. 2014. "Learning to export from neighbors." *Journal of International Economics*, 94(1): 67–84.

Galor, Oded, and Joseph Zeira. 1993. "Income distribution and macroeconomics." *The Review of Economic Studies*, 60(1): 35–52.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik instruments: What, when, why, and how." *American Economic Review*, 110(8): 2586–2624.

Goodman, Bryna. 1995. *Native place, city, and nation: Regional networks and identities in Shanghai, 1853–1937.* University of California Press.

Greif, Avner. 1993. "Contract enforceability and economic institutions in early trade: The Maghribi traders' coalition." *The American Economic Review*, 525–548.

Greif, Avner. 1994. "Cultural beliefs and the organization of society: A historical and theoretical reflection on collectivist and individualist societies." *Journal of Political Economy*, 102(5): 912–950.

Greif, Avner, and Guido Tabellini. 2017. "The clan and the corporation: Sustaining cooperation in China and Europe." *Journal of Comparative Economics*, 45(1): 1–35.

Heath, Rachel. 2018. "Why do firms hire using referrals? Evidence from Bangladeshi garment factories." *Journal of Political Economy*, 126(4): 1691–1746.

Honig, Emily. 1992. *Creating Chinese ethnicity: Subei people in Shanghai, 1850-1980.* New Haven:Yale University Press.

Honig, Emily. 1996. *Regional identity, labor, and ethnicity in contemporary China.* Berkeley, California:Institute of East Asian Studies, University of California.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and manufacturing TFP in China and India." *Quarterly Journal of Economics*, 124(4): 1403–1448.

Imbert, Clement, Marlon Seror, Yifan Zhang, and Yanos Zylberberg. 2022. "Migrants and firms: Evidence from China." *American Economic Review*, 112(6): 1885–1914.

Kerr, William R, and Martin Mandorff. 2023. "Social networks, ethnicity, and entrepreneurship." *Journal of Human Resources*, 58(1): 183–220.

Levine, Ross, and Yona Rubinstein. 2017. "Smart and illicit: Who becomes an entrepreneur and do they earn more?" *The Quarterly Journal of Economics*, 132(2): 963–1018.

Lucas, Robert E. 1978. "On the size distribution of business firms." *The Bell Journal of Economics*, 508–523.

Lu, Jiangyong, Yi Lu, and Zhigang Tao. 2014. "Pure exporter: Theory and evidence from China." *The World Economy*, 37(9): 1219–1236.

Macchiavello, Rocco, and Ameet Morjaria. 2015. "The value of relationships: Evidence from a supply shock to Kenyan rose exports." *American Economic Review*, 105(9): 2911–45.

Macchiavello, Rocco, and Ameet Morjaria. 2021. "Competition and relational contracts in the Rwanda coffee chain." *The Quarterly Journal of Economics*, 136(2): 1089–1143.

Ma, Laurence J. C., and Biao Xiang. 1998. "Native place, migration and the emergence of peasant enclaves in Beijing." *The China Quarterly*, 155: 546.

McMillan, John, and Christopher Woodruff. 1999. "Interfirm relationships and informal credit in Vietnam." *The Quarterly Journal of Economics*, 114(4): 1285–1320.

Melitz, Marc J. 2003. "The impact of trade on intra-industry reallocations and aggregate industry productivity." *Econometrica*, 71(6): 1695–1725.

Mogstad, Magne, Alexander Torgovitsky, and Christopher R Walters. 2021. "The causal interpretation of two-stage least squares with multiple instrumental variables." *American Economic Review*, 111(11): 3663–3698.

Munshi, Kaivan. 2003. "Networks in the modern economy: Mexican migrants in the U. S. labor market." *Quarterly Journal of Economics*, 118(2): 549–599.

Munshi, Kaivan. 2011. "Strength in numbers: Networks as a solution to occupational traps." *Review of Economic Studies*, 78(3): 1069–1101.

Munshi, Kaivan. 2014. "Community networks and the process of development." *Journal of Economic Perspectives*, 28(4): 49–76.

Murphy, Kevin M, Andrei Shleifer, and Robert W Vishny. 1991. "The allocation of talent: Implications for growth." *The Quarterly Journal of Economics*, 106(2): 503–530.

Peng, Yusheng. 2004. "Kinship networks and entrepreneurs in China's transitional economy." *American Journal of Sociology*, 109(5): 1045–1074.

Rauch, James E. 2001. "Business and social networks in international trade." *Journal of economic literature*, 39(4): 1177–1203.

Rosenthal, Stuart S, and William C Strange. 2020. "How close is close? The spatial reach of agglomeration economies." *Journal of Economic Perspectives*, 34(3): 27–49.

Roy, Andrew Donald. 1951. "Some thoughts on the distribution of earnings." *Oxford Economic Papers*, 3(2): 135–146.

Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti. 2011. "Growing like China." *American Economic Review*, 101(1): 196–233.

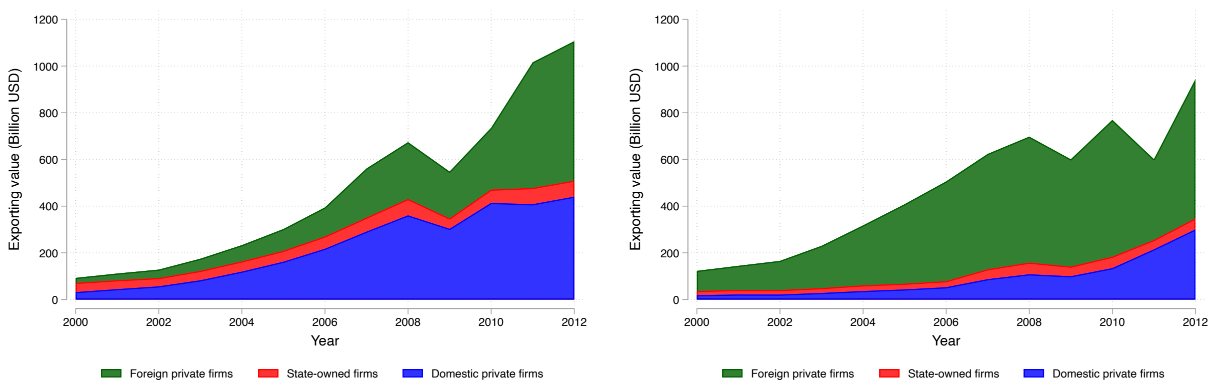
Tang, Yulu. 2024. "To follow the crowd? Benefits and costs of migrant networks."

Zhang, Chunni, and Yu Xie. 2013. "Place of origin and labour market outcomes among migrant workers in urban China." *Urban Studies*, 50(14): 3011–3026.

Zhu, Xiaodong. 2012. "Understanding China's growth: Past, present, and future." *Journal of Economic Perspectives*, 26(4): 103–124.

Appendix A: Export Accounting

There are two types of exports in China: production exports and processing exports. The latter activity is restricted to the assembly of imported inputs for resale abroad. Based on their productivity and skill intensity, production exporters are superior to domestic producers who, in turn, are superior to processing exporters (Dai, Maitra and Yu, 2016). Given our interest in the transition from domestic production to higher value exporting, 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.

While indirect exporters may be less productive than direct exporters, how do they compare with domestic producers? To answer this question, we turn to the Above Scale database, which provides total revenues and export revenues for all firms with annual revenues above 5 million Yuan, in each year over the 2000-2009 period. The Above Scale database can be merged with the

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%.

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.

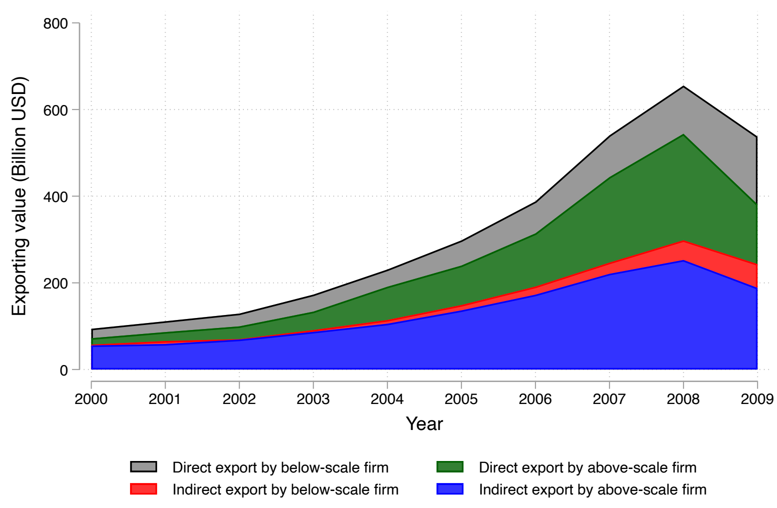


Figure A2: Export Accounting

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

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

Table A2: Capital Intensity of Different Type of Firms

Data source:	Above Scale: 2000-2009	Census: 2004, 2008
Dependent variable:	log (K/L)	
	(1)	(2)
Direct export share	0.018*	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%.

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

Appendix B: The Model

1. Proposition 1

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

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

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

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

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

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

Proof of Proposition 1:

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

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

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

Observe that T is an upper bound on network size. Hence, $\theta_d(\overline{p}) \log T$ is an upper bound on the network effect in the domestic market. It follows that (15) is a sufficient condition for $\log \omega^*_{dt} > a$.

Next, we show that $\log \omega^*_{et'} > \log \omega^*_{dt}$, for all $t \geq t'$, if (16) is satisfied. From (5):

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

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

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

$\log C_{dt}$, $\log C_{dt'}$ are bounded below by q_{d1}, assuming min. $n_0 = 1$. $\log C_{et'}$ is bounded above by $q_{eT} + \theta_e(\overline{p}) \log T$. It follows that (16) is a sufficient condition for the preceding inequality to be satisfied.

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

Condition (15) ensures that some low ability agents always choose the traditional occupation, as ζ (e.g., interest rate r) is high enough relative to ability lower bound a, terminal output market size and maximum network size. Condition (16) sets γ (i.e., incremental cost of exporting plant investments I) large enough relative to the export market premium δ, home and export market sizes, interest rate and technology parameters, to ensure that the ability threshold for specializing in exports will always be higher than for entry into the home market. As in the Melitz model, this ensures positive selection into exports. Condition (17) imposes a lower bound on the scope diseconomy cost β relative to the other parameters, to ensure that the threshold for mixed exporters exceeds that for entry into export specialization. Unlike the Melitz model, this ensures existence of an intermediate range of entrepreneurs who specialize in exports. Finally, (18) requires ability to be sufficiently dispersed to ensure a positive mass of mixed exporters in every cohort.

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., $K_{d,t-1}K_{e,t-1} > 0$:

$$W_{mt}(\omega; K_{d,t-1}, K_{e,t-1}) = \max_{K_{dt} \geq K_{d,t-1}, K_{et} \geq K_{e,t-1}} [\pi_{dt}(\omega; K_{dt}) + \pi_{et}(\omega; K_{et}) - \beta + \phi W_{m,t+1}(\omega; K_{dt}, K_{et})] \tag{19}$$

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

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

$$\begin{aligned} W_{et}(\omega; K_{e,t-1}) \quad = \quad & \max_{K_{dt} \geq 0, K_{et} \geq K_{e,t-1}} [\pi_{et}(\omega; K_{et}) + \mathcal{I}_{K_{dt}>0}[\pi_{dt}(\omega; K_{dt}) - \beta \\ & + \phi W_{m,t+1}(\omega; K_{dt}, K_{et})] + (1 - \mathcal{I}_{K_{dt}>0})\phi W_{e,t+1}(\omega; K_{et})] \end{aligned} \tag{20}$$

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

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

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

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

$$W_{ot}(\omega) = \max\{\omega^{\sigma} + \phi W_{o,t+1}(\omega); W_{dt}(\omega, 0); W_{et}(\omega, 0); W_{mt}(\omega; 0, 0)\} \tag{22}$$

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:

$$\begin{aligned} W_{mt}(\omega) &= \Pi_{Dt}(\omega) + \Pi_{Et}(\omega) - \beta + \phi W_{m,t+1}(\omega) \\ W_{et}(\omega) &= \max\{\Pi_{Et}(\omega) + \phi W_{e,t+1}(\omega); W_{mt}(\omega)\} \\ W_{dt}(\omega) &= \max\{\Pi_{Dt}(\omega) + \phi W_{d,t+1}(\omega); W_{mt}(\omega)\} \\ W_{ot}(\omega) &= \max\{\omega^{\sigma} + \phi W_{o,t+1}(\omega); W_{dt}(\omega); W_{et}(\omega); W_{mt}(\omega)\} \end{aligned} \tag{23}$$

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

$$\omega^{\sigma} + \phi W_{o,t+1}(\omega) = \Pi_{Dt}(\omega) + \phi W_{d,t+1}(\omega) \tag{24}$$

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

$$W_{ot} = \max\{\omega^\sigma + \phi W_{o,t+1}(\omega); W_{dt}(\omega)\} \tag{25}$$

at all dates t. (25) 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.,

$$\Pi_{Dt}(\omega) + \phi W_{d,t+1}(\omega) = \Pi_{Et}(\omega) + \phi W_{e,t+1}(\omega) \tag{26}$$

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

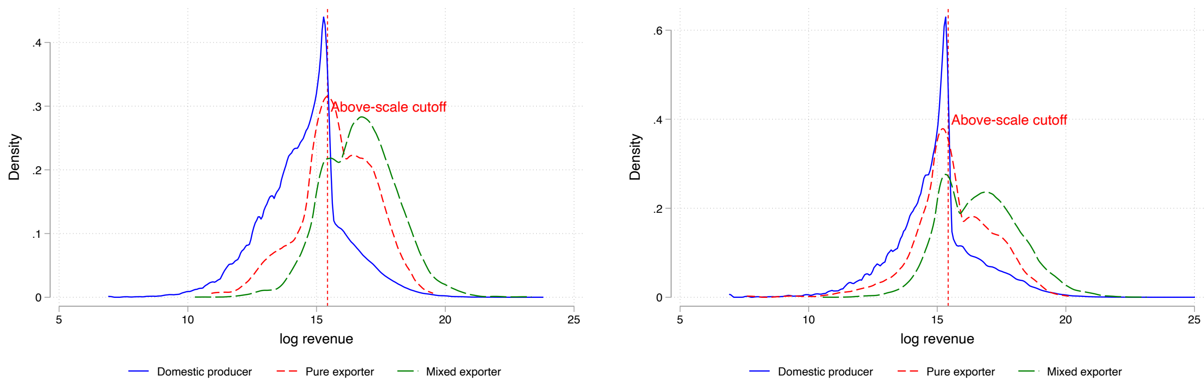
Table B1 describes the composition of firms in 2004 and 2008, based on the preceding classification. Export firms constitute a tiny fraction, around 2-3%, of all manufacturing firms and pure exporters comprise around 15% of all exporters. Notice that these firms can be ranked with respect to their revenue: 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

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 database.
Data restricted to manufacturing firms. Revenue measured in Yuan.

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 and, as noted in Appendix C, there are discrepancies between the revenues reported in the inspection database and the economic census. This is especially important for the current analysis because revenues and exports must match closely to identify pure exporters.

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 prefecture-time period face the same wage, w, we can nevertheless solve for the profit maximizing labor input and then rewrite the revenue equation as follows:

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

Taking logs,

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

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

2. 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. (2022), the crop price shock, ϵ_{ct}, is calculated by estimating the following equation:

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

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

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

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

Step 3: 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}. 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 shift-share instrument is thus constructed as:

$$IV = \frac{AS_{jt}}{d_{jk}}.$$

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.

3. 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 Appendix Table C1, Column 1.

(a) 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 Appendix Table C1, 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 Appendix Table C1, Column 2, 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. If own (family) wealth is used to finance business, as in Song, Storesletten and Zilibotti (2011), then a negative price shock will curtail the operations of entrepreneurs from agricultural families. This is true regardless of the location in which they are active and will result in a decline in their revenues. We account for this in Appendix Table C1, 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 Appendix Table 2 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 C1: Robustness Check for Shift-Share IV

Sample:	all	outside birth county	excluding agricultural processing	all	all
Dependent variable:	log revenue				
	(1)	(2)	(3)	(4)	(5)
Log network size	1.314***	0.567***	1.302***	1.461***	1.344***
	(0.098)	(0.152)	(0.097)	(0.080)	(0.109)
Agriculture income shock	–	–	–	0.384**	–
				(0.149)	
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Prefecture-time effects	Yes	Yes	Yes	Yes	Yes
Distance-time effects	No	No	No	No	Yes
Kleibergen-Paap F	64.07	67.37	64.27	98.06	48.15
Observations	5,211,514	3,270,885	5,100,144	5,211,514	5,211,514

Note: Network size is constructed from SAIC registration data and Customs data.
Firm fixed effects are purged by first-differencing prior to estimation.
Instruments 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 multiplier: 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.

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 prefecture-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. The firm fixed effects that we include in the estimating equation will not account for such variation. To address the preceding concern, we include distance interacted with time effects in the estimating equation. As observed in Table C1, Column 5 the results are robust to the inclusion of these additional variables.

(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, the interaction of the shares with time must also be considered when examining the validity of the shift-share instrument. For example, suppose that (historical) cultivation of a particular crop is associated with an entrepreneurial culture or a greater willingness to bear risk in the local population. If these traits have a differential effect on firm 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.

Table C2: 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	1.669***	1.788***	1.104***	1.604***	1.239***	1.305***	1.646***
	(0.119)	(0.122)	(0.120)	(0.079)	(0.114)	(0.085)	(0.184)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	19.01	13.39	6.822	17.17	5.314	9.262	3.760
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	5,211,514	5,211,514	5,211,514	5,211,514	5,211,514	5,211,514	5,211,514

Note: Network size is constructed from SAIC registration data and Customs data.
Firm fixed effects are purged by first-differencing prior to estimation.
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. Appendix Table C2 reports results with firm revenue as the dependent variable, using the share for each crop interacted with time effects (and the distance multiplier) as instruments for network size. We report estimates with all 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 C1, Column 1. This indicates that no crop has a separate and independent effect on firm performance, validating the exogeneity of the corresponding shares.

4. Robustness of Revenue Results

Table C3: Second-Stage Estimates of Revenue Equations: Located Outside Birth County

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	0.436***	1.244***	0.663***	0.342***	0.830***	1.388***
	(0.019)	(0.048)	(0.029)	(0.083)	(0.201)	(0.133)
Prefecture-time effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	62.22	62.22	167.2
Observations	3,270,885	3,270,885	45,564	3,270,885	3,270,885	45,564

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 C4: Second-Stage Estimates of Revenue Equations: Birth County Fixed Effects

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	0.423***	1.205***	0.608***	0.914***	2.348***	1.161***
	(0.017)	(0.043)	(0.028)	(0.115)	(0.246)	(0.126)
Prefecture-time effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth county fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	–	–	–	74.63	74.63	175
Observations	5,211,514	5,211,514	126,901	5,211,514	5,211,514	126,901

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%.

5. First-Stage Estimates of the Fresh Exporter Propensity Equation

As discussed in Section 4.1, export network duration and domestic 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 Appendix Table C5, Columns 1-2.

Table C5: First-Stage Estimates of the Fresh Exporter Propensity Equation

Dependent variable:	change in domestic network term	change in export network term	change in domestic network term	change in export network term
	(1)	(2)	(3)	(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	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Export network duration * initial entry	–	–	-0.030***	-0.038***
			(0.004)	(0.006)
Domestic network duration * initial entry	–	–	-0.003***	0.008***
			(0.001)	(0.003)
Prefecture-year fixed effects	Yes	Yes	Yes	Yes
Observations	22,573	22,573	22,573	22,573

Note: Network size is constructed from SAIC registration data and Customs data.
Change in domestic network term is measured by $\sum_{t'=t_{ejk}+1}^{t} \frac{\theta_d \log n_{jk,t'-1}}{(t-t_{ejk})(\delta-1)(1-\alpha)} - \sum_{t'=t_{ejk}+1}^{t-1} \frac{\theta_d \log n_{jk,t'-1}}{(t-1-t_{ejk})(\delta-1)(1-\alpha)}$
Change in export network term is measured by $\sum_{t'=t_{ejk}+1}^{t} \frac{\theta_e \log n_{ejk,t'-1}}{(t-t_{ejk})(\delta-1)(1-\alpha)} - \sum_{t'=t_{ejk}+1}^{t-1} \frac{\theta_e \log n_{ejk,t'-1}}{(t-1-t_{ejk})(\delta-1)(1-\alpha)}$
Instruments include export network duration, domestic network duration, and their interactions with initial entry. Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

With two endogenous variables and two instruments, we are just identified in Columns 1-2. Domestic network duration must, therefore, shift the dependent variable in Column 1 and export network duration must shift the dependent variable in Column 2. We see that the coefficient on the export network duration variable is statistically significant in both columns, but this is simply because that variable appears in the denominator of both the domestic network term and the export network term. For it to be a valid instrument, it must shift the numerator of the latter term. This appears to be the case, judging from the switch in the sign of the export network duration coefficient from Column 1 to Column 2. In contrast, the domestic network duration variable does not have sufficient statistical power to shift the domestic network term in Column 1. The coefficient on this variable switches sign from Column 1 to Column 2, on account of the domestic overhang effect and in line with the corresponding estimates in the first-stage Table 2. However, average domestic network size is a very large and slow moving statistic, which may explain why the instrument lacks power in Column 1 but is precisely estimated in Column 2.

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 domestic network duration interaction, in particular, is precisely estimated and the domestic network duration coefficients (interacted and uninteracted) are jointly significant in Column 3. The four variables in Columns 3-4 are thus used as instruments when estimating the fresh exporter propensity equation.