Community Networks and the Growth of Private Enterprise in China*

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Abstract

This paper identifies and quantifies the role played by community networks organized around the hometown in the growth of private enterprise in China. The model that we develop generates predictions for the dynamics of firm entry, sectoral and spatial concentration, and firm size, across birth counties with different levels of social connectedness (measured by population density) when networks are active. We validate each of these predictions over a twenty year period with unique administrative data that covers the universe of registered firms and provides information on entrepreneurs' birth counties. The rich set of results that we obtain, taken together, allow us to rule out alternative non-network-based explanations. Additional results provide direct support for the network channel, indicating that spillovers occur within the birth county (and, going down even further, within clans within the county). Having validated the model, we estimate its structural parameters and conduct counter-factual simulations, which indicate that entry over the 1995-2004 period would have been 64% lower (with a comparable decline in the stock of capital) in the absence of community networks. Additional counter-factual simulations shed light on the design of optimal industrial policy in economies where networks are active or have the potential to be activated.

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1 Introduction

China has witnessed the same degree of industrialization in three decades as Europe did in two centuries (Summers, 2007). This economic transformation began in the early 1980's with the establishment of township-village enterprises (TVE's) and accelerated with the entry of private firms in the 1990's. Starting with almost no private firms in 1990, there were 15 million registered private firms in 2014, accounting for over 90% of all registered firms and 60% of aggregate industrial production. The surge in the number of private firms has had major macroeconomic consequences. China is the largest exporter in the world today and, depending on how the accounting is done, the world's largest or second-largest economy (Wu, 2016).

While China's growth has been impressive by any yardstick, what is perhaps most striking about this growth is that it occurred without the preconditions that are generally believed to be necessary for economic development; i.e. without effective legal systems or well functioning financial institutions (Allen *et al.*, 2005). The government compensated for some of these institutional limitations by providing infrastructure and credit (Long and Zhang, 2011; Wu, 2016). However, there were clearly other powerful forces at work that allowed millions of entrepreneurs, most of whom were born in rural areas, to establish and grow their businesses. Allen *et al.* (2005) and Song *et al.* (2011) hint at the nature of these forces by noting that alternative channels based on reputation and relationships must have been present to support such a high level of growth in the absence of market institutions. And case studies of production clusters; e.g. Fleisher *et al.* (2010) and Nee and Opper (2012) indicate that long-established relationships among relatives and neighbors (from the rural origin) substituted for legally enforced contracts between firms. Our analysis, which utilizes comprehensive data covering the universe of registered firms over many years, advances this line of research by identifying and quantifying the role played by informal community networks in the growth of private enterprise in China.

China is divided into approximately 2,000 counties and 250 cities (which are further divided into urban districts). There is an emerging literature that describes the role played by hometown or birth county networks in facilitating China's unprecedented rural-urban labor migration; e.g. Honig (1996), Ma and Xiang (1998), Zhao (2003). If the sending county is the domain around which migrant labor networks are organized, then we expect that this will also be the domain around which business networks supporting county-born entrepreneurs are organized. Our strategy to identify a role for birth county networks exploits variation in social connectedness across counties. Entrepreneurs born in counties with greater social connectedness will have access to better performing business networks, regardless of where they are located, which will have verifiable consequences for selection into entrepreneurship, business choices, and firm outcomes. The important difference between our formulation and the standard specification of productivity growth generated by agglomeration effects is that networks are based on the social origins of entrepreneurs rather than the destinations they select.

The analysis proceeds in the following steps. First, we construct a measure of social connectedness in the population of each county. We measure social connectedness by population density. The basic idea is that local social interactions within counties are increasing in spatial proximity, which is increasing in population density. More frequent social interactions allow for more effective social enforcement and, hence, higher levels of trust and economic cooperation. This argument goes through even if the clan within the county is the

social unit around which business networks are organized (as argued by Peng (2004) and Greif and Tabellini (2017)). However, it may not apply to urban neighborhoods, which typically comprise newcomers from many origins. If social heterogeneity is increasing sufficiently steeply in urban population density and individuals prefer to interact within their group, then the frequency of local interactions (and associated levels of trust) could even be decreasing in population density. This is certainly true of large, densely populated, cities where residents typically interact very little with their neighbors. Using data from the China Family Panel Survey (CFPS), which is designed to cover a representative sample of the Chinese population, we show that the frequency of local social interactions and trust in local residents are both increasing in population density, but only in counties and not in cities. The empirical analysis thus focuses on entrepreneurs born in counties (although the city-born entrepreneurs will serve as a useful placebo group). Their firms account for two-thirds of all registered firms in China.

Having documented a positive relationship between social connectedness (measured by population density) and trust in Chinese counties, the second step in the analysis is to link social connectedness in a county to the quality of business networks that emerge endogenously from that county. Sustaining high productivity often requires the help of other entrepreneurs. Markets for help are missing due to the inherent difficulties in verifying such help. This is the motivation for network formation in our analysis. Although 60% of the county-born entrepreneurs establish their firms outside their birth counties, they maintain close social connections to their hometown.[1] Business networks, and the norms of cooperation that support these networks, will thus continue to be organized around the hometown. Following the argument above, networks drawn from higher population density birth counties will sustain higher levels of mutual help and will thus be of higher quality.

The third step in the analysis is to derive the relationship between network quality and the dynamics of entry, sectoral and spatial concentration, and firm size. In our model of network dynamics, there are many counties of origin, distinguished by their social connectedness. An equal-sized cohort of agents is born in each period in each origin. Each agent makes a once-and-for-all occupational choice, selecting between a traditional, non-entrepreneurial, sector and two business sectors. The profit in the traditional sector is an increasing function of the agent's ability. The profit in the business sectors is determined by the agent's ability, the capital that is invested in the firm, and 'community' TFP (CTFP), which reflects the network effects described above.[2] CTFP is a dynamically evolving community level variable, which depends on the size of the incumbent network; i.e. the stock of entrepreneurs from the community who previously selected into that sector, and social connectedness at the origin (which determines network quality).

The network dynamics in each community commence with a small exogenous number of entrepreneurs in each business sector, and a slight advantage in one sector. A fixed fraction of agents receive an opportunity to become an entrepreneur in each subsequent cohort. Each such agent receives a single referral to enter

[1] Although our analysis concentrates on the interactions between firms, the incentive problems that give rise to networks of firms from the same hometown will also arise within firms. We would thus expect the key personnel in the firm to be largely drawn from the same hometown. Focussing on the county-born entrepreneurs who locate their firms outside their birth counties, 74% of the key personnel (major shareholders and senior managers) in their firms are born in the same county. If we randomly assigned key individuals to firms within sector-destinations, the counter-factual statistic would be 4%.

[2] Although the model is set up so that networks operate through the productivity channel, all the results would go through if networks, instead, provided credit to their members. We ignore mark-ups in output prices and wedges in factor prices (including the interest rate) in our model to compare and contrast the results on firm size with those obtained in the misallocation literature (via price distortions).

one of the business sectors, with the fraction of agents receiving referrals from a given sector equal to the share of incumbent entrepreneurs from their community already in that sector. There are thus two sources of dynamic increasing returns in our model. One source is the complementarity between network quality and size; an additional entrant in any period induces additional entry in the next period, with a compounding effect in subsequent periods that is amplified in high quality networks. This dynamic multiplier, associated with post-entry network benefits, is augmented by the second source of increasing returns operating through the referrals process, which increasingly channels firms into the initially (slightly) favored sector. Greater sectoral concentration generates greater aggregate entry by channeling firms into a single sector where they can take better advantage of the increasing returns generated by network size. The two sources of dynamic increasing returns thus reinforce each other, with the flow of entrants and sectoral concentration evolving together and increasing more steeply over time when networks are of higher quality; i.e. when they are drawn from populations with greater social connectedness.

Among the agents receiving a referral in a given birth cohort, only those with ability above a threshold level will select into business. This threshold declines over time (across successive cohorts) as CTFP and, hence, profits in the business sector grow, with a steeper decline in more socially connected populations because their networks are growing especially fast. Higher CTFP thus has two conflicting effects on the initial size of the marginal entrant's firm: the direct effect (for a given level of ability) is to increase firm size by raising firm level TFP, but the negative selection on ability works in the opposite direction to lower the firm's TFP. In our model, the latter effect dominates; the marginal entering firm will be unambiguously smaller in more socially connected populations, with this (negative) relationship growing stronger over time as their networks strengthen. Under specific conditions on the model parameters, this result is shown to hold for average firm size as well. This contrasts with the model's predictions for the post-entry growth in firm size. This growth is driven by changes in CTFP and is independent of ability. Thus, firms owned by entrepreneurs from more socially connected origin counties will start smaller but subsequently grow faster.

Our use of a predetermined population-based measure of social connectedness as the source of forcing variation in the empirical analysis avoids many of the pitfalls encountered by analyses based on endogenously determined network characteristics. Nevertheless, it is possible that population density is correlated with other factors that directly determine entry, concentration, and firm size. We systematically account for this possibility by examining alternative models, which relax different assumptions of our model, while simultaneously shutting down the network component. These models introduce new sources of heterogeneity at the origin, which are correlated with population density, and, in addition, allow firms from different origins to have access to destinations of varying quality. We show that additional heterogeneity at the origin, with higher population density counties having larger populations, higher education, or lower payoffs in the traditional sector can generate higher entry without a role for networks. However, these alternative models cannot explain the dynamic patterns of sectoral and spatial concentration that are driven by network complementarities in our model, nor can they explain why firms from high population density origins start small but subsequently grow relatively fast.

We consequently add heterogeneity at the destination to the alternative model. If firms from higher

population density origins having better, and increasing, access to destinations that are growing relatively fast, due to superior infrastructure or agglomeration externalities, then network effects cannot be distinguished from agglomeration effects (if firms from each origin locate at a unique set of destinations). In practice, however, firms from multiple origins will locate at the same destination. Including destination-time period dummies in the estimating equation, our model, but not the alternative model, predicts that firms from higher population density origins will continue to grow faster (within destinations) on account of their hometown networks. In contrast, there is no variation in firm growth within destinations in the alternative model. One way to incorporate heterogeneity within destinations, without networks, would be to allow firm growth to vary with ability (this is not a feature of our model). If firms from higher population density origins have higher ability, then they will grow faster even within destinations. However, this alternative model cannot explain the negative selection on ability, and the associated implications for initial firm size, that are generated by our network-based model.[3] In sum, we consider an exhaustive set of alternative models, which allow for heterogeneity at the origin, destination, and in entrepreneurial ability. None of these models, even a model that allows for heterogeneity along all of these dimensions, can match the predictions of our parsimonious model with networks.

In the fourth step of our analysis, we test the predictions of the model with unique administrative data covering the universe of registered firms in China that we have obtained from the State Administration of Industry and Commerce (SAIC). The following information is available for each firm: establishment date, 4-digit sector, location, ownership-type, registered capital (initial and subsequent changes), and a list of major shareholders and managers, with their citizenship ID. The county of birth can be extracted from the citizenship ID, and the firm's legal representative is designated as the "entrepreneur" in the analysis.[4] The analysis is restricted to private firms and covers the 1990-2009 period, starting with the first wave of private entry and ending when the initial (explosive) growth phase starts to weaken. As discussed, population density proxies for social connectedness in counties but not in cities. The core analysis thus focuses on county-born entrepreneurs using population density from the 1982 population census, prior to large-scale labor migration in China, as a predetermined measure of social connectedness in their birth counties. As predicted by the model, we establish that the flow of entrants and sectoral (and spatial) concentration are (i) increasing in birth county population density at each point in time, (ii) increasing over time, and (iii) increasing more steeply in population density over time.[5] In addition, we establish that the marginal entrant's ability, measured by his education (adjusted for the education distribution in his birth cohort-birth county) and marginal and average initial capital are decreasing over time within birth county-sectors, more steeply in higher population density birth counties.

Although the SAIC registration database is well suited to examine entry, sectoral and location choice, and initial firm size, it is less useful for analyses of firm growth. Given the administrative costs involved, firms do

[3] One alternative model that can explain the co-existence of smaller initial firm size and relatively rapid subsequent growth is the neoclassical growth model. However, initial conditions, which lead to subsequent convergence, are accidentally (randomly) determined in this model, which is at odds with the negative selection on ability from higher population density origins that is predicted by our model.

[4] The legal representative and the largest shareholder are born in the same county 90% of the time.

[5] Although we do not explicitly model location choice, the predictions for spatial concentration (across locations outside the birth county) are identical to those for sectoral concentration.

not adjust their registered capital from year to year. We thus turn to the SAIC inspection database, which includes annual asset information from 2004 onward, and the 1995, 2004, and 2008 rounds of the industrial census, which also includes asset information, to test the model's predictions for firm growth. We estimate a positive and significant relationship between birth county population density and the average annual growth of the entrepreneur's firm with both datasets, and an increase in the growth rate over time (from 1995-2004 to 2004-2008) as predicted by the model. The results on firm growth, and on initial firm size, entry, and concentration are robust to including additional origin characteristics and destination-time period dummies in the estimating equation; if anything, the results are stronger within destinations. The model generates a rich set of predictions with respect to birth county population density when community networks are active, and we are able to validate each of them.

In a direct test of the mechanism underlying the network model, we estimate the relationship between initial entry in the 1990-1994 period, by firms from a given birth county in a particular sector-destination, and subsequent entry by firms from that birth county. Providing support for the network multiplier effect, we find that one additional initial entrant results in seven additional entrants over the 2000-2004 period and nine additional entrants over the 2005-2009 period. The initial effects are, moreover, stronger for firms from higher population density counties. In contrast, conditional on the number of initial entrants from the birth county, the total number of initial entrants in the sector-destination has no predictive power for the number of subsequent entrants. This striking result indicates that the birth county is indeed the domain around which business networks are organized in China and that these networks operate independently within sector-destinations.[6] Analyses of agglomeration effects that ignored birth county information would evidently paint an erroneous picture of spillover effects in China.

Having tested and validated the model with networks, the fifth step in the analysis is to quantify the impact of these networks on firm entry and output (measured by capital stock). To do this we estimate the structural parameters of the model and then conduct a counter-factual experiment in which the networks are shut down. Although the model is extremely parsimonious, it does a good job of matching entry and initial capital within sectors, across the range of birth county population densities, within the sample period for the structural estimation (1995-2004) and out of sample. This increases our confidence in the results of the counter-factual experiment, which estimates that entry would have declined by as much as 64% over the 1995-2004 period (with a comparable decline in the total capital stock) had the networks not been active. Given the dynamic increasing returns that are generated by the networks, the long-term consequences of their absence would have been even more substantial.

Given the large network externalities that we have estimated, a natural question to ask is whether the Chinese government could have accelerated growth by providing firms with subsidized credit. To answer this question, we examine a third counter-factual policy experiment in which all entering firms in the 1995-

[6]We do not take a position about whether the network is organized around the birth county or the spatially localized clan within the county. Although the clan composition of the birth county population is unavailable, the clan affiliation of the entrepreneurs in our data can be inferred from their surnames and birth counties (Peng, 2004). Estimating the relationship between initial entry and subsequent entry at the level of the clan, we find that spillovers are concentrated within the clan, although they do extend beyond its boundaries within the county. This allows us to test and validate an additional prediction of the model, which is that the clan concentration among entering entrepreneurs should be increasing over time and increasing in birth county population density at each point in time.

2000 period received a credit subsidy. The profit increase generated by the subsidy in the 1995-1999 period does not offset the cost to the government of providing the subsidy. However, the direct effect of the one-time subsidy is dwarfed by the positive spillover effect on firm profits in the subsequent 2000-2004 period, especially in higher population density birth counties, which is generated by the additional firms that were induced to enter in 1995-1999. If the government took account of these spillovers, which are not internalized by individual entrants, and its objective was to maximize total profit, then the optimal policy would be to target the subsidy to birth counties with higher population densities. A second counter-factual policy experiment examines the impact of such a targeted subsidy, which unambiguously increases profits relative to the untargeted subsidy, while at the same time reducing the size of entering firms (drawn disproportionately from high population density birth counties with stronger networks).

Our model is deliberately set up so that there are no mark-ups in output prices or wedges in factor prices. The preceding result thus highlights a key insight of our research, which is that while small firms and wide dispersion in firm size and productivity may be symptomatic of price distortions, and market inefficiencies more generally, in developing economies (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009), in economies with such inefficiencies (and the networks that emerge in response to these inefficiencies) a more successful second-best response may, paradoxically, be accompanied by smaller firms and greater dispersion. The additional implication of our research is that attempts to stimulate growth by offering subsidies to potential entrepreneurs should take account of both individual ability, which determines independent business success, and social affiliation, which determines the spillovers that lead to further entry, in economies where networks are active. Existing efforts to stimulate entrepreneurship through business training programs or business plan competitions, as described in (McKenzie and Woodruff, 2014) and (McKenzie, 2017), do not take account of these spillovers, potentially resulting in a substantial loss in efficiency. At the same time, the distributional consequences of policies that attempt to exploit network externalities must also be considered, as discussed in the concluding section.

2 Institutional Setting

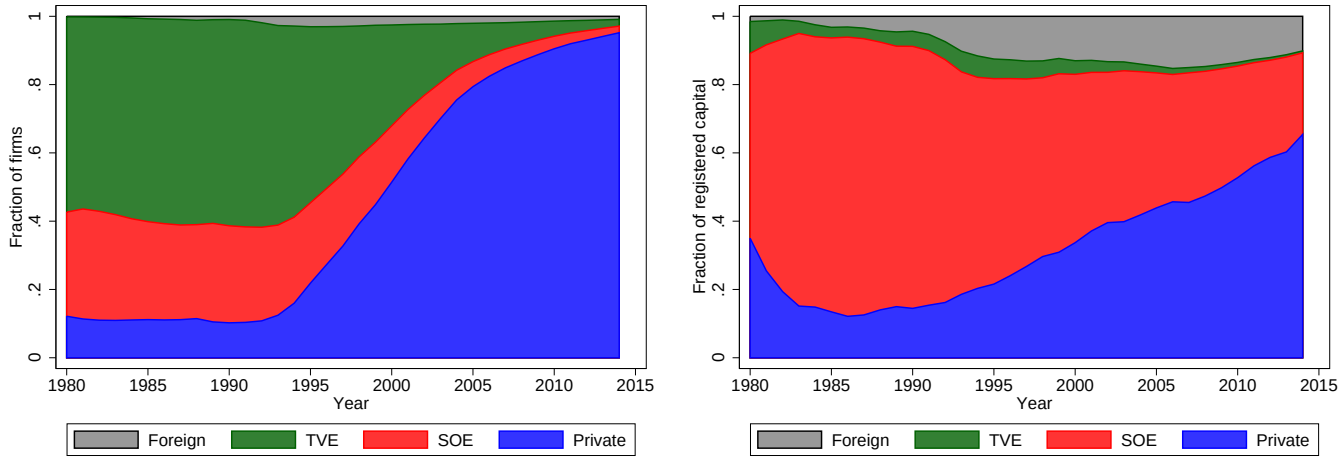
2.1 Community Networks and Private Enterprise in China

The core administrative data set that we utilize for the empirical analysis comprises the universe of registered firms in China, regardless of their size, from 1980 onwards. These firms are classified as township-village enterprises (TVE's), state owned enterprises (SOE's), foreign owned firms, and private (domestically owned) firms. Our interest is in the last category. New firms enter the database each year, while a fraction of incumbents exit. We can thus trace the growth of the private sector in China from its inception in the early 1990's, which coincided with the phasing out of the TVE's. As documented in Figure 1a, private firms accounted for approximately 10% of all firms in the early 1990's. Subsequently, they grew extremely rapidly and by 2014 they accounted for over 90% of all firms.

While private firms may have increased substantially in numbers, what was their contribution to overall output? To answer this question, we examine the evolution of registered capital, by firm-type, over time.[7]

[7]The initial registered capital represents the total amount paid up by the shareholders. This amount is deposited with the

Figure 1. Distribution of Firms, by Type



(a) Number of Firms

(b) Registered Capital

Source: SAIC registration database.

Figure 1b reports the share of total registered capital, by firm-type, over the 1980-2014 period. As with their numbers, the share of registered capital held by private firms grows steeply from the early 1990's onwards and by 2014 they hold 60% of total registered capital in the Chinese economy.

The preceding descriptive analysis suggests that private firms played an important role in China's rapid growth over the past decades. But what forces allowed private firms to enter and, thereafter, to grow? It is generally believed that governments at the local (county), provincial, and central level played a critical role in China's economic transformation. Local governments provided the infrastructure to support production clusters located throughout the country, which are a distinctive feature of the Chinese economy (Long and Zhang, 2011). Provincial governments and the central government supported firms by giving them subsidized credit and by aggressively promoting exports (Wu, 2016). Our research shifts focus from the government to the role played by informal community networks in spurring private enterprise in China.

Case studies of Chinese production clusters; e.g. Huang *et al.* (2008), Ruan and Zhang (2009), and Fleisher *et al.* (2010) consistently find that the impetus for their formation came from within, with groups of entrepreneurs setting up firms with little external support. The involvement of local governments is found to come later, through the provision of infrastructure such as roads, markets, and quality control. What supporting mechanisms allowed these early entrants to come together and commence production in an often initially rural location? There is an emerging literature on the role played by social networks or *guanxi* in facilitating China's historically unprecedented rural-urban labor migration over the past decades; e.g. Zhao (2003), Zhang and Li (2003), Hu (2008). This literature describes how migrant networks are organized around the rural hometown, complementing a well established body of work that takes the position that ethnicity in China is defined by the native place; e.g. Honig (1992, 1996), Goodman (1995). Migrants from the same rural origin move to the city in groups and most migrants end up living and working with *laoxiang* or "native-place

State Administration of Industry and Commerce (SAIC) in China, and can be used to pay the firm's operating expenses before it becomes cash flow positive. Access to bank credit is also dependent on the firm's registered capital, which is why firms will often choose to increase their registered capital over time.

fellows" (Cai Fang, 1997; Ma and Xiang, 1998; Zhang and Xie, 2013). In Chinese cities, migrant-peasant 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 peasants from a single county or two neighboring counties. If the sending county is the domain around which migrant labor networks are organized, then we expect that this will also be the natural domain around which business networks supporting county-born entrepreneurs are organized.[8]

Counties in China are divided into villages, which consist, in turn, of one or more clans or lineages (Peng (2004), Tsai (2007)). These clans historically supported the business activities of their members (in the pre-communist period) and it has been argued that this role has re-emerged in the modern Chinese economy (Peng (2004), Zhang (2017), Greif and Tabellini (2017)). We remain agnostic about the boundary of the social unit from which business networks are drawn in this paper; i.e. whether it is the county or the clan. As discussed below, the county characteristic that we use as the source of forcing variation in the empirical analysis would apply to the county as a whole and to all clans within the county, and thus our results would go through in either case.

2.2 Social Connectedness and Economic Cooperation in Chinese Counties

Our strategy to identify the role played by birth county networks in supporting entrepreneurship exploits exogenous variation in social connectedness in the population of these counties. Greater social connectedness supports higher levels of economic cooperation, which we will show has consequences for firm entry, sectoral and spatial concentration, and firm size when hometown business networks are active.

We proxy social connectedness by population density. The basic idea is that the number of social interactions that each individual has with local residents in each time period is increasing in their spatial proximity, which, in turn, is increasing in population density. More frequent social interactions support higher levels of economic cooperation. To make this argument more precise, consider a simple environment in which each individual needs help from the community, defined by the population of the county or by his clan within the county, for some task in each period. We focus on the case where each community is a homogenous social group with symmetric interactions and payoffs. One individual is selected randomly from the community to provide this help. The level of help is a real number $e \geq 0$: this generates benefit $V(e)$ to the recipient, where V is an increasing and concave function of e, while the provider incurs a personal cost γe. In each period, each individual is a recipient of help, as well as a provider of help to one other individual (on average). A norm of effort, e, provided by each help-giver, if it could be sustained by some means, would thus generate a per capita expected payoff of $V(e) - \gamma e$. The (utilitarian) socially optimal level of help is $e^* = argmax[V(e) - \gamma e]$, while the Nash equilibrium of the one-shot game entails zero help.

We now examine what levels of help can be sustained in an incentive compatible manner by community norms, which are based on social interactions. Any downward deviation from a group norm of effort e that becomes known to other members of the community in a given period is punished by social sanctions.

[8] A similar argument has been made in past research in India, where the endogamous caste or *jati* is the common domain around which networks supporting rural-urban migration, business, and other functions are organized (Munshi and Rosenzweig, 2006, 2016; Munshi, 2011).

This takes the form of a one-time penalty inflicted on the deviator at no cost to the punisher (e.g., a reprimand, or exclusion from a collective benefit or activity).[9] While the recipient of the help knows whether his randomly selected partner deviated from the effort norm and could impose the sanction in response, community enforcement relies on third party sanctions — imposed in addition by others in the community who come to learn about the deviation. The deviation could be observed by some others in the community, who communicate it to those they meet, and the latter in turn communicate to others. In this way news spreads within the community depending on the frequency of social interactions. Let this frequency be denoted by σ, which we assume is rising in population density p. Consequently the expected total sanction $S(\sigma)$ imposed on the deviator is increasing in interaction frequency σ, and thus in density p.[10] An effort level e can be supported in equilibrium if $V(e) - \gamma e \geq V(e) - S(\sigma(p))$. It follows that the maximal supportable level of help is $e(p) = \frac{S(\sigma(p))}{\gamma}$, which is increasing in p.[11]

A community with a higher population density can thus support higher levels of trust and cooperation. If the community is the county, then this implies that counties with higher population densities will be associated with more frequent social interactions and greater economic cooperation. This argument can be extended to the case where the county population is not homogenous, but, instead, is fragmented into smaller social groups or clans. Suppose that each county is partitioned into different clans $j = 1, \ldots$, where clan j has demographic weight ζ_j satisfying $\zeta_j \geq 0, \sum_j \zeta_j = 1$. The clan composition of the county is represented by the vector $\zeta \equiv \{\zeta_j\}_j$. Assume that cooperation is sustained only within clans, not across clans. Thus, while individuals may interact freely with all residents of the local area, it is only interactions within the clan that are relevant for social enforcement. Assume that the frequency of relevant interactions σ_j in clan j is an increasing function $\sigma(\zeta_j, p)$ of clan size ζ_j and population density p in the county. Then the level of help e_j exchanged within clan j equals $e(\sigma(\zeta_j, p))$. If social composition ζ is independent of p, it follows that an increase in p raises economic cooperation within every clan, and therefore the average level of cooperation in the county. Under this assumption, social heterogeneity within counties does not affect our argument, as it is orthogonal to p. In the absence of such an assumption, we would have to incorporate the indirect effect of p on cooperation as it alters social heterogeneity; if the latter reduces average cooperation as is frequently observed to be the case, then we would more generally need heterogeneity to not be increasing 'too much' in population density.

One other qualification needs to be noted: the positive relationship between population density and economic cooperation that may hold in a rural county may not hold in the city. Population densities are much higher in cities than in counties on average. Based on the 1982 population census, which is prior to large-scale rural-urban migration in China, the population density in counties was 30 individuals per square km. on average, whereas the corresponding average in cities was 140 individuals per square km. However, this higher population density is accompanied by much greater social heterogeneity. Cities are comprised

[9] It is common to model sanctions in the form of self-enforcing breakdown of cooperation in subsequent periods. We adopt a simpler specification where the penalty takes the form of a one-shot self-enforcing sanction.

[10] This is a very simplified version of enforcement via informal community norms where higher frequency of social interactions enables greater cooperation. For more detailed analyses of game theoretic models with this feature see Kandori (1992) and Ellison (1994).

[11] The implicit assumption here is that equilibrium effort in the highest population density county, $e(\overline{p})$, does not exceed the socially optimal effort e^*.

of newcomers, by definition, and the social enforcement that can be supported within long-established clans or among local residents in counties (who have been living together for generations) may not be sustainable in urban neighborhoods. If social heterogeneity is increasing sufficiently steeply in population density, then even the frequency of local social interactions may not be increasing in population density (this is certainly true in very large cities).

Table 1a provides empirical support for our distinction between counties and cities. China is divided into approximately 2,000 counties and 250 prefecture-level and province-level cities (which are further divided into urban districts). The China Family Panel Survey (CFPS) covers a representative sample of households in these counties and cities. The family module of the CFPS (2010) includes the frequency of social interactions between the primary respondent and local residents; i.e. individuals living in the local area, which is the village in the county and the neighborhood in the city. The social interactions are divided into entertainment, visits, and chatting.[12] Population density in the county and in the urban district (for city residents), is derived from the 1982 population census and is measured as a Z-score. We see in Table 1a that the frequency of each type of local interaction is increasing in population density (significantly for chatting) with county residents, whereas the sign of this relationship is reversed for city residents.

Table 1b, which is based on the adult individual module of the CFPS (2010) looks at who the respondents chat with most, distinguishing between local residents, relatives, and classmates (the three most popular categories). In counties, higher population density is associated with a significantly increased likelihood that the respondent reports chatting most with a local resident and a significantly reduced likelihood of chatting with a relative. In cities, in contrast, higher population density is associated with a decline in the likelihood that the respondent chats most with a local resident and with a relative, although these effects are not significant at conventional levels.

Table 1a. Frequency of Local Social Interactions and Population Density

Dependent variable:	number of interactions per month with local residents					
Purpose:	entertainment	visits	chat	entertainment	visits	chat
Family's location:	county			city		
	(1)	(2)	(3)	(4)	(5)	(6)
Population density	0.208	2.006	5.420***	-0.065	-0.408*	-0.343
	(0.335)	(1.268)	(1.808)	(0.102)	(0.237)	(0.523)
Constant	1.246***	3.613***	18.013***	0.999***	3.391***	13.595***
	(0.193)	(0.724)	(0.930)	(0.216)	(0.442)	(1.158)
Observations	8,675	8,675	8,675	3,256	3,256	3,256

Source: family module of China Family Panel Survey (2010).
Population density in the county or city (urban district) based on the 1982 population census.
Population density is measured in units of 10,000 people per square Km, and then converted to Z-score.
Standard errors clustered at the birthplace level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

The differences in social interactions that we have documented map into differences in trust, which is closely associated with economic cooperation. The adult individual module of the CFPS (2012) collected

[12]Entertainment includes playing Mahjong or cards, reading newspapers, listening to radio,and watching TV. Visits means going to the home of a local resident. Chatting is defined as a face-to-face interaction without any other activity.

Table 1b. Interaction Partners and Population Density

Dependent variable:	indicates whether the respondent chats most with					
Source of interaction:	local resident	relative	classmate	local resident	relative	classmate
Respondent's location:	county			city		
	(1)	(2)	(3)	(5)	(6)	(7)
Population density	0.063**	-0.077**	-0.002	-0.011	-0.001	0.006
	(0.029)	(0.036)	(0.017)	(0.008)	(0.013)	(0.004)
Constant	0.223***	0.515***	0.146***	0.129***	0.605***	0.154***
	(0.016)	(0.018)	(0.009)	(0.013)	(0.019)	(0.009)
Observations	20,357	20,357	20,357	7,070	7,070	7,070

Source: adult individual module of China Family Panel Survey (2010).
Dependent variables indicate whether the respondent chats most with a local resident, a relative, and a classmate, respectively, on a daily basis.
Excluded interaction partners include colleagues, social workers, babysitters, property managers, and teachers.
Population density in the county or city (urban district) based on the 1982 population census.
Population density is measured in units of 10,000 people per square km, and then converted to Z-score.
Standard errors clustered at the birthplace level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

information on trust in local residents and in outsiders; i.e. individuals living outside the local area who the respondent meets for the first time. Trust is measured as an ordinal variable, taking values from 0 to 10.[13] We see in Table 2, Column 1 that trust in local residents is increasing in population density for respondents residing in counties. However, population density has no impact on trust in outsiders for those respondents in Column 2, nor does it have an impact on trust in either local residents or outsiders for city residents, in Columns 3-4. The results on social interactions and trust, taken together, indicate that population density is positively associated with economic cooperation in Chinese counties. The discussion that follows shows how the same social enforcement that sustains this economic cooperation could have been used to support business networks organized around the birth county or the clan, regardless of where they are located.

2.3 Linking Birth Counties to Business Networks

Sustaining high productivity often requires the help of other entrepreneurs operating in the same sector-destination. Chinese production clusters are characterized by a high degree of specialization by entrepreneurs in specific stages of production, extensive exchanges of intermediate goods, and flexible adjustments to workloads and product specifications in response to volatile market demand. Sustaining high productivity in this economic environment requires considerable mutual help. This is hard to generate via market transactions, owing to inherent problems of verifying help sought and received, coupled with a weak legal environment. Cooperation is based instead on community norms, backed by social ties among the entrepreneurs in question (Nee and Opper, 2012). Even for entrepreneurs that have located at destinations different from their original hometown, such norms are based on maintenance of social connections at the hometown. Migrant

[13]The question on trust is designed to match the well known and frequently used question on trust in the World Values Survey (WVS). The WVS measures trust as an ordinal variable that takes values from 1 to 4. The level of trust in the WVS is assessed for the respondent's family, in his neighborhood, among people that the respondent knows personally, among people he meets for the first time, among people of another religion, and among people of another nationality. The CFPS measures trust in parents, neighbors, Americans, strangers, cadres, and doctors. Our analysis focuses on trust in neighbors or local residents and strangers; i.e. people the respondent meets for the first time (and who thus live outside the local area). These are the two categories that overlap with the WVS.

Table 2. Trust and Population Density

Dependent variable:	trust in local residents	trust in outsiders	trust in local residents	trust in outsiders
Respondent's location:	county		city	
	(1)	(2)	(3)	(4)
Population density	0.482***	0.027	0.001	0.015
	(0.153)	(0.208)	(0.056)	(0.046)
Constant	6.610***	2.202***	6.312***	2.180***
	(0.082)	(0.109)	(0.097)	(0.090)
Observations	19,637	19,637	6,248	6,248

Source: adult individual module of China Family Panel Survey (2012).
Trust is an ordinal variable, and takes value from 0 to 10.
Population density in the county or city (urban district) based on the 1982 population census.
Population density is measured in units of 10,000 people per square km, and then converted to Z-score.
Standard errors clustered at the birthplace level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

entrepreneurs typically have close family members (such as aged parents) in the hometown, and visit the hometown frequently. They (or close family members) continue to interact socially in the hometown, despite having set up firms elsewhere. Consequently, cooperation norms can continue to be backed by social sanctions imposed in the hometown.

To make this argument more precise, let the size of the network, which consists of entrepreneurs from the same birth county or clan who have already entered a sector-destination in period t be denoted by n_t. The TFP of an entrepreneur with individual talent ω at this destination equals $f(\omega)A_t$ where f is an increasing function of ω and $A_t = A_0(1+\nu h)^{n_t}$, with h denoting help provided by each member of the network to every other member. As help provided by different network members are mutually complementary, there are increasing returns with respect to the size of the network (for given per-member help). The 'quality' of the network depends on help provided by each member, which in turn depends on how socially connected their hometown is, for the following reason. The levels of help provided in the business sector are mutually observable to network members. Failure to provide a community help norm by any member is punished via social sanctions back in the hometown. The frequency of social interactions in the hometown, and hence the population density p, determines the maximal incentive compatible level of business help $h(p)$ that can be sustained, where $h(.)$ is increasing in p.[14] This implies that $A_t = A_0(1+\nu h(p))^{n_t}$. Letting $\theta(p)$ denote $\log(1+\nu h(p))$, this reduces to

$$A_t = A_0 \exp(\theta(p) n_t) \tag{1}$$

We will use this expression in the model that follows to derive the relationship between $\theta(p)$ and the dynamics of firm entry, sector-destination concentration, and firm size when community networks are active.

The important difference between our formulation and the standard specification of productivity growth generated by agglomeration effects is that networks are based on the social origins of entrepreneurs rather than the destinations they select: $\theta(p)$ reflects social connectedness in the birth county and n_t is the number

[14] Let the cost of help for any member be $\gamma' h n_t(p)$, and expected sanctions imposed back in the home county for failing to provide help be $S'(p)$. Then, following the argument above, the maximal help that can be supported by home county sanctions equals $h(p) \equiv \frac{S'(p)}{\gamma' n_t(p)}$, which is increasing in p if $S'(p)$ is increasing more steeply in p than $n_t(p)$.

Table 3. Composition of Listed Individuals in the Firm, by Birth Place Population Density

Dependent variable:	fraction of listed individuals from the legal representative's birth county	
Birth location:	county	city
	(1)	(2)
Birth place population density	0.010***	-0.026***
	(0.002)	(0.002)
Mean fraction	0.741	0.608
Counter-factual fraction with random assignment	0.056	0.090
Observations	488,529	236,985

Source: Registration Database (State Administration of Industry & Commerce).
Sample restricted to firm's operating outside their legal representative's birth county. Counter-factual fraction with random assignment for such a firm is measured by the number of listed individuals from the legal representative's birth county in its sector-location divided by the total number of listed individuals (among all firms whose legal representatives were born outside their birth county) in that sector-location.
"Listed individuals" includes major investors and top managers, but excludes the legal representative.
Population density in the county or city (urban district) based on the 1982 population census.
Population density is measured in the units of 10,000 people per square km, and then converted to Z-score.
Standard errors clustered at the birthplace level reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

of firms from that county operating in a given sector-destination. In the standard agglomeration model, the θ parameter would measure exogenous sector-destination characteristics and n_t would be the total number of firms operating in that sector-destination (irrespective of the social origin of their respective entrepreneurs). We will exploit this difference in the empirical analysis to distinguish between birth county network effects and agglomeration effects.

We complete this section by providing evidence that firms remain linked to their hometown, regardless of where they are located. While the model will assume, for analytical convenience, that each firm consists of a single entrepreneur, in practice there are multiple key individuals (major shareholders and top managers) in a registered firm. These individuals must exert effort and contribute in different ways to the firm, and the moral hazard problem that applies to the provision of help between firms will also be relevant within the firm. Using the same logic as above, cooperation within the firm will be backed by social sanctions in the hometown. More effective social sanctions will, in addition, be associated with greater hometown representation within the firm in equilibrium. The firm registration database, which we utilize for the core empirical analysis in this paper, includes a list of key individuals; i.e. major shareholders and managers in each firm. The citizenship ID is reported for each listed individual, from which the first six digits reveal the birth county.[15] The firm's legal representative is treated as the key individual or "entrepreneur" in the analysis that follows.[16] Table 3, Column 1 reports the fraction of listed individuals in the firm who are born in the legal representative's birth county, restricting attention to the 60% of firms that are located outside their

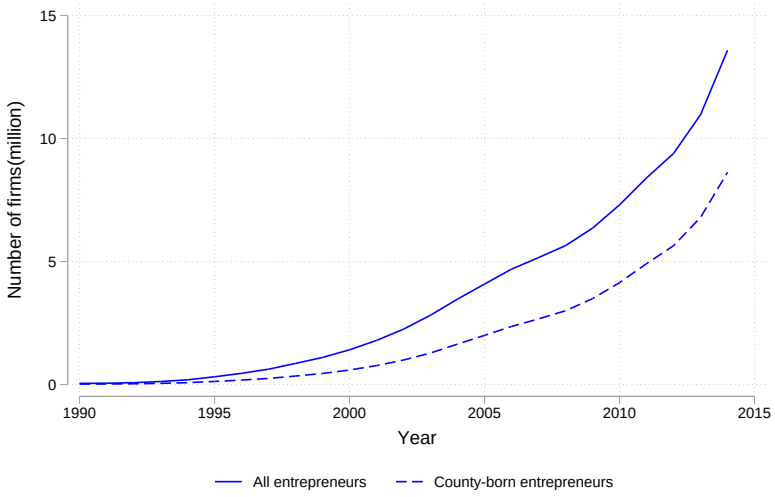
[15]Citizenship ID's were first issued in September 1985 and people born after that date are given an ID at birth. Those born before that date were registered in the county or city where they resided at the time. Given the limited opportunities for labor migration in that period and the cost of moving due to the Hukou System, almost all rural-born individuals resided in their birth-counties in 1985. The only exceptions were college students, college graduates, and soldiers, but these numbers were small. The first six digits of the citizenship ID thus reveals the county of birth, with few exceptions, even for those born before September 1985.

[16]This individual is legally responsible for the firm's liabilities. 75% of legal representatives are shareholders in their firms. The legal representative and the largest shareholder belong to the same birth county in over 90% of firms.

legal representative's birthplace. On average, 74% of the listed individuals in those firms belong to the legal representative's birth county, as compared with the statistic that would be obtained by random assignment, which is just 6%. Column 1 also reports the estimated relationship between the fraction of listed individuals from the legal representative's birth county and its population density. The coefficient on population density is positive and significant, consistent with the hypothesis that firms remain tied to their hometown, and that greater social connectedness in the hometown maps into greater representation by members of the hometown in the firm (even when it is located elsewhere). Table 3, Column 2 reports the same relationship for legal representatives born in city-districts. We saw no evidence that population density in cities was positively associated with local economic cooperation and, indeed, the coefficient on population density is negative and significant in Column 2. Our analysis will thus focus on county-born entrepreneurs and their firms.

Figure 2 describes the growth in the total number of private firms and in the number of firms owned by county-born entrepreneurs over the 1990-2014 period. County-born entrepreneurs make up about two-thirds of all entrepreneurs in China and their firms are just slightly smaller than the average registered firm. The contribution of these entrepreneurs, most of whom are first-generation businessmen, to Chinese economic growth has thus been substantial. Our objective in the analysis that follows is to identify and quantify the role played by hometown networks in supporting the explosive entry and subsequent growth of their firms.

Figure 2. Growth of Private Enterprise, by Birthplace of Entrepreneurs



Source: SAIC registration database.

3 A Model of Network Dynamics

3.1 Population and Technology

There are many counties of origin; each generates a network of entrepreneurs with an independent trajectory. We assume the absence of any interactions across networks drawn from different origins, and will later justify this assumption empirically. Hence, we focus on the dynamics of a single network originating in a given origin. Each origin has a given, exogenous, level of social connectedness represented by a real-valued

parameter $p \geq 0$; this will determine the productivity spillover within networks of entrepreneurs who are born there. The resulting variations in network dynamics with respect to the p parameter plays a key role in our analysis.[17]

At every origin there are equal-sized cohorts of new agents born at dates $t = 1, 2, ...$, who live for ever thereafter. Each agent is born with a random ability draw ω from an i.i.d. distribution. To obtain closed form solutions, we assume that the distribution of $\log \omega$ is uniform on $[0, 1]$. Every cohort t agent makes a once-for-and-all choice of occupation at t. Everyone has the option to enter a traditional, non-entrepreneurial (T) sector; some agents will have an opportunity to enter either of two business sectors B_1, B_2. The different sectors can also be re-interpreted as different destinations within the same sector; hence the model applies either to sectoral or locational choices. Denote total entry into sector B_i by past cohorts by $n_{i,t-1}$.

Profits are increasing and concave in ability in the traditional sector: the profit of an agent with ability ω in the T sector is ω^σ, where $\sigma \in (0, 1)$. It will turn out to be linear in ability in each business sector. So low ability agents would be better off staying in the traditional sector, while high ability agents might want to switch to becoming entrepreneurs.

In sector B_i at date t, an entrepreneur with ability ω who selects capital size K has a production function

$$y = A_{it}\omega^{1-\alpha}K^\alpha \tag{2}$$

where $\alpha \in (0, 1)$ is the capital elasticity, and A_{it} denotes 'community' TFP, which takes the form (as explained in the previous section):[18]

$$A_{it} = A_0 \exp(\theta(p)n_{i,t-1}) \tag{3}$$

Note that the TFP of each agent actually depends on his own ability draw, besides A_{it}. Hence 'community TFP' A_{it} can be interpreted as the TFP of the lowest ability agent (with $\omega = 1$) in the community: we shall refer to it as CTFP from now onwards. CTFP is a dynamically evolving community level variable. It depends on the size ($n_{i,t-1}$) of the incumbent network, and on its quality $\theta(p)$ which is rising in p. The exponential relationship implies that the rate of growth of CTFP over time is proportional to the (quality-weighted) increase in network size. This represents the first source of network complementarity in the model, reflecting gains from intra-network cooperation in improving productivity for those who have already entered sector i. A second source of network complementarity that we introduce below will pertain to 'referrals' or 'access' to particular business sectors. The interaction between the two sources of network complementarity will generate the increase in sectoral concentration, with respect to p and over time, that is an important feature of our model.

All agents incur the same cost of capital r which is exogenous and fixed across all t, and all origins. We are thus abstracting from possible network complementarities operating via internal capital markets, as in Banerjee and Munshi (2004), which arise in response to financial market imperfections. To the extent that larger and higher quality networks lower borrowing costs for their members, the resulting dynamics turn

[17] We could assume, instead, that multiple clans from the same birth county generate multiple networks. As long as p applies to each clan, all the results that follow go through.

[18] The A_0 term incorporates market size, the product price, and labor productivity. Labor is not included as a variable input in the production function because it is not observed in our data. With the Cobb-Douglas specification of the production function, the optimal labor input can be derived as a function of the model's parameters and is thus subsumed in the A_0 term.

out to be very similar to those generated via productivity spillovers, and would thus amplify the dynamics generated by the latter alone. We also assume a fixed price of the product (normalized to unity) which is unaffected by supply from the network. This abstracts from price collusion among network members, as well as limits to market size in a competitive context. These seem plausible in the Chinese setting, where most sectors are comprised of a large number of origin county networks, and both domestic and international market opportunities are large.[19]

3.2 Occupational Choice

To determine occupational choice, we first calculate the profits a new agent in any cohort with a given ability ω expects to earn upon entering a given business sector, when the CTFP in that sector is expected to be A. The latter is a sufficient statistic for the specific date, sector in question, existing network size and quality (which determine CTFP as per (3)). The optimal capital size K must maximize $A\omega^{1-\alpha}K^{\alpha} - rK$, and thus satisfies:

$$\log K(\omega, A) = \log \omega + \log \phi + \frac{1}{1-\alpha} \log A - \frac{1}{1-\alpha} \log r \tag{4}$$

(where $\phi \equiv \alpha^{\frac{1}{1-\alpha}}$). The resulting profit satisfies

$$\log \Pi(\omega, A) = \log \omega + \log \psi + \frac{1}{1-\alpha} \log A - \frac{\alpha}{1-\alpha} \log r \tag{5}$$

(where $\psi \equiv \phi^{\alpha} - \phi$). If we allowed for credit networks organized around the origin county and parameterized the interest rate as $r = r_0 exp(-\eta(p) n_{i,t-1})$, then the productivity channel operating through the A term and the credit network channel would not be separately identified. Although the model is set up so that networks operate through the productivity channel, all the results that follow would go through if, instead, they operated through the credit channel.

A fixed fraction $k \in (0, 1)$ of agents in every cohort receive an opportunity to become an entrepreneur. Each such agent receives an opportunity to enter one of the two business sectors. The fraction that get an opportunity to enter B_i equals $s_{i,t-1}$, which is the share of incumbent entrepreneurs already in that sector. This is the second source of network complementarity in our model, operating via aspirations, access to information, or referrals provided by older members from the same origin in a given sector.

Of the new agents receiving an offer, the ones that will decide to enter are those who receive a higher profit in that sector than in the traditional occupation. These agents will be endowed with a level of ability that exceeds a threshold $\underline{\omega}$:

$$\log \omega > \log \underline{\omega} \equiv \frac{1}{1-\sigma} [\log \frac{1}{\psi} - \frac{1}{1-\alpha} \log A + \frac{\alpha}{1-\alpha} \log r] \tag{6}$$

This threshold lies in the interior of the ability distribution if

$$(1-\alpha) \log \frac{1}{\psi} + \alpha \log r - (1-\sigma)(1-\alpha) < \log A < (1-\alpha) \log \frac{1}{\psi} + \alpha \log r \tag{7}$$

[19] Based on the registration data, firms from a given origin county account for 13% of firms at the destinations where they locate, on average (within narrow two-digit sectors). This statistic is based on all entrepreneurs, including those who locate their firms in their county of birth.

We assume this holds at the beginning of the process for each sector, i.e., $\log A_0$ satisfies this inequality, and we will restrict attention to 'early phases of industrialization' when it continues to be true (i.e., until T such that $\log A_{iT}$ also satisfies it). At later dates it may fail to be true if CFTP rises sufficiently; then *all* agents will want to become entrepreneurs irrespective of their ability. Such later stages will be characterized by some slowing down of the entry process, as the range of abilities that prefer to enter ceases to expand (having reached the maximum limit). In the Chinese data we see some slowing down around 2009, partly as a result of the worldwide financial crisis in 2007-08. So the empirical analysis will be restricted to the first two decades of private enterprise expansion, from 1990 to 2009.

Notice that agents receiving an entrepreneurial opportunity make their decision *selfishly* and *myopically* in the model. The former assumption implies that they ignore the consequences of their entry decisions on the profits of other agents. The latter states that they make their choice solely to maximize their date–t profits, ignoring consequences at later dates. This enables us to compute the entry dynamics recursively, simplifying the analysis considerably. As network size cannot ever decrease over time and its quality does not change, and neither do profits in the traditional sector, this amounts to a conservative bias in entry decisions: those deciding to enter based on a myopic calculation would also want to enter if farsighted, while some others deciding to stay out on myopic grounds may wish to enter when they anticipate future network growth which will raise the returns to entrepreneurship. If agents were more far-sighted, they would have to forecast current and future levels of entry from the same origin county, generating strategic complementarity of entry decisions within each cohort. This extension is considered in Appendix A, where entry decisions at t are based on the discounted sum of profits at t and $t+1$, rather than t alone. We show there under some natural conditions that a unique rational expectations equilibrium exists, whose comparative statics are similar to those in the simpler myopic model. Intuitively, the network complementarities would be further amplified with farsighted behavior: higher network quality (represented by $\theta(p)$) or historical size will induce even higher levels of entry.

3.3 Dynamics of Entry and Concentration

The two business sectors have identical 'fundamentals'. At the beginning of the process ($t = 0$), there is a small, exogenous number n_{i0} of older entrepreneurs (from cohorts preceding $t = 1$) who have already entered B_i. These represent the initial conditions for the dynamics. These historical entry levels will not be exactly balanced across the two sectors; without loss of generality suppose $n_{10} > n_{20}$ so B_1 has an initial edge. This slight difference in initial conditions, together with the two sources of network complementarity that we incorporate in our model, will be sufficient to increasingly channel entrants (particularly those from high-p origins) into the dominant sector over time.

To derive entry in subsequent cohorts, we start with the threshold condition (6), which determines the measure of agents from cohort t who would choose to enter sector B_i if they had the opportunity. Combining this with the fraction $ks_{i,t-1}$ of those agents that have an opportunity to enter (as well as expression (3) for CFTP), we can derive the volume of entry e_{it} in cohort t into B_i as a function of the state variables

$n_{i,t-1}, s_{i,t-1}$:

$$e_{it} = k s_{i,t-1}[B + C\theta(p) n_{i,t-1}]$$

where $B \equiv 1 - \frac{1}{1-\sigma}\log\frac{1}{\psi} - \frac{\alpha}{(1-\sigma)(1-\alpha)}\log r + \frac{1}{(1-\sigma)(1-\alpha)}\log A_0$ and $C \equiv \frac{1}{(1-\sigma)(1-\alpha)}$. This expression reduces further to

$$e_{it} = L s_{i,t-1} + \kappa(p) N_{t-1} s_{i,t-1}^2 \tag{8}$$

where L denotes kB; $\kappa(p)$ denotes $Ck\theta(p)$ which is rising in p, and $N_{t-1} \equiv n_{1,t-1} + n_{2,t-1}$ denotes the aggregate number of business entrepreneurs from past cohorts from the same origin.[20]

Aggregating (8) across the two sectors $i = 1, 2$, we obtain an expression for the dynamics of aggregate entry:

$$N_t - N_{t-1} \equiv E_t \equiv e_{1t} + e_{2t} = L + \kappa(p) N_{t-1} H_{t-1} \tag{9}$$

where $H_{t-1} \equiv s_{1,t-1}^2 + s_{2,t-1}^2$ denotes the Herfindahl Hirschman Index for sectoral concentration at $t-1$. This index can be expressed as a function of the share of sector 1 alone, since $H_{t-1} = s_{1,t-1}^2 + [1 - s_{1,t-1}]^2$. Note that H_{t-1} is increasing in $s_{1,t-1}$ if $s_{1,t-1} > \frac{1}{2}$. We will show below that sector 1 will remain bigger for all t, given that it is bigger at $t = 0$. We thus use H_{t-1} and $s_{1,t-1}$ interchangeably as measures of concentration in the discussion below.

Equations (8, 9) can be used to derive an expression for the dynamics of concentration:

$$\begin{aligned} s_{1t} \equiv [\frac{N_t}{n_{1t}}]^{-1} &= [\frac{L + N_{t-1} + \kappa(p) N_{t-1} H_{t-1}}{L s_{1,t-1} + n_{1,t-1} + \kappa(p) N_{t-1} s_{1,t-1}^2}]^{-1} \\ &= [1 + (\frac{1}{s_{1,t-1}} - 1)\{\frac{L + N_{t-1} + \kappa(p) N_{t-1}(1 - s_{1,t-1})}{L + N_{t-1} + \kappa(p) N_{t-1} s_{1,t-1}}\}]^{-1} \end{aligned} \tag{10}$$

Equations (9, 10) characterize the evolution of the two dimensional state variable (N_t, s_{1t}) representing the aggregate incumbent stock of firms originating from a given county and their allocation between the two sectors. The following Proposition uses these equations to derive the dynamics of entry and concentration with respect to p.

Proposition 1 *(a) Entry E_t, the stock of entrepreneurs N_t, and concentration H_t are rising in t (for any given p) and in p (at any given t).*

(b) $E_t - E_{t-1}$ and $H_t - H_{t-1}$ are both rising in p, if $\kappa(p) < 1$ for all p and the share of the larger sector at $t-1$ is not too close to 1 (e.g., below $\frac{3}{4}$).

The reasoning is as follows. The stock of entrepreneurs is obviously nondecreasing in t as entry flows are non-negative. Next, observe that using (10) we can obtain the following expression for the change in share of sector 1 over time:

$$s_{1t} - s_{1,t-1} = \kappa(p) N_{t-1} \frac{(2 s_{1,t-1} - 1)(1 - s_{1,t-1}) s_{1,t-1}}{(L + N_{t-1})(2 - s_{1,t-1}) + \kappa(p) N_{t-1}(s_{1,t-1}^2 + 1 - s_{1,t-1})} \tag{11}$$

[20] Setting $s_{i,t-1}$ to one, equation (8) collapses to the entry equation in Munshi's (2011) single-sector model of network dynamics. In Munshi's (2011) model, variation across communities is generated by differences in outside options – the σ parameter in our model, which is embedded in L – rather than by differences in social connectedness, p. While both models generate an increase in the flow of entrants over time, our model generates additional predictions for the dynamics of concentration and firm size.

A recursive argument implies that the share of sector 1 must rise over time (and therefore remain larger than $\frac{1}{2}$ forever). Given $s_{10} > \frac{1}{2}$ it follows that $s_{11} > s_{10}$. Applying the same reasoning to each successive time period, $s_{1,t-1} > \frac{1}{2}$ for any $t-1$, which implies that the share of sector 1 must be higher at t than at $t-1$. Hence sectoral concentration rises in t; equation (9) then implies that E_t is rising in t.

Consider next how a higher p alters the dynamics, given initial conditions. We claim that it raises aggregate entry E_t (and hence N_t) as well as H_t at every date t. This follows from an inductive argument. Observe first that it must be true for E_t (and N_t) at $t = 1$, given the initial conditions N_0, H_0, upon applying equation (9) at $t = 1$. Next observe that the right-hand-side of (10) is rising in p, given any N_{t-1} and $s_{1,t-1} > \frac{1}{2}$. Hence s_{11} must be rising in p, given the initial conditions. So the result holds at $t = 1$. Next suppose it holds until some date $t-1$, i.e., N_{t-1} and H_{t-1} are rising in p. Equation (9) then implies E_t (and N_t) is rising in p. Moreover, observe that the right-hand-side of (10) is rising in N_{t-1} and in $s_{1,t-1}$, given p and $s_{1,t-1} > \frac{1}{2}$. The share s_{1t} will then be increasing in p because it is increasing in $s_{1,t-1}$, N_{t-1} and $\kappa(p)$ respectively. Induction now ensures this will be true at every t. This establishes part (a) of Proposition 1.

Turn now to part (b). Taking first differences of (9)

$$E_{t+1} - E_t = \kappa(p)[N_t H_t - N_{t-1} H_{t-1}] = \kappa(p)[E_t H_t + N_{t-1}(H_t - H_{t-1})] \tag{12}$$

Since $\kappa, E_t, H_t, N_{t-1}$ are all rising in p, the result would hold for entry if it were also true for concentration (i.e., $H_t - H_{t-1}$ is rising in p). A sufficient condition for this to hold is that it is true for s_{1t}: i.e., if $s_{1,t} - s_{1,t-1}$ is rising in p (since $H_t - H_{t-1} = 2(s_{1t} - s_{1,t-1})(s_{1t} + s_{1,t-1} - 1)$, and we have already shown that $s_{1t}, s_{1,t-1}$ are rising in p). However, this sufficient condition cannot hold for large enough values of t, for the simple reason that the share of the dominant sector B_1 is bounded above by 1. If it rises at a fast rate initially, it approaches 1 and then must 'flatten out'. So after a sufficient amount of time has passed, a high p origin could be almost entirely concentrated in sector B_1, while the share of this sector is continuing to rise for lower p origins.

Part (b) states that the result holds if the share of sector 1 is not too large, e.g., smaller than $\frac{3}{4}$, and $\kappa(p) < 1$. It is easily checked that $\kappa(p) < 1$ implies that the denominator of the right-hand-side of (11) is decreasing in $s_{1,t-1}$. And the numerator is increasing in $s_{1,t-1}$ if $s_{1,t-1} < \frac{3}{4}$ (since this implies $s_{1,t-1}(1 - s_{1,t-1}) > \frac{1}{6}$). Then $s_{1t} - s_{1,t-1}$ is rising in $s_{1,t-1}$, as well as in N_{t-1} and κ. Part (b) then follows from the fact that $s_{1,t-1}, N_{t-1}$ are rising in p.

3.4 Firm Size Dynamics

Next we turn to predictions concerning entrepreneurial ability and firm size. We first show that network effects generate an adverse selection phenomenon: as community TFP grows with the incumbent stock over time, the threshold for entry falls, and entrepreneurs with weaker talent start entering. This adverse selection on individual talent outweighs the productivity benefit derived from a larger network, implying that marginal entrepreneurs that enter are of lower productivity and hence enter with smaller firm sizes. The same applies to comparisons at any given t across different p origins: marginal entrants from higher p origins, with stronger networks, enter with smaller firm sizes. If $\sigma \in (\frac{1}{2}, 1)$ this is true also for the average entrant: firms from high p origins enter with smaller initial capital. All firms face the same cost of capital and there

are no mark-ups in our model. The preponderance of small and seemingly unproductive firms often noted in developing countries, which is typically attributed to wedges in factor prices and mark-ups in output price in the misallocation literature, may just be a manifestation of strong network effects! Our model implies that their own productivity understates their contribution via spillovers to their network.

In contrast, post-entry growth rates of firm size for any given cohort are rising in p and over time. In our model, growth in firm size is independent of the entrepreneur's ability (the adverse selection phenomenon is irrelevant) and is determined entirely by changes in CTFP. Because CTFP is increasing over time and increasing in p at each point in time, firm growth has the same properties. Firms from high-p origins start smaller, but subsequently grow faster. This dual prediction will be especially helpful in distinguishing our network-based model from alternative models, as discussed in the next section.

Proposition 2 *Averaging across sectors:*

(a) Initial capital and ability of marginal entrants (also of average entrants if $\sigma > \frac{1}{2}$) in cohort t is decreasing in t (for any given p) and in p (for any given t), and decreasing more steeply in p across successive cohorts.

(b) The growth rate of capital of incumbent entrepreneurs of any past cohort t from $t'-1(>t)$ to t' is rising in p and in t' (more steeply with higher p).

To verify (a), observe that the ability threshold for entrants is decreasing in CTFP, A, from (6). With regard to initial firm size, there are two conflicting effects of a higher CFTP: the direct effect, for a given level of ability, would induce a higher firm size by raising firm level TFP, but this would be offset by the negative selection on ability, which lowers firm TFP and size. In our model, the latter effect dominates. Substituting from (6) in (4), initial capital size of the marginal entrant satisfies

$$\log K_{it}^m = U - \frac{\sigma}{(1-\sigma)(1-\alpha)} \log A_{it} \tag{13}$$

where $U \equiv \log \phi - \frac{1}{1-\sigma} \log \psi - \frac{1}{1-\alpha} \log r$, and $\log A_{it}$ denotes log CFTP at t. Initial capital of the marginal entrant is unambiguously decreasing in CFTP.

Next consider the ability and size of the average (rather than marginal) entrant. Note that the average entrant has (log) ability $\frac{1+log\omega_{it}}{2}$, which is decreasing in CFTP. Substituting from (6) in (4), the capital size of the average entrant satisfies:

$$\log K_{it}^a = W + \frac{1-2\sigma}{2(1-\alpha)(1-\sigma)} \log A_{it} \tag{14}$$

where $W \equiv \log \phi + \frac{1}{2} + \frac{1}{2(1-\sigma)} \log \frac{1}{\psi} - \frac{2-\alpha-2\sigma}{2(1-\alpha)(1-\sigma)} \log r$. Expression (14) shows that higher CFTP is also negatively correlated with firm size of the average entrant, but if and only if $\sigma > \frac{1}{2}$. When this condition holds, the drop in the minimum ability threshold (when CFTP rises) is steep enough to outweigh the direct positive effect of CFTP.

Part (a) of Proposition 2 follows directly from the preceding discussion, based on variation in CTFP, and (13) and (14). CTFP (in logs) can be expressed as, $log(A_{it}) \equiv logA_0 + \theta(p)n_{i,t-1}$. Averaging across sectors,

the $n_{i,t-1}$ term in the preceding expression is replaced by N_{t-1}, which is rising in t (for any given p) and in p (at any given t) from Proposition 1. Moreover, the change in N_t over time; i.e. E_{t-1}, is also increasing in p, to complete the argument.

Now turn to part (b). Observe that (4) implies that the capital at date $t' > t$ of an average cohort t entrepreneur is given by

$$\log K^a_{itt'} = \frac{1 + \log \omega_{it}}{2} + \log \phi - \frac{1}{1-\alpha} \log r + \frac{1}{1-\alpha} [\log A_{it} + \theta(p) \sum_{l=t}^{t'-1} e_{il}] \tag{15}$$

implying a growth rate at period t':

$$\log K^a_{it,t'} - \log K^a_{it,t'-1} = \frac{1}{1-\alpha} \theta(p) e_{it'} \tag{16}$$

Averaging across sectors, $e_{it'}$ is replaced by $E_{t'}$ in the equation above. $E_{t'}$ is rising in p (for any given t') and in t' (for any given p, but more steeply with higher p) from Proposition 1, to establish part (b).

3.5 Alternative Models

To what extent do the preceding results rely on network spillovers across birth county members? Could they be obtained, instead, by relaxing different assumptions of our model, while shutting down the network component? These questions are relevant because although population density is plausibly associated with social connectedness and, hence, network quality, it could also be correlated with other factors that independently determine the dynamics of entry, concentration, and firm size. The discussion that follows systematically examines this possibility by introducing new sources of heterogeneity at the origin, which are, in turn, correlated with population density, and by allowing firms from different origins to have favorable access to destinations of varying quality. Our model treats sectors and destinations interchangeably. Because destination heterogeneity is an important alternative that we must consider, entrepreneurs choose between destinations rather than sectors (for ease of exposition) in the models that follow.

3.5.1 Origin Heterogeneity

Our model assumes that the stock of potential entrepreneurs, k, is constant across origin counties and over time. Suppose that we relax this assumption and let $k(p,t)$ be a twice differentiable function satisfying $k_p > 0, k_t > 0, k_{pt} > 0$. This could be because higher population density counties simply have larger populations that are growing relatively fast over time or because their residents have greater wealth or preferred access to finance, which facilitate entry into business. An additional source of origin heterogeneity could be in payoffs in the traditional occupation across counties. Our model assumes that the payoff, ω^σ, where ω is individual ability, is the same in all counties and constant over time. However, the payoff could be lower in higher population density counties because there is a larger population for a given amount of resources (such as agricultural land). It is also possible that this population pressure is increasing over time. We allow for this possibility by representing the payoff in the traditional sector by $\omega^\sigma v(p,t)$, where $v(p,t)$ is a twice differentiable function satisfying $v_p < 0, v_t < 0, v_{pt} < 0$.[21]

[21] An alternative interpretation of $v(p,t)$ is that it represents the payoff from origin-based networks operating in the traditional sector.

Abstract for the time being from heterogeneity across destinations, so the TFP of any entrepreneur with talent ω at any destination at time t is $\omega^{1-\alpha}A_t$, with A_t growing exogenously over time. Moreover, an exogenous share s_i of potential entrepreneurs at each origin have the opportunity to enter any given destination. Owing to the absence of network effects, neither A_t nor s_i depend on p.

The ability threshold for entry into destination i from an origin with population density p in this alternative model would equal

$$\log \underline{\omega}_i(p;t) = \frac{1}{1-\sigma}\left[\log\frac{1}{\psi} + \frac{\alpha}{1-\alpha}\log r - \frac{1}{1-\alpha}\log A_t + \log v(p,t)\right] \tag{17}$$

while the expression for entry flows is:

$$e_i(p,t) = s_i k(p,t)\left[1 + Z + \frac{1}{(1-\alpha)(1-\sigma)}\log A_t - \frac{1}{1-\sigma}\log v(p,t)\right] \tag{18}$$

where $Z \equiv \frac{1}{1-\sigma}\log\psi + \frac{\alpha}{(1-\alpha)(1-\sigma)}\log r$. The entry flows will be rising in p and in t, and the slope with respect to p will be rising in t. The alternative model can thus generate our model's predictions for entry. However, the share of different destinations will be constant and independent of p. In order to obtain the same predictions for spatial concentration generated by the network model, the shares s_i of different destinations would have to (exogenously) depend on p and t in a way that exactly delivers these results. Although we do not explicitly incorporate sectors in the alternative model, it would similarly need to be augmented to exactly match our model's predictions for the dynamics of sectoral concentration.

With $\sigma \in (\frac{1}{2}, 1)$ the initial capital of entrants would fall over time due to the increase in A_t and the decline in $v(p,t)$, and would also falling in p (due to the $v(p,t)$ term). However, post-entry growth of firm size would be driven entirely by rising productivity at the destinations, A_t, which does not vary with the origins of entrepreneurs. Hence this model would not generate result (b) of Proposition 2 concerning post-entry growth in firm size across origin counties.

3.5.2 Destination Heterogeneity

Now consider the implications of varying productivity levels and growth rates across destinations. This could reflect the effect of geography, the support provided by local governments (through credit and infrastructure), or agglomeration spillovers. The latter depend on the total number of firms at a destination, regardless of their origin. Let A_{it} denote productivity at destination i at t, which does not vary with the origins of entrepreneurs. Suppose in addition that high p origins have better, and increasing, access to the faster growing destinations. For instance, if there are two destinations and productivity at destination 1 is higher and growing faster than at destination 2, then the share $s_1(p,t)$ is increasing in t and in p (more steeply over time). The expressions for entry thresholds and entry flows are now

$$\log \underline{\omega}_i(p;t) = \frac{1}{1-\sigma}\left[\log\frac{1}{\psi} + \frac{\alpha}{1-\alpha}\log r - \frac{1}{1-\alpha}\log A_{it} + \log v(p,t)\right] \tag{19}$$

$$e_i(p,t) = s_i(p,t) k(p,t)\left[1 + Z + \frac{1}{(1-\alpha)(1-\sigma)}\log A_{it} - \frac{1}{1-\sigma}\log v(p,t)\right] \tag{20}$$

This model which incorporates both origin and destination heterogeneity would generate the same predictions as Proposition 1 for entry and concentration. There would be greater total entry from high p origins

owing to the supply-side heterogeneity at the origin, besides greater access to the faster growing destination. Concentration would rise over time for entrepreneurs from all origins, owing to faster entry growth into destination 1. This would be more pronounced for the high p areas, so concentration would rise in p and $p * t$. Entry thresholds from high-p areas would be lower due to higher A_{it} (averaged across destinations) or lower $v(p,t)$, so the initial capital size result in part (a) of Proposition 2 would also go through. The average rate of growth of firm size (where we average across destinations) would be higher for high-p origins, owing to their preferred access to the faster growing destination.

The alternative model specified above can generate the predictions of our model relating to the dynamics of entry, concentration, and firm size because the key $s_i(p,t)$, A_{it} terms are exogenously specified to match the endogenous evolution of these terms in our model. If firms from each origin locate at a unique set of destinations, then our network-based model would not be distinguishable from the alternative model with destination heterogeneity. In practice, however, firms from multiple origins will locate at the same destination. Destination-time period dummies can then be included in the estimating equation. Conditional on these dummies, we still expect firms from higher-p origins to grow faster on average because their growth is driven by changes in CTFP. In contrast, there is no relationship between firm growth and p in the alternative model once destination-time period dummies are included because there is no longer any variation within destinations.

One way to incorporate heterogeneity within destinations, without networks, would be to allow firm growth to vary with the entrepreneur's ability (this is not a feature of our model). A positive relationship between p in the origin county and firm growth would then be obtained even within destination-time periods if entrepreneurs from higher p origins have higher ability on average. However, this alternative model would not explain why firms from higher p origins, with higher ability, nevertheless have lower initial capital. One final model that we consider, which can reconcile both our results on firm size is the neoclassical growth model; if initial firm size is randomly determined, then firms that start small will grow faster. Although the randomness is difficult to justify (indeed, we find that firms that start smaller have lower ability), we will allow for this possibility by estimating the relationship between p and firm growth, conditional on destination-time period fixed effects and initial capital.[22]

4 Empirical Analysis

4.1 The Data

The primary data source that we use to test the model is the firm registration database maintained by the State Administration of Industry and Commerce (SAIC). We have received special permission to use the entire database, with firm and individual identifiers, for our research. The following information is available for each firm: establishment date (and exit date if relevant), 4-digit sector, location, ownership-type, registered capital (initial and subsequent changes), and the list of major shareholders and managers,

[22] One model that can generate both our firm-size results without requiring initial capital to be randomly determined is based on Banerjee and Munshi's (2004) analysis of the Tirupur garment cluster. They find that outsiders, who face a higher cost of capital because they have weaker local credit networks, start with smaller firms and then grow faster (because they are positively selected on ability). In the Chinese data, however, firms from high-p origins, who start smaller and then grow faster, are *negatively* selected on ability.

with their citizenship ID. As discussed, the birth county can be recovered from the citizenship ID and we denote the firm's legal representative as the "entrepreneur" when testing the model. Although the database includes the universe of Chinese firms registered since 1980 in China, the analysis that follows is restricted to private firms and covers the 1990-2009 period. We will see that the negative selection on ability predicted by the model in the initial (explosive) growth phase starts to weaken by this point in time. Starting with a relatively small number of private firms in 1990, there were 7.3 million registered private firms in 2009. Our unique data thus allows us to trace the initial growth phase of private enterprise in China in its entirety. In contrast, previous analyses of firms in China have relied on a publicly available database of manufacturing firms with sales above a threshold level (5 million Yuan) over the shorter 1998-2008 period; e.g. Hsieh and Klenow (2009), Song *et al.* (2011), Brandt *et al.* (2012), Aghion *et al.* (2015). The above-scale firms account for less than 15% of all private firms in the registration database in 2008.

Although the registration database is well suited to examine entry, sectoral and location choice, and initial capital investments, it is less useful for analyses of capital growth. Registered capital does change, but given the administrative costs involved, these changes will not track perfectly with changes in the firm's assets over time. For the analysis of firm growth, we thus turn (separately) to the industrial census, which was conducted in 1995, 2004, and 2008 and the SAIC's inspection database, which includes annual firm-level information on assets and sales from 2004 onwards.

To verify the quality of the SAIC administrative data, which are used for much of the analysis, we linked firms by their ID's across the industrial census and the registration and inspection databases. The correlation in reported firm assets between the 2008 industrial census and the inspection database is 0.63. The correlation in the total number of firms, by sector and birth county of the entrepreneurs, in the 2008 industrial census and the registration database is 0.85. The SAIC data are reported by firms. The industrial census information is collected by enumerators. Despite the fact that the data are collected independently, there is a relatively high degree of consistency across the different firm-level data sources that we use in the analysis.

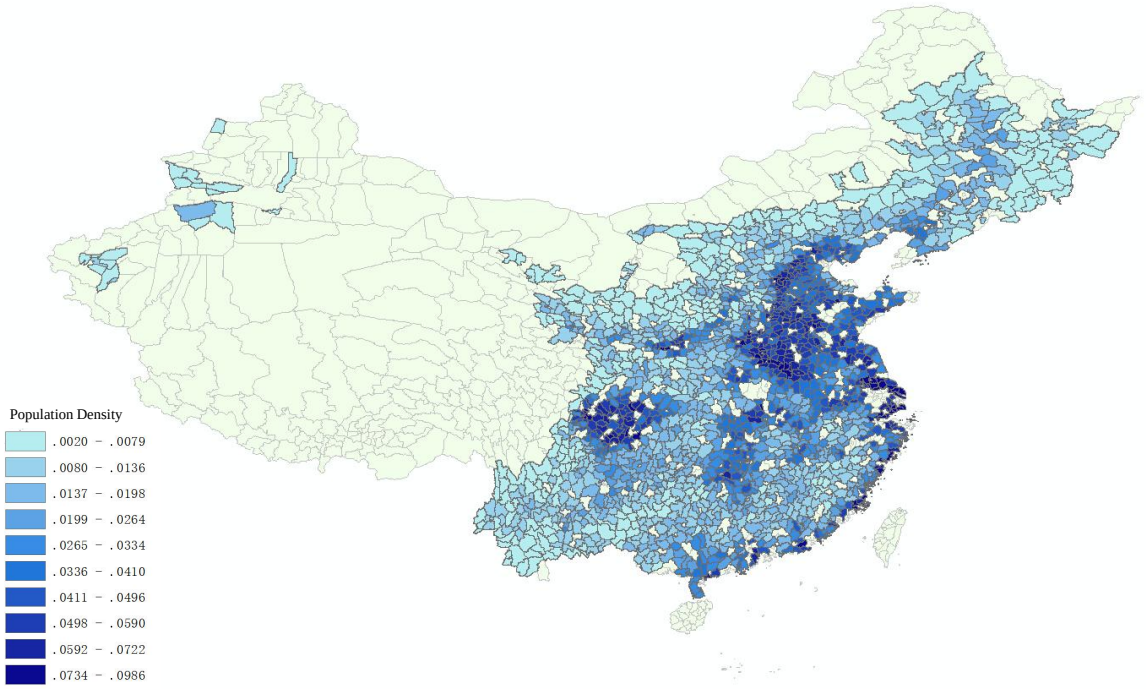
The discussion in the preceding section indicates that the model generates testable predictions that distinguish it from alternative explanations. To test these predictions, however, there must be sufficient variation in population density across counties. Figure 3 plots population density across Chinese counties, excluding counties below a threshold density.[23] The population density in this figure, and in all the analyses, is derived from the 1982 population census. This is before the first wave of privatization in the early 1990's and the accompanying rural-urban labor migration.[24] There is substantial variation in this pre-determined measure of social connectedness, which ranges from 20 to 1000 people per square km across counties, and we will see below that this variation is sufficient to test the model's predictions with a high degree of statistical confidence. Note that while we focus on the county-born entrepreneurs to test the model, the empirical analysis will place no restrictions on where firms locate; there are 3,235 counties and urban districts where

[23]Population density is measured in units of 10,000 people per square km. The threshold density is set at 0.002; i.e. 20 people for square km. This excludes sparsely populated regions such as Western China, Inner Mongolia, and Tibet, which supply few entrepreneurs, from the analysis.

[24]The advantage of using a predetermined measure of social connectedness in the analysis is that it avoids the possibility that changes in population density in later time periods are generated by endogenously determined network-based migration. Nevertheless, as documented in Appendix Figure C.1 using successive rounds of the population census, the ranking of counties with respect to population density is invariant over time.

firms locate in our data. Moreover, the relationship between population density and the model's outcomes for entrepreneurs born in cities will serve as a useful placebo test. Because social connectedness is not increasing in population density in cities, we do not expect to validate the predictions of the model with these entrepreneurs.

Figure 3. Population Density across Counties



Source: 1982 population census.

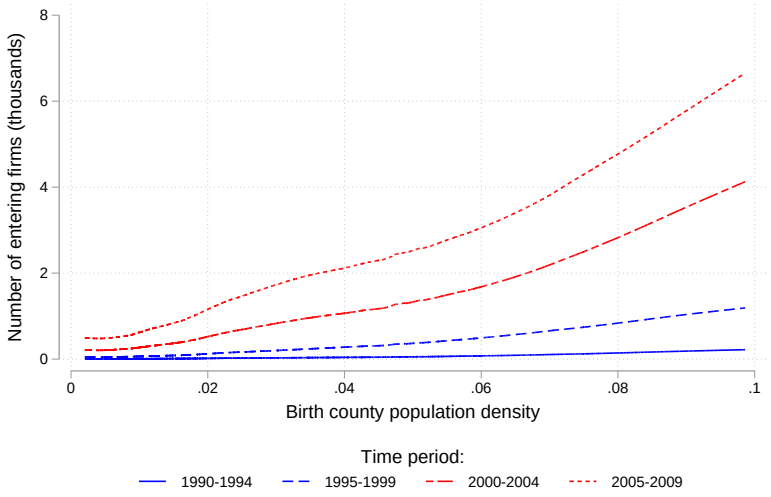
4.2 Evidence on Firm Entry

The model predicts that firm entry is (i) increasing in origin county social connectedness at each point in time, (ii) increasing over time, and (iii) increasing more steeply in social connectedness over time. This is a statement about the flow of firms rather than the stock, and so we will measure entry in five-year windows over the 1990-2009 period. Figure 4 reports nonparametric estimates of the relationship between the entry of firms from each birth county and 1982 population density, our measure of social connectedness, in that county in each time period. The entry patterns in the figure are consistent with the model's predictions, with the parametric estimates that follow providing statistical support for each prediction.[25]

Table 4 reports parametric estimates corresponding to Figure 4, separately by time period. This allows us to test the prediction that entry is increasing in population density at each point in time. Although we have shown that population density is positively correlated with social connectedness in a county, it could potentially be correlated with other origin characteristics that directly determine the model's outcomes. As

[25] Appendix Figure C.2 reports the corresponding nonparametric relationship between population density in the birth county and the stock of firms (measured at the end of each time period). The predictions of the model apply to both firm entry; i.e. the flow and the stock of firms. In practice, however, the stock will also take account of exits, which play no role in the model. We see in Figure C.2 that the model's predictions for the stock of firms go through as well, despite the exits.

Figure 4. Firm Entry and Population Density



Source: SAIC registration database and 1982 population census.

discussed, origin heterogeneity and, more generally, any non-network explanation cannot generate all the results of our model. However, origin heterogeneity can explain the entry results. Population density is positively associated with the county's population and a larger population is mechanically associated with greater entry. Counties with higher population densities also have more educated populations, based on literacy rates from the 1982 census. If education is a proxy for ability, then there will be greater entry in more educated counties because there is positive selection on ability into entrepreneurship in the model. Finally, the traditional occupational structure in the county could determine the propensity to enter business. We thus include 1982 population, 1982 literacy, and the 1982 occupational structure (measured by the agriculture share and industry share, with services as the excluded category) in an augmented specification of the estimating equation in Table 4, Columns 5-8. The estimated coefficients on the additional regressors (not reported) are all statistically significant. Nevertheless, the coefficient on the birth county population density variable remains positive, as predicted by the model, and is highly significant in each time period. Notice also that the mean of the dependent variable and the population density coefficient are increasing across time periods, in line with predictions (ii) and (iii) above. Formal tests of these predictions are reported later in this section.

An important alternative explanation for the model's predictions is that there is heterogeneity across destinations, with entrepreneurs born in higher population density birth counties having access to faster growing destinations. Given that firms from multiple origin counties will locate at each destination, we can flexibly accommodate this alternative by including destination-time period dummies in the estimating equation. But first we check whether firms from higher population density counties indeed locate in destinations that receive more entrants overall (owing to geography, local infrastructure, or agglomeration effects). The dependent variable in Table 5 is a synthetic measure of entry for each birth county in each time period, which is constructed as the weighted average of total entry (from all other origins) across all the sector-destinations where firms from that birth county locate. The weight on each sector-destination in a given time period is the fraction of entrants from the birth county who locate there. We see in Table 5, in contrast with Table

Table 4. Firm Entry and Population Density

Dependent variable:	number of entering firms							
Time period:	1990-1994	1995-1999	2000-2004	2005-2009	1990-1994	1995-1999	2000-2004	2005-2009
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth county population density	0.030***	0.186***	0.622***	1.060***	0.013***	0.092***	0.289***	0.448***
	(0.003)	(0.018)	(0.055)	(0.088)	(0.003)	(0.013)	(0.035)	(0.052)
Mean of dependent variable	0.031	0.208	0.787	1.560	0.031	0.208	0.787	1.560
Control variable	No	No	No	No	Yes	Yes	Yes	Yes
Observations	1,624	1,624	1,624	1,624	1,624	1,624	1,624	1,624

Note: number of entering firms from each birth county in each time period is measured in thousands.
Population density is measured in units of 10,000 people per square km, and then converted to Z-score.
Control variables include population, education and occupation distribution in the birth county.
Population is measured in millions and education is measured by the percent of the population that is literate.
Occupation distribution is measured as the share of workers in the birth county in agriculture and industry. Service is the excluded category.
Number of firms is obtained from the SAIC registration database and population density, population, education and the occupation distribution are derived from the 1982 population census.
Robust standard errors are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

4, that there is no relationship between population density in the birth county and our synthetic measure of total entry in the destinations where firms located. Indeed, the coefficient on population density is negative in the first three time periods (and statistically significant in the first period). Entrepreneurs from higher population density birth counties do not locate in faster growing destinations.

As a robustness exercise to reinforce this point, we include sector fixed effects and destination fixed effects in the estimating equation in Table 6. This equation is estimated separately in each time period and so the fixed effects capture the changing fortunes of sectors and destinations over time.[26] Birth county population density continues to have a positive and significant effect on entry in each time period in Table 6. A comparison of the results obtained with the specification in Table 4, Columns 5-8, and the specification in Table 6 indicates that the inclusion of the fixed effects actually increases the point estimates. Consistent with the results in Table 5, this indicates that entrepreneurs born in high population density counties select sectors and destinations that had relatively *low* total entry (from all origins) on average.

4.3 Evidence on Concentration

The model predicts that sectoral concentration of the stock of firms, measured by the Herfindahl Hirschman Index (HHI), is (i) increasing in origin county social connectedness at each point in time, (ii) increasing over time, and (iii) increasing more steeply in social connectedness over time. As with firm entry, we measure social connectedness by birth county population density, restricting attention to entrepreneurs born in counties. Figure 5a reports nonparametric estimates of the relationship between sectoral concentration at the two-digit level and 1982 population density in the birth county in five-year intervals from 1994 to 2009. The HHI is based on the stock of existing firms (net of exits) and is adjusted for the fact that measured concentration could vary with the number of firms and the number of sectors just by chance, using a normalization derived

[26]Entry in Table 6 is measured at the birth county-sector-destination level in each time period. The number of entrants is multiplied by the county-specific product of the number of sectors and the number of destinations so that the dependent variable reflects average entry at the level of the county.

Table 5. Synthetic Entry and Population Density

Dependent variable:	synthetic entry			
Time period:	1990-1994	1995-1999	2000-2004	2005-2009
	(1)	(2)	(3)	(4)
Birth county population density	-0.012***	-0.001	-0.005	0.004
	(0.004)	(0.024)	(0.026)	(0.025)
Constant	0.351*	2.833***	6.353***	4.946***
	(0.191)	(0.905)	(1.197)	(0.951)
Observations	1,624	1,624	1,624	1,624

Note: synthetic entry (in thousands) in each time period is measured by the weighted average of total entry (from all origins excluding the birth county) across all sector-destinations for a given birth county. The weight on a given sector-destination is the fraction of total entrants from the county who located at that sector-destination in that time period.
Control variables include population, education and occupation distribution in that birth county.
Birth county characteristics, including population density, are derived from the 1982 population census. Number of entrants obtained from the SAIC registration database.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table 6. Firm Entry and Population Density (with sector and destination fixed effects)

Dependent variable:	number of entering firms			
Time period:	1990-1994	1995-1999	2000-2004	2005-2009
	(1)	(2)	(3)	(4)
Birth county population density	0.014**	0.118***	0.382***	0.575***
	(0.006)	(0.037)	(0.101)	(0.126)
Mean of dependent variable	0.0725	0.483	1.673	3.024
Observations	1,085,169	1,085,169	1,085,169	1,085,169

Note: firm entry (in thousands) measured at the birth county-time period-sector-destination level.
For a given birth county, all sectors and destinations that ever have entrants are included in all time periods (assigned zero entry where necessary). To adjust for differences in the number of sectors and destinations across birth counties, the number of entrants is multiplied by the number of sectors × the number of destinations.
Control variables include population, education and occupation distribution in the birth county.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

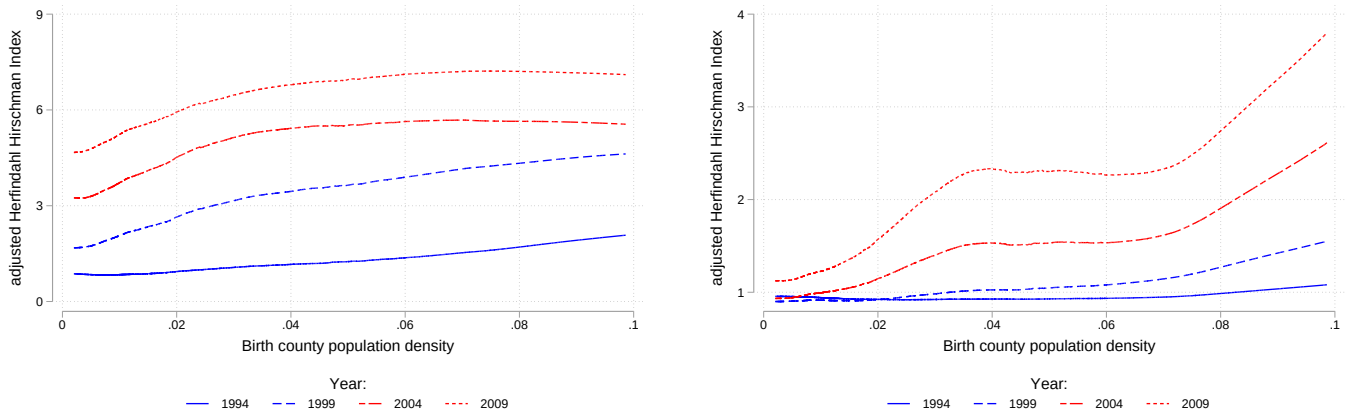
in Appendix B.[27] The adjusted HHI is evidently increasing in population density at each point in time and increasing over time, although it is difficult to visually assess whether the slope of the relationship gets steeper over time.

While firms choose between sectors in the model without regard to location, it is possible that the network spillovers are (in part) geographically constrained. If that is the case, then the model's predictions for sectoral concentration apply, without modification, to spatial concentration (within sectors) for firms that are located outside their birth county.[28] Figure 5b reports nonparametric estimates of the relationship between spatial concentration, within one-digit sectors, and population density in the birth county in five-year intervals. As with the analysis of sectoral concentration, the spatial concentration within each sector for a given birth county is based on the stock of firms (net of exits) and is adjusted for the number of firms that are located outside

[27] Previous attempts to examine the spatial distribution of production; e.g. Ellison and Glaeser (1997), Duranton and Overman (2005), have also taken account of this feature of all concentration statistics.

[28] The choice between locating inside or outside the birth county is more complicated because transportation costs are obviously lower when the entrepreneur chooses to stay back home. This home bias could be stronger in higher population density birth counties, while at the same time firms from those counties that locate elsewhere could be more spatially concentrated.

Figure 5. Concentration and Population Density



(a) Sectoral Concentration

(b) Spatial Concentration

Source: SAIC registration database and 1982 population census.
Sectoral concentration measured by the Herfindahl Hirschman Index (HHI) across two-digit sectors, divided by the expected HHI that would be obtained by random assignment, given the number of entrants and the number of sectors at each point in time.
Spatial concentration, within one-digit sectors, is measured by the Herfindahl Hirschman Index (HHI) across destinations (outside the birth county) divided by the expected HHI that would be obtained by random assignment, given the stock of firms and number of destinations at each point in time.

the birth county and the number of external destinations, which would generate variation in the measured HHI just by chance.[29] Matching the predictions of the model, the spatial HHI is evidently (i) increasing in birth county population density in each time period, (ii) increasing over time, and (iii) increasing more steeply over time.

Table 7 reports parametric estimates corresponding to Figure 5a and Figure 5b. Population density in the birth county has a positive and significant effect on (adjusted) sectoral and spatial concentration at each point in time. The mean of the dependent variable and the population density coefficient are increasing over time, in line with predictions (ii) and (iii), which we test formally below.[30]

Table 8 formally tests the model's predictions for changes over time and for changes in the birth county population density effect over time with all three outcomes; i.e. firm entry, sectoral concentration, and spatial concentration. Data from all time periods are pooled and the estimating equation now includes birth county population density, time period, and the interaction of these variables. To preserve space, we only report the coefficient on the time period variable and the interaction coefficient. Restricting the sample to county-born entrepreneurs in Table 8, Columns 1-3, the time period coefficient and the interaction coefficient are positive and significant with the number of entrants, sectoral concentration, and spatial concentration as the dependent variables, as predicted by the model. As a placebo test, we restrict the sample to entrepreneurs born in urban districts in Table 8, Columns 4-6. Population density is not positively associated with social

[29] To maintain consistency across time periods, we only include birth county-sectors that have multiple entrants in all time periods. This is not a constraint in the sectoral analysis because all birth counties have multiple entrants in each time period.

[30] The discussion on alternative explanations indicates that origin heterogeneity can generate the patterns of entry predicted by our model. Origin heterogeneity is less of a concern with the analysis of concentration. Nevertheless, we verify that the concentration results are robust to the inclusion of the additional birth county characteristics in Appendix Table D.1. The results are essentially the same as in Table 7, except that the population density coefficient is increasing monotonically over time even with sectoral concentration as the dependent variable. Recall from Proposition 1 that the HHI cannot increase beyond a point. This might explain why the population density coefficient flattens out after 1999 in Columns 1-4 of Table 7, but not in Appendix Table D.1 where it is substantially smaller in size.

Table 7. Sectoral and Spatial Concentration and Population Density

Dependent variable:	adjusted HHI across sectors				adjusted HHI across destinations			
Year:	1994	1999	2004	2009	1994	1999	2004	2009
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth county population density	0.224***	0.754***	0.773***	0.767***	0.024**	0.121***	0.301***	0.524***
	(0.022)	(0.051)	(0.052)	(0.059)	(0.012)	(0.018)	(0.036)	(0.056)
Mean of dependent variable	1.039	2.839	4.622	6.065	0.941	1.019	1.319	1.820
Observations	1,622	1,624	1,624	1,624	5,479	15,132	23,753	26,784

Note: sectoral concentration measured across two-digit sectors and spatial concentration, within one-digit sectors, is measured across destinations. Concentration statistics are adjusted for expected concentration due to random assignment.
Sector fixed effects included in the regression with spatial HHI as the dependent variable.
Robust standard errors are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

connectedness in cities and thus we do not expect to find support for the model's predictions with this set of entrepreneurs. The time period coefficient and the interaction coefficient are both positive and significant with entry as the dependent variable, but as discussed, many alternative models can generate this result without a role for birth county networks. The model's predictions for concentration are less easy to explain away. Reassuringly, the interaction coefficient for the city-born entrepreneurs is *negative* and significant with sectoral concentration as the dependent variable and statistically indistinguishable from zero with spatial concentration as the dependent variables, contrary to the predictions of our model.

Table 8. Entry, Concentration, and Population Density (time and interaction effects)

Birth location:	county			city district		
Dependent variable:	number of entrants	sectoral HHI	spatial HHI	number of entrants	sectoral HHI	spatial HHI
	(1)	(2)	(3)	(4)	(5)	(6)
Time period	0.517***	1.686***	0.343***	0.661***	0.319***	2.288***
	(0.016)	(0.020)	(0.014)	(0.026)	(0.008)	(0.083)
Birth place population density × time period	0.353***	0.165***	0.163***	0.355***	-0.024***	0.055
	(0.029)	(0.019)	(0.017)	(0.041)	(0.004)	(0.045)
	(0.029)	(0.019)	(0.017)	(0.041)	(0.004)	(0.045)
Observations	6,496	6,494	71,148	3,224	3,222	20,285

Note: the estimating equation includes, in addition, birthplace population density and a constant term.
Number of entering firms from each birth county in each time period is measured in thousands.
Sectoral concentration measured by Herfindahl Hirschman Index (HHI) across two-digit sectors divided by the expected HHI that would be obtained by random assignment.
Spatial concentration, within one-digit sectors, is measured by the Herfindahl Hirschman Index (HHI) across destinations (outside the birth county) divided by the expected HHI that would be obtained by random assignment.
Population density is measured in units of 10,000 people per square km, and then converted to Z-score.
Time period is an ordinal variable taking value from 1 to 4 corresponding to successive five-year time windows over the 1990-2009 period.
Number of entrants and concentration statistics are derived from the SAIC registration database and population density is derived from the 1982 population census.
Standard errors clustered at birthplace level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

4.4 Evidence on Firm Size

The model predicts that the ability and the initial capital of the marginal entrant is (i) decreasing in birth county social connectedness at each point in time, (ii) decreasing over time, and (iii) decreasing more steeply in social connectedness over time. If the negative selection on ability that accompanies a stronger network dominates the positive productivity effect of that network for inframarginal firms, then the preceding predictions apply to the average entrant as well. However, only the positive network productivity effects are relevant for post-entry growth rates of firm size.

Figure 6a reports the relationship between a measure of ability, based on education, of the marginal entrepreneur and population density in his birth county. It is standard practice to proxy for ability with education. In a developing economy, the level of education will vary across birth cohorts and in the cross-section (across birth counties) for the same level of ability, depending on the supply of schooling. Our measure of ability is thus the entrepreneurs' percentile rank in his birth county-birth cohort education distribution.[31] The marginal entrant is the entrepreneur who is placed at the bottom one percentile of the ability distribution among entering entrepreneurs in each birth county-sector-time period. We see in Figure 6a that the marginal entrant's measured ability declines over time; from around the 70^{th} percentile of his birth county-birth cohort education distribution in the 1990-1994 period to just around the 40^{th} percentile in the 2005-2009 period. The relationship between the marginal entrant's ability and population density is also negative in each time period and grows steeper over time.[32] Notice, however, that there is a bottoming out by the last, 2005-2009, period. Our model is only designed to capture firm dynamics up to this point, which is why the empirical analysis does not extend beyond 2009. For the analysis of negative selection that follows, and for the structural estimation, the analysis period will be restricted even further to the 1990-2004 period.

Figure 6b reports complementary nonparametric estimates of the relationship between marginal initial capital, measured in logs, and 1982 population density in the birth county in five-year windows over the 1990-2009 period. Marginal initial capital is defined as the bottom one percentile of the initial capital distribution at the birth county-sector-time period level.[33] As predicted by the model, marginal initial capital is decreasing over time and decreasing in birth county population density in each time period.[34]

Notice from Figure 6b that the decline in initial capital with birth county population density does not grow steeper over time (as implied by the model). One reason why this might be the case is because marginal initial capital within birth county-sector-time periods is averaged across sectors in the figure. Although this is not a feature of our model, the capital requirement will vary across sectors, and this must be accounted for in the empirical analysis. Table 9 allows for this by studying the change in the ability of entering entrepreneurs

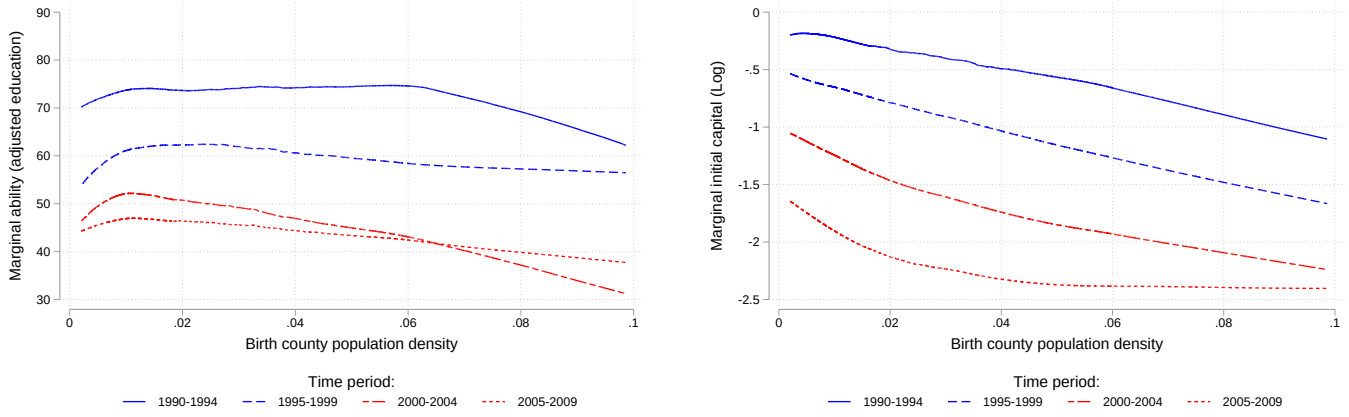
[31] The education distribution is constructed in each county for birth cohorts from 1920 to 1989 in five-year intervals, based on data from the 2000 population census. Each entrepreneur is assigned to a birth cohort interval based on his birth year, which is available from the registration database, and his position in the relevant education distribution is determined on the basis of his education, which is also obtained from the registration database. The coverage for the education variable is not complete in the SAIC registration database, with a significant minority of entrepreneurs not reporting this information. This has no bearing on the complementary analysis of firm size, which includes all registered firms.

[32] Appendix Table D.2 reports parametric estimates corresponding to Figure 6a, separately in each time period. These estimates indicate that birth county population density has a negative and significant effect on marginal education among entering entrepreneurs at each point in time.

[33] The initial capital for a firm is determined by its initial registered capital, which can be recovered from the SAIC registration database.

[34] Appendix Table D.2 reports parametric estimates corresponding to Figure 6b, separately by time period. The population density coefficient is negative and significant in each time period.

Figure 6. Marginal Ability, Marginal Initial Capital and Population Density



(a) Marginal Ability

(b) Marginal Initial Capital

Source: SAIC registration database and 1982 population census.
The entrepreneur's ability is measured by his percentile rank in his birth county- birth cohort education distribution (obtained from the 2000 population census.
The marginal entrepreneur is defined as the individual at the bottom one percentile of the ability distribution among entering entrepreneurs in a given birth county-sector-time period.
Marginal initial capital is defined as the bottom one percentile of the initial capital distribution at the birth county-sector-time period level.

and their capital investments over time, within birth county-sectors. The analysis is restricted to the 1990-2004 period because our measure of marginal ability and initial capital both bottom out (and flatten out) in the 2005-2009 period in Figures 6a and 6b. We see in Table 9, Column 1, which includes birth county-sector fixed effects, that the marginal entrant is drawn from lower down in his birth county-cohort education distribution over time and that this decline in our measure of ability is significantly steeper for entrants from higher population density counties, as predicted by the model. Table 9, Columns 2-3 use the distribution of initial capital (in logs) in each entering cohort of firms, in five-year windows over the 1990-2004 period, to identify the marginal entrant (the bottom one percentile) and the average entrant by birth county-sector. Including birth county-sector fixed effects in the estimating equation, we see that both the marginal entrant's initial capital and the average entrant's initial capital are decreasing significantly over time. Although the coefficient on the time period-birth county population density interaction is also negative and significant with the marginal entrant's initial capital as the dependent variable, the interaction coefficient is positive (albeit small in magnitude and statistically insignificant) with average initial capital as the dependent variable.

The analysis of firm size thus far has not accounted for destination choices, and the possibility that variation in these choices across birth counties could be driving the results. Table 9, Columns 4-5 thus includes destination fixed effects, in addition to birth county-sector fixed effects in the estimating equation.[35] Both marginal initial capital and average initial capital are declining significantly over time, as in Columns 2-3. Moreover, the coefficient on the time period-birth county population density interaction is now negative and significant with both dependent variables, as predicted by the model. As with the analysis of firm entry,

[35]The marginal entrant's initial capital and the average entrant's initial capital are now based on the distribution of capital in each birth county-sector-destination-time period. The sample in Columns 5-6 is restricted to birth county-sector-destinations with entrants in the initial period. Similarly, the sample in Columns 3-4 is restricted to birth county-sectors with entrants in the initial period.

accounting for destination effects only strengthens our results.

Table 9. Evidence on Negative Selection

Dependent variable:	marginal ability	marginal initial capital	average initial capital	marginal initial capital	average initial capital
	(1)	(2)	(3)	(4)	(5)
Time period	-18.532***	-0.882***	-0.115***	-0.655***	-0.109***
	(0.409)	(0.012)	(0.008)	(0.009)	(0.007)
Birth county population density × time period	-1.040***	-0.028**	0.002	-0.069***	-0.022***
	(0.394)	(0.012)	(0.008)	(0.010)	(0.007)
Mean of dependent variable	49.36	-1.744	-0.401	-1.223	-0.374
Observations	21,028	43,579	43,579	46,417	46,417
Origin-sector fixed effects	Yes	Yes	Yes	Yes	Yes
Destination fixed effects	No	No	No	Yes	Yes

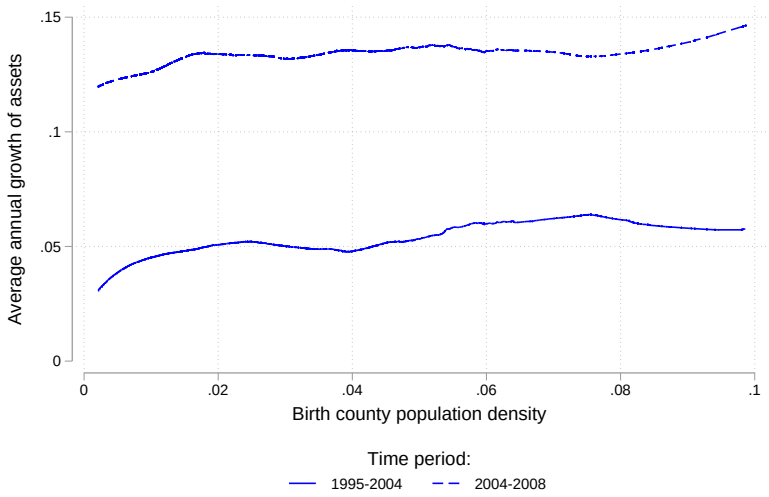
Note: the marginal entrepreneur is defined as the individual at the bottom one percentile of the ability (adjusted education) distribution among entering entrepreneurs in a given birth county-sector-time period.
Initial capital (in million Yuan) is measured in logs.Marginal initial capital defined by the bottom one percentile of the initial capital distribution at the birth county-sector-time period level. Average initial capital is the mean of the distribution.
Time period is an ordinal variable taking value from 1 to 3 corresponding to successive five-year time windows over the 1990-2004 period.
Education and initial capital are obtained from the SAIC registration database and birth county population density is derived from the 1982 population census.
Standard errors clustered at birth county-sector level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Conditional on having entered, the model predicts that firms from higher population density counties will grow faster. As noted, the registration data are not suitable for computing growth rates because the firm's registered capital does not track perfectly with changes in its assets. Information on firm assets is available, however, in the industrial census and the SAIC inspection database. The industrial census reports firm assets in the 1995, 2004, and 2008 rounds. The SAIC inspection database has reasonable coverage from 2004 onwards. We can thus compute the average annual growth rate over the 1995-2004 and 2004-2008 periods with the industrial census and, to be consistent, over the 2004-2008 period with the inspection data.[36] Figure 7 reports asset growth, separately in the 1995-2004 period and the 2004-2008 period, based on the industrial census. The average annual growth of assets is increasing in population density in each time period and increasing over time, as predicted by the model, in contrast with the patterns that we observe in the data for initial firm size.

Table 10, Columns 1 and 3 report estimates from a parametric specification corresponding to Figure 7, while Columns 2 and 4 add destination fixed effects and the firm's initial capital to the estimating equation. Recall that one alternative explanation for why firms from high population density birth counties start small and then grow faster is mechanical convergence (with initial size being accidentally determined). What we observe, instead, is that firms that are larger to begin with, subsequently grow faster. Table 10, Columns 5-6 repeats the analysis with SAIC inspection data, which include all sectors (not just manufacturing, as in the industrial census).[37] The consistent finding across specifications is that population density in the birth

[36]The average annual growth between period t and t' is computed as the difference in log assets in t' and t divided by $t' - t$.
[37]Data coverage for seven provinces is poor with the inspection data and these provinces are thus dropped from the analysis.

Figure 7. Asset Growth and Population Density



Source: Industrial census (1995, 2004, 2008) and 1982 population census.
Firm-level average annual growth of assets is averaged up to the birth county-sector level in each time period.

county has a positive and significant effect on firm growth.[38]

Table 10. Growth of Assets and Population Density

Dependent variable:	annual growth of assets					
Source:	industrial census		industrial census		inspection data	
Time period:	1995-2004		2004-2008		2004-2008	
	(1)	(2)	(3)	(4)	(5)	(6)
Birth county population density	0.006***	0.007*	0.004**	0.003**	0.004***	0.002*
	(0.002)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Initial capital	–	0.002***	–	0.001***	–	0.001***
		(0.000)		(0.000)		(0.000)
Mean of dependent variable	0.0528	0.0557	0.133	0.136	0.106	0.110
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Destination fixed effect	No	Yes	No	Yes	No	Yes
Observations	5,517	5,664	31,234	64,258	18,701	43,470

Note: firm-level average annual growth of assets is averaged up to the birth county-sector level in specifications with sector fixed effects and to the birth county-sector-destination level in specifications with sector fixed effects and destination fixed effects.
Initial capital (in million Yuan) obtained from the SAIC registration database and birth county population density is derived from the 1982 population census.
Standard errors clustered at birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

4.5 Testing the Mechanism

In our model, initial entry generates subsequent entry through a compounding network effect over time, which is reinforced by the channelling of new entrants into particular sectors or destinations. This relationship between initial entry and subsequent entry underlies the results that we derive for the dynamics of aggregate

[38] A pooled regression (not reported) which combines industrial census data over both time periods indicates, in addition, that firm growth is increasing significantly over time. While our model can explain this result, it must be augmented, perhaps by introducing credit constraints, to explain why initial capital has a positive and significant effect on firm growth.

entry, concentration, and firm size across origin counties. To examine this fundamental relationship more formally, within a particular sector-destination, consider a simplified version of our model with a single sector. Retaining the notation of our model, the entry equation then reduces to

$$e_t = k[B + C\theta(p)n_{t-1}] \tag{21}$$

This equation can be solved recursively, starting from period 1, to derive a closed-form solution for the relationship between entry in period t, e_t, and initial entry or, equivalently, the stock of firms, n_0, which we treat as exogenous in the model:

$$e_t = k[B + C\theta(p)n_0][1 + kC\theta(p)]^{t-1} \tag{22}$$

From the equation above, initial entry, n_0, has a positive effect on subsequent entry, e_t, with this effect growing steeper over time because $1 + kC\theta(p) > 1$. Moreover, the effect of n_0 at any date t is increasing in p because $\theta(p)$ is increasing in p.

We test this fundamental relationship in Table 11a by estimating the effect of initial entry on subsequent entry within birth county-sector-destinations. Initial entry is measured in the 1990-1994 period, when private firms were just starting to emerge, and subsequent entry is measured separately in 2000-2004 and 2005-2009. The estimating equation includes birth county-sector fixed effects.[39] The benchmark specification, reported in Columns 1-2, includes, in addition, the total number of initial entrants, regardless of their birth county, in each sector-destination in the estimating equation. The number of initial entrants from the birth county in a given sector-destination has a positive and significant effect on the number of subsequent entrants; one additional initial entrant generates seven additional entrants in the 2000-2004 period and nine additional entrants in the 2005-2009 period. Conditional on the number of initial entrants from the birth county, the total number of initial entrants in a given sector-destination has no effect on subsequent entry from that birth county in that sector-destination. This last result provides empirical support for the key assumption in the model that the birth county is the domain within business networks are organized in China and that these networks operate independently. It also provides support for the assumption that individual networks cannot influence the price of the product. If the members of the network could collude (depending on their market share) or there were limits to market size, then the total number of entrants, conditional on the number of entrants from the birth county, would also be relevant.[40]

It has been argued that Chinese cities are too small (Au and Henderson, 2006a). This stylized fact has been explained by restrictions on migration due to China's *hukou* system (Au and Henderson, 2006b; Desmet and Rossi-Hansberg, 2013) and by competition between local governments, giving rise to multiple production clusters in the same sector (Long and Zhang, 2012). Our model and the supporting empirical evidence provide an alternative explanation for China's low spatial concentration, which is that agglomeration effects are restricted to firms from the same birth county. Although firms from a given birth county will concentrate,

[39] All destinations which had a positive number of entrants by 2000-2004 and 2005-2009, respectively, for a given birth county-sector are included in the estimating equation.

[40] If all firms from the same origin collude, but there is competition across (origin-based) networks at the destination, then we would expect to see a negative effect of entry from other origins. While pricing may be non-competitive in China (see, for example, Brooks *et al.* (2016), the origin-based networks do not appear to be directly associated with these distortions.

in particular sectors and locations, over time, there is no tendency for firms from different birth counties to agglomerate. There would appear to be substantial gains from expanding the scope of inter-firm spillovers, and recent experimental evidence indicates that this is indeed the case (Cai and Szeidl, 2017).

Table 11a. The Effects of Initial Entry on Subsequent Entry (within birth place)

Dependent variable:	subsequent entrants from the birth place					
Birth location:	county		county		city district	
Time period:	2000-2004	2005-2009	2000-2004	2005-2009	2000-2004	2005-2009
	(1)	(2)	(3)	(4)	(5)	(6)
Initial entrants from the birth place	7.120***	8.935***	5.239***	5.796***	7.830***	6.994***
	(0.711)	(0.972)	(1.065)	(1.356)	(0.959)	(0.982)
All initial entrants at the destination	0.054	-0.020	–	–	–	–
	(0.050)	(0.057)				
Initial entrants from the birth place × birth place population density	–	–	1.361**	2.262**	-0.073	-0.437**
			(0.619)	(0.991)	(0.240)	(0.220)
Mean of dependent variable	3.065	3.128	3.065	3.128	4.001	3.515
Observations	413,452	804,918	413,452	804,918	313,520	449,207

Table 11b. The Effect of Initial Entry on Subsequent Entry (within clan)

Dependent variable:	subsequent entrants from the clan			
Time period:	2000-2004	2005-2009	2000-2004	2005-2009
	(1)	(2)	(3)	(4)
Initial entrants from the clan	3.275***	4.082***	2.434***	2.713***
	(0.330)	(0.355)	(0.315)	(0.310)
All initial entrants at the destination from the birth county	0.031***	0.051***	0.013	0.008
	(0.007)	(0.012)	(0.013)	(0.019)
Initial entrants from the clan × birth place population density	–	–	0.641**	1.071***
			(0.267)	(0.334)
Initial entrants from the birth county × birth place population density	–	–	0.013*	0.031**
			(0.007)	(0.014)
Mean of dependent variable	1.372	1.392	1.372	1.392
Observations	888,331	1,743,760	888,331	1,743,760

Note: number of entrants is measured at the (two-digit) sector-destination level.
Initial entry is derived over the 1990-1994 period.
Clan is defined by the same surname group and the same birth county.
All specifications include birth place-sector fixed effects.
Number of entrants is obtained from the SAIC registration database and birth place population density is derived from the 1982 population census.
Standard errors clustered at birthplace-sector level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

While the model predicts that initial entry will have a compounding effect on future entry when networks are active, it also generates the stronger prediction that the effect of initial entry should be larger for higher population density birth counties. We test this prediction in Table 11a, Columns 3-4 by interacting the number of initial entrants from the birth county, within sector-destinations, with its population density. The interaction coefficient is positive and significant, as predicted by the model, for entry in 2000-2004 and in

2005-2009 as the dependent variable.[41] As a placebo test, we restrict the sample in Table 11a, Columns 5-6 to entrepreneurs who are born in cities. Population density is not positively associated with social connectedness in cities and thus we do not expect the interaction of initial entry and population density in their birth locations to have a positive effect on subsequent entry. Initial entry has a positive and significant effect on subsequent entry, in 2000-2004 and 2005-2009. However, the coefficient on the interaction with birthplace population density is *negative* (and significant with entry in 2005-2009 as the dependent variable).

We remain agnostic about the domain of the hometown network in this paper; i.e. whether it covers the entire birth county or the clan within the county. As discussed in Section 2.2, if clan concentration is not decreasing too steeply in population density, our results go through either way. Although the clan composition of the birth county population is unavailable, the clan affiliation of the entrepreneurs in the SAIC registration database can be inferred from their birth counties and surnames (Peng (2004)). We thus repeat the preceding analysis at the level of the clan to assess empirically whether it is, in fact, the domain of the network.

To derive the relationship between initial entry and subsequent entry when the clan constitutes the domain of the network, consider a county with two clans, a majority clan M and a minority clan m, with demographic weights $\zeta_M \equiv \mu(> \frac{1}{2}), \zeta_m \equiv 1-\mu$. Assume that economic cooperation occurs at the level of the clan and that the stock of potential entrepreneurs is partitioned across the two clans in proportion to their relative sizes. The entry equation for clan $j \in \{M, m\}$ can then be specified as

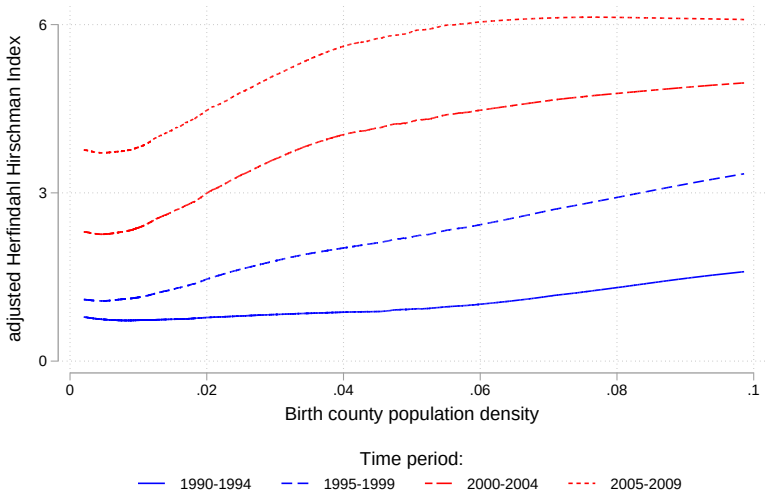
$$e_{jt} = k\zeta_j[B + C\theta(\zeta, p)n_{j0}][1 + k\zeta_j C\theta(\zeta_j, p)]^{t-1} \tag{23}$$

where, following the discussion in Section 2.2, network quality $\theta(\zeta_j, p)$ is increasing in ζ_j and p. Initial entry, n_{j0}, has a positive effect on subsequent entry, with this effect growing stronger over time. In addition, if clan composition in a county is independent of p, then it follows that the effect of n_{j0} on entry at any subsequent date t is increasing in p.

We test the preceding prediction in Table 11b by estimating the effect of initial entry in the 1990-1994 period on subsequent entry, separately in 2000-2004 and 2005-2009, at the clan-sector-destination level. The estimating equation includes birth county-sector fixed effects as well as the total number of initial entrants from the birth county into that sector-destination (to allow for the possibility that network spillovers extend beyond the clan). The coefficient on the number of initial entrants, at the level of the clan and the county, is positive and significant in Table 11b, Columns 1-2, although the former is an order of magnitude larger. As predicted, the initial effects grow larger over time; i.e. from 2000-2004 to 2005-2009. Columns 3-4 interact initial entry with the population density of the birth county. The initial effects are larger for higher population density birth counties, at the level of the clan and the county, in 2000-2004 and in 2005-2009.

[41] Although we assume in the model that initial entry is randomly assigned, entrepreneurs will, in practice, locate relatively close to their home counties. The persistence in this distance effect could explain the correlation between initial entry and subsequent entry. We address this concern in Appendix Table D.3 by including the distance from the birth county to the destination under consideration in the estimating equation. The coefficient on the distance variable is negative and significant, but the remaining coefficients are unaffected by the inclusion of this variable. An additional concern is that if locations that were initially selected by entrepreneurs from high population density counties grew relatively fast, then this would explain why the interaction of birth county population density and initial entry has a positive effect on subsequent entry. We address this concern by implementing a test that is closely related to the test reported in Table 5. A synthetic variable is constructed to measure total entry in subsequent periods (from all other origins) at the destinations where firms from a given birth county initially located. The coefficient on the birth county population density variable in Appendix Table D.4 is small in magnitude and statistically insignificant with synthetic entry in 2000-2004 and 2005-2009 as the dependent variables.

Figure 8. Clan Concentration and Population Density



Source: SAIC Registration database and 1982 population census.
Clan concentration measured by the Herfindahl Hirschman Index (HHI) across surnames of the entrepreneur from a given birth county, divided by the expected HHI that would be obtained by random assignment, given the stock of firms and the number of surnames at each point in time.

The results in Table 11b indicate that spillovers are concentrated within the clan, although they do extend beyond its boundaries. Assuming, for simplicity, that the spillovers operate exclusively within the clan, our model generates predictions for the concentration of business activity within clans drawn from the same birth county, across counties with different population densities and over time. With two clans, clan concentration among entering entrepreneurs (measured by the Herfindahl Hirschman Index) will be locally montonically increasing in the share of the majority clan or, equivalently, in the ratio of its share to the share of the smaller clan:

$$\frac{e_{Mt}}{e_{mt}} = \frac{e_{M1}}{e_{m1}} \left[\frac{1 + kMC\theta(M,p)}{1 + kmC\theta(m,p)} \right]^{t-1} \tag{24}$$

Because the term in square brackets is greater than one, clan concentration among entering entrepreneurs is increasing over time in all origin counties. If $\theta(\zeta_j, p)$ is multiplicatively separable in ζ_c and p, then clan concentration among entering entrepreneurs is increasing in p at each date t (because the term in square brackets is increasing in p). Figure 8 reports the relationship between the clan concentration of entering entrepreneurs, measured by the Herfindahl Hirschman Index, and population density in their birth county at each point in time. Clan concentration among entering entrepreneurs is increasing over time and increasing in birth county population density at each point in time, precisely as our model of network-based cooperation would predict when networks (organized within the clan) are active.[42]

[42] Appendix Table D.5 reports parametric estimates corresponding to Figure 8, separately in each time period. These estimates indicate that birth county population density has a positive and significant effect on clan concentration among entering entrepreneurs at each point in time. A pooled regression (not reported), using all time periods, also indicates that clan concentration is increasing over time.

5 Structural Estimation and Quantification

The model generates predictions for two independent outcomes: entry at the sector level and firm size. Sector-specific entry is aggregated up to compute total entry and is also used to construct concentration statistics. Firm-specific capital investment, together with the assumed distribution of ability in the population and the endogenously generated pattern of entry, is used to derive marginal initial capital, average initial capital, and capital growth in each birth county-sector. The structural estimation is thus based on two equations, with sector-specific entry and average initial capital (by sector) for each birth county in each time period as the dependent variables.

Based on the corresponding equations in the model, (8) and (14), and retaining its notation, we estimate the following structural equations:

$$e_{ci,t} = G(\alpha, \sigma, r, A_0) k_c s_{ci,t-1} + \frac{\theta}{(1-\sigma)(1-\alpha)} k_c s_{ci,t-1} \cdot pn_{ci,t-1} \tag{25}$$

$$logK^a_{ci,t} = H_t(\alpha, \sigma, r, A_0, f_t) + \frac{\theta(1-2\sigma)}{2(1-\sigma)(1-\alpha)} pn_{ci,t-1} \tag{26}$$

$e_{ci,t}$ measures the number of entrants and $logK^a_{ci,t}$ measures average initial capital (in logs) for birth county c and sector i in time period t. $n_{ci,t-1}$ is the stock of firms from that birth county that are already established in that sector at the beginning of the time period. $s_{ci,t-1}$ denotes the share of sector i in the stock of firms originating from county c at $t-1$. k_c measures the number of potential entrepreneurs from the birth county. k_c was set to be equal across birth counties and time periods in the model. For the structural estimation, the number of potential entrepreneurs in each birth county is derived from the 1990 population census, based on the characteristics of actual entrepreneurs when they established their firms (which is derived, in turn, from the SAIC registration database).[43] Capital is measured in the model in physical units, whereas in the data it is measured in monetary units. The mapping from physical units to monetary units changes over time owing to changes in the price of capital goods. This is especially relevant in the structural estimation because the objective is to match predicted and actual firm size in each time period. f_t thus represents the time period specific mapping from physical capital to the price of capital goods in period t. We parameterize the $\theta(p)$ function to be increasing linearly in p: $\theta(p) = \theta p$, with the restriction that $\theta(0) = 0$. The network effect is thus represented by a single parameter, θ.

The structural equations are linear in observed variables; (i) $k_c s_{ci,t-1}$ (ii) $k_c s_{ci,t-1} pn_{ci,t-1}$ (iii) $pn_{ci,t-1}$, with four reduced-form coefficients.[44] One of these coefficients, H_t, cannot be used to identify the structural parameters because f_t is unobserved. This leaves three reduced-form coefficients and five structural parameters: $\alpha, \sigma, r, A_0, \theta$. We noted in Section 3 that the productivity channel and the credit channel for the network effect cannot be separately identified. Although the model is parameterized to allow networks to increase productivity, we remain agnostic about the specific channel through which the networks operate. For the structural estimation, we allow the network to operate through the productivity channel as in the

[43] We see in Appendix Figure C.3 that most entrepreneurs in the registration database have at least high school education and that most were aged 25-44 when their firm was established. k_c is thus specified to be the number of men born in county c, aged 25-44, with at least high school education, as reported in the 1990 population census.

[44] The functional forms for $G(\alpha, \sigma, r, A_0)$ and $H_t(\alpha, \sigma, r, A_0, f_t)$ are obtained directly from (8) and (14), with the addition of the separable f_t term in the H_t function.

model, setting r to 0.2 (which is in line with estimates of the average interest rate faced by Chinese firms).[45] The productivity multiplier is set to one in all sectors; i.e. $A_0 = 1$. As in the model, variation in productivity across sectors (and origin counties) is generated entirely by the network effect; $exp(\theta p \cdot n_{ci,t-1})$. We thus abstract from variation in product prices, labor productivity, and agglomeration effects in the structural estimation. The objective will be to assess how well our parsimonious model is able to match the observed dynamics of entry and firm size.

To accommodate differences in the capital requirement across sectors, we do, however, allow the α parameter, which measures the marginal returns to capital, to vary across four broad sector categories: high-tech services, wholesale and retail services, manufacturing and transportation, and heavy industry (mining, electricity, and construction). This increases the number of structural equations to eight, given that there are now two equations in each sector category, and the number of structural parameters to be estimated to six; $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \sigma, \theta$. The structural parameters are estimated by matching on entry and average initial capital in each birth county-sector-time period.[46] Initial entry in each birth county-sector is based on the number of entrants in 1990-1994 and, if there is no entry in that time period, on the number of entrants in 1995-1999. Sectors are defined at the one-digit level in the structural estimation to ensure that there is positive initial entry in (almost) all birth county-sectors and the model is estimated over the 1995-2004 period; i.e. over two time periods.

Parameter estimates, with bootstrapped standard errors in parentheses, are reported for the benchmark model in Table 12, Column 1.[47] The σ coefficient lies between 0.5 and 1, satisfying the condition, derived in the model, which ensures that average initial capital is decreasing in birth county population density. The adjustment from physical capital to capital in monetary units, f_t, appears additively in the H_t function and, thus, can be estimated separately in 1995-1999 (period 1) and 2000-2004 (period 2). Table 12, Column 2 reports estimates with the forward looking model, derived in Appendix A. Entry must now be derived as the solution to a nonlinear equation, satisfying a fixed point condition, in each birth county-sector-time period.[48] Notice that the θ parameter declines substantially when we allow for forward looking behavior. This is because potential entrants require less of a "push" from the network when they take account of future benefits. Table 12, Column 3 reports estimates with an augmented model that allows for spillovers at the sector level, regardless of the county of birth. An additional $n_{i,t-1}$ term is thus included in equations (25) and (26). Although the coefficient on $n_{i,t-1}$, λ, is very precisely estimated, notice that the θ coefficient is very similar in magnitude in Columns 1 and 3.

[45] In our model, r, is the sum of the real interest rate and the depreciation rate. Hsieh and Klenow (2009) assume that the real interest rate is 0.05 in an economy, such as the U.S., with perfect financial markets and that the depreciation rate is 0.05. Using the same production function as Hsieh-Klenow and data from the Chinese industrial census, Brandt *et al.* (2016) estimate the real interest rate to be 0.15 in 1995 and 2004 and 0.18 in 2008. We thus set r to 0.2.

[46] Although the number of reduced form coefficients now exceeds the number of structural parameters, the model places additional restrictions on the reduced form coefficients that must hold across sector categories. For example, the ratio of the coefficients on $k_c s_{ci,t-1} \cdot pn_{ci,t-1}$ and $pn_{ci,t-1}$ in (25) and (26), respectively, must be $2/(1-2\sigma)$ in each sector category. The identification of the structural parameters is now more difficult to assess analytically and, hence, we verified that the parameters continue to be (just) identified by estimating the model with different values of r. The point estimates of the structural parameters do change in response, but the predicted entry and average initial capital (for each value of p) remain unchanged.

[47] When matching on entry and initial capital, we weight the error term by the reciprocal of the (bootstrapped) standard deviation of the mean of each variable. The unweighted estimates are very similar to what we report in the table.

[48] The discount factor per year, δ is set to 0.8 when estimating the model with foresight. Because one time period is five years, this works out to $0.8^{2.5} = 0.56$.

Table 12. Structural Estimates

Model:	benchmark	forward looking	with sector-level spillovers
σ	0.775	0.776	0.777
	(0.001)	(0.000)	(0.001)
θ	0.395	0.125	0.359
	(0.054)	(0.004)	(0.011)
λ	–	–	0.00003
			(0.000002)
α_1	0.137	0.119	0.138
	(0.009)	(0.001)	(0.007)
α_2	0.189	0.179	0.194
	(0.020)	(0.001)	(0.020)
α_3	0.192	0.177	0.197
	(0.011)	(0.003)	(0.016)
α_4	0.236	0.226	0.240
	(0.004)	(0.002)	(0.004)
f_1	0.223	0.233	0.216
	(0.004)	(0.003)	(0.016)
f_2	0.189	0.208	0.184
	(0.005)	(0.003)	(0.012)

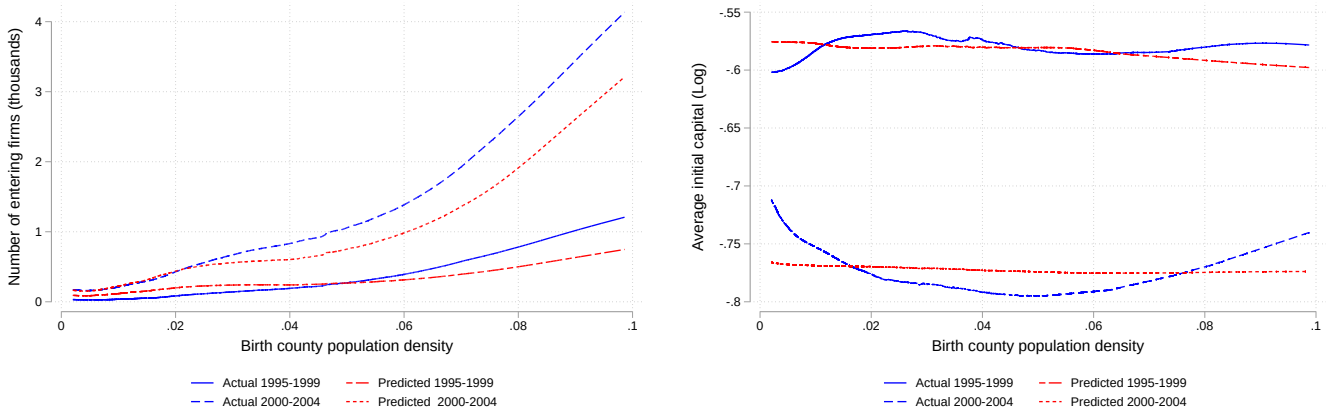
Note: the parameters are estimated by matching on entry and average initial capital (log), measured at the birth county-sector-time period level. When matching, the error term is weighted by the reciprocal of the bootstrapped standard deviation of the mean of each variable.
The model is estimated over two time periods, 1995-1999 and 2000-2004, taking entry in the first period, 1990-1994, as given.
Sectors are defined at the one-digit level when measuring entry and capital, but the α parameter is estimated at the aggregate sector level: (1) new technological services; (2) wholesale, retail and business service; (3) manufacturing and transportation; (4) heavy industry (mining, electricity & construction)
The discount factor per year δ is set to 0.8 in the forward looking model.
Bootstrapped standard errors in parentheses.
Number of entrants and average initial capital are derived from the SAIC registration database and birth place population density is derived from the 1982 population census.

Figure 9a assesses the goodness of fit of the benchmark model by comparing actual and predicted entry across birth counties in each time period. The model that we estimate is extremely parsimonious, with just six parameters. Nevertheless, it does a good job of predicting entry across nearly 2,000 birth counties and over ten years. Figure 9b repeats this exercise with average initial capital and, once again, we see that the model predicts variation across birth counties fairly accurately. Once the capital adjustment factor is included in each time period, note that actual and predicted average initial capital will match on levels by construction.

To formally test the goodness of fit of the model, we would want to compare predicted and actual outcomes (entry and average initial capital) at each level of population density, p. Given the large number of counties, with distinct values of p, we compare, instead, the estimated population density coefficient with actual and predicted data (generated by each of the three models in Table 12). The dependent variable is either entry or average initial capital.[49] Since the structural estimates are based on two time periods, the estimating equation includes birth county population density and a binary time period variable, which takes the value one in 2000-2004 and zero in 1995-1999. The estimated population density coefficients in Appendix Table D.6a are statistically indistinguishable with actual data and data generated by the benchmark model. Moreover, the benchmark model does a better job of matching the population density coefficient estimated with actual

[49]Entry is measured at the birth county-time period level and average initial capital is measured at the birth county-sector-time period level to be consistent with the tests of the model above.

Figure 9. Actual and Predicted, Entry and Initial Capital



(a) Entry **(b)** Initial Capital

Source: SAIC registration database, model generated data, and 1982 population census.

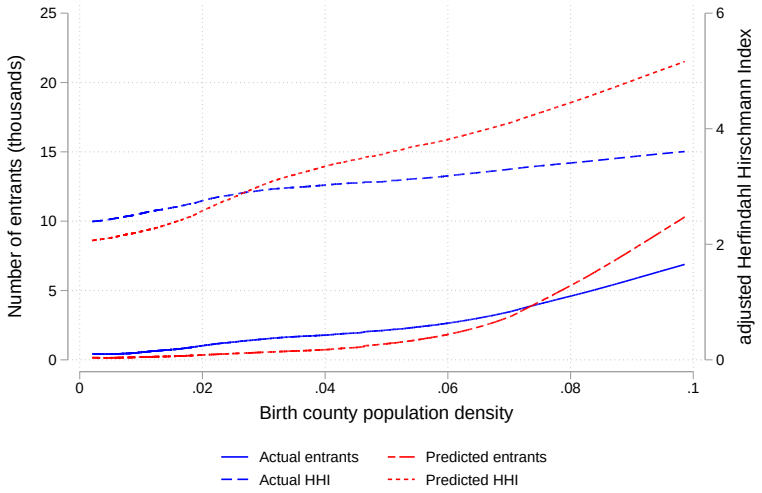
data than both the forward looking model and the model that allows for additional sector-level spillovers.

A more stringent test of the structural model is to assess its out of sample predictions. The model is estimated over the 1995-1999 and 2000-2004 periods. Figure 10 compares actual and predicted entry and sectoral concentration in the subsequent 2005-2009 period.[50] The model does a good job of predicting firm entry and sectoral concentration, although it does over-shoot at higher birth county population density levels. As with the in-sample predictions, we independently assess the model's ability to match the data by comparing population density coefficients, estimated with actual data and model generated data in Appendix Table D.6b. Because there is now a single period, 20005-2009, the estimating equation includes a single regressor; birth county population density. The population density coefficients estimated with actual data and data generated by the benchmark model are close in magnitude and statistically indistinguishable with firm entry as the dependent variable. As with the in-sample predictions, the benchmark model does a better job of matching the population density coefficient estimated with the actual data than either the forward looking model or the model with sector-level spillovers. However, none of the models are quite as successful in predicting sectoral concentration, with the benchmark model performing slightly worse than the other two models.

With a single θ parameter common to all birth counties and sectors in the model, cross-sectional variation is generated by differences in population density and initial entry alone. Nevertheless, the model is able to match the data quite well, across counties and sectors, even out of sample. The estimated parameters can thus be used for counter-factual simulations. A major objective of our research is to quantify the role played by community networks in the growth of private enterprise in China. This is accomplished by setting the θ parameter to zero and then generating counter-factual entry and capital investment over the sample period. The results of this exercise, with the benchmark model, are reported in Figure 11a. It is evident from the figure that the number of entrants would have been substantially reduced in the absence of community networks, particularly in higher population density birth counties. Based on our estimates, the total number

[50] We cannot test the model's ability to predict initial capital beyond the sample period because the mapping from physical capital to capital in monetary units is unavailable.

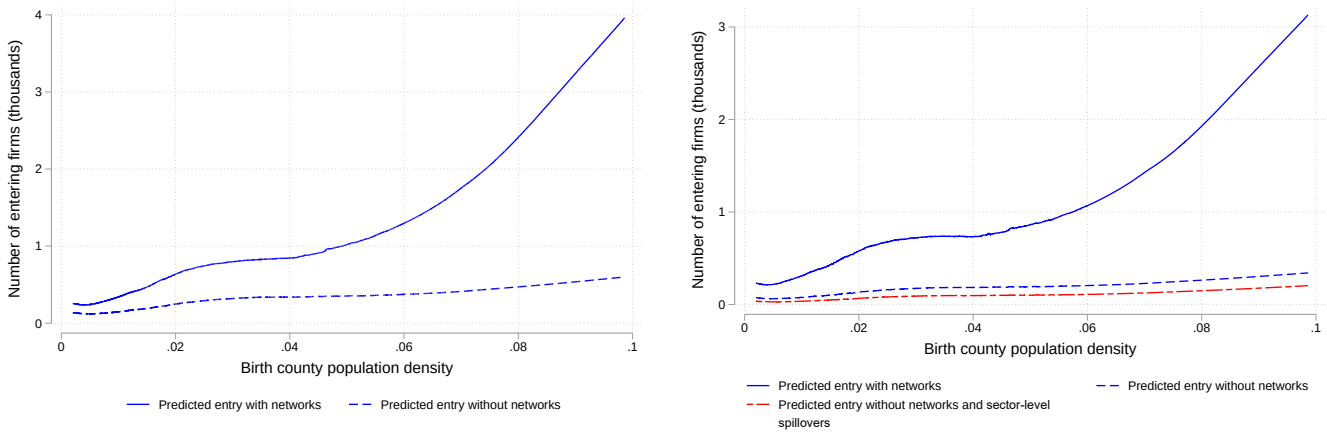
Figure 10. Out of Sample Tests - Entry and Sectoral Concentration, 2005-2009



Source: SAIC registration database, model generated data, and 1982 population census.
Number of entrants and sectoral concentration computed at the birth county level in 2005-2009 with actual and model generated data.

of entrants would have declined by 64% over the 1995-2004 period if the networks had not been active. In a related counter-factual exercise, the total stock of capital in 2004 (taking account of the number of number of firms that entered, their initial capital, and the subsequent growth in their capital) would have declined by 65% had the networks been absent. Figure 11b repeats the counter-factual entry analysis with the augmented model that allows for sector-level spillovers. Notice that these spillovers have almost no impact on entry, in contrast with the substantial impact that we estimate for the birth county-sector spillovers.

Figure 11. Counter-Factual Simulation: Effect of Community Networks on Entry and Total Initial Capital



(a) Benchmark identification

(b) Identification with sector-level spillovers

Source: Model generated data and 1982 population census.

An important objective of industrial policy in any developing economy is to stimulate entrepreneurship. It has been claimed that the government played a critical role in accelerating China's growth by providing firms with subsidized credit; e.g. Song *et al.* (2011), Wu (2016). In the absence of a market-based allocation mechanism, a natural question to ask is which firms should have been targeted for the subsidy. To answer

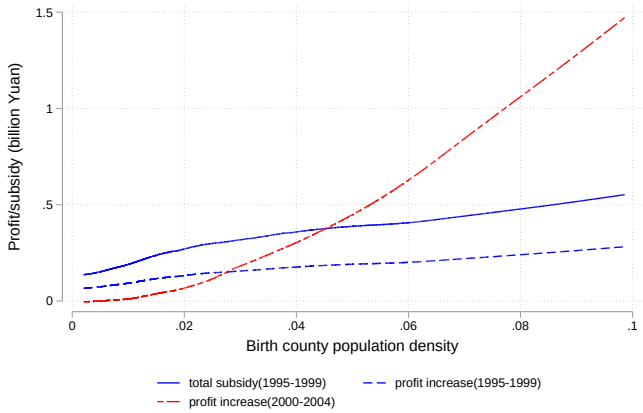
this question, we examine a counter-factual policy experiment in which all entering firms in the 1995-1999 period received credit at an interest rate of 0.15; i.e. with a subsidy of 0.05. This subsidy would have had two effects; it would have induced additional firms to enter at the margin and it would have increased the profit of all (marginal and infra-marginal) entrants. As observed in Figure 12a, the total profit increase generated by the subsidy in 1995-1999 is less than the cost to the government, across all birth counties. However, the spillover effect of the one-time subsidy on profits in the subsequent, 2000-2004, period is substantial (and even larger than the direct effect on profits in high population density counties). This is because the credit subsidy induces additional entry, which through the compounding network effect generates large profit increases in the more socially connected counties. With an annual discount factor of 0.8, the return on the subsidy, based on the additional (discounted) profits that were generated over the 1995-1999 and 2000-2004 periods minus the cost of the subsidy, would have been 12% for countries above the mean population density and -45% for counties below the mean.

Figure 12b reports the impact of an alternative government program, which only gives the subsidy to those origin counties who would have increased their profits over the 1995-2004 period by more than the amount of subsidy they received in the preceding counter-factual experiment. To keep the total amount of the subsidy constant, the interest rate for the targeted counties is now reduced to 0.11. The increase in profits minus the subsidy received is reported across the population density distribution in the figure, both for the original subsidy scheme and for the targeted subsidy scheme. As can be seen, the targeted program does strictly better if the government's objective is to maximize total profit. Notice also that average initial capital, which is declining with population density, declines even more steeply with the more efficient targeted program.

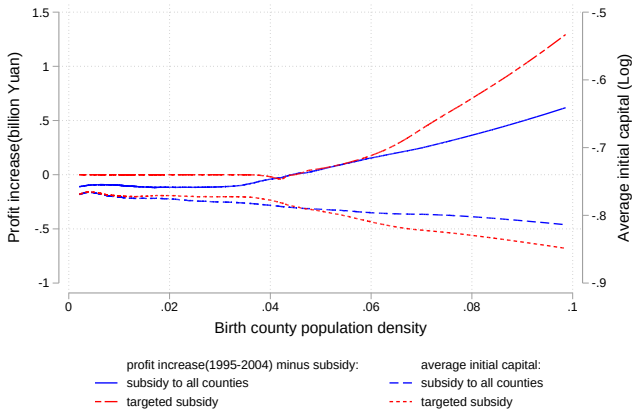
Two stylized facts motivate a large and growing macro-development literature on misallocation: (i) that the variation in marginal productivity and, hence, firm size within narrow sectors is too wide in developing economies, and (ii) that firms in those economies are too small (Peters (2016)). Although a number of mechanisms have been proposed to explain these facts; e.g. Caunedo (2016), Asker *et al.* (2014), Peters (2016), and Akcigit *et al.* (2016), perhaps the simplest is based on a model with mark-ups in output prices and wedges in factor prices (Restuccia and Rogerson (2008), Hsieh and Klenow (2009, 2014)). There are no price distortions in our model or in the structural estimation. Networks arise in our model because there is a missing market for productivity-enhancing assistance. We are, nevertheless, able to generate the stylized facts, and a distinguishing feature of our network-based mechanism is that efficiency-enhancing policies could actually result in even smaller firms and even greater dispersion in firm size in equilibrium (as observed in Figure 12b).[51] More generally, we would not want to infer that one developing economy is less efficient than another developing economy because it has smaller firms or greater dispersion in firm size. Indeed, these characteristics may be symptomatic of a more dynamic economy in which underlying community networks are responding more effectively to market frictions.

[51] In our analysis, the marginal value product of capital does not vary across firms by construction. If we had used credit market imperfections to motivate network formation instead, then a efficiency-enhancing policy that exploited network spillovers would have increased the dispersion in marginal productivity within sectors (due to variation in interest rates across networks) as well.

Figure 12. Counter-Factual Simulation: Effect of Interest Rate Subsidy on Profits



(a) Subsidy to all counties



(b) Targeted subsidy vs. subsidy to all counties

Source:Model generated data and 1982 population census.

6 Conclusion

In this paper, we identify and quantify the role played by community networks, organized around the birth county, in the growth of private enterprise in China. The model that we develop generates predictions for the dynamics of firm entry, sectoral and spatial concentration, and firm size across birth counties with different levels of social connectedness (measured by population density) when networks are active. We validate each of these predictions over a twenty year period with unique administrative data that covers the universe of registered firms and provides information on entrepreneurs' birth counties. The rich set of results that we obtain, taken together, allow us to rule out alternative non-network explanations. Additional results provide direct support for the network channel, indicating that spillovers occur within the birth county (and, going down even further, within clans within the county). Having validated the model, we estimate its structural parameters and conduct counter-factual simulations.

The first simulation shuts down the community networks. Our estimates indicate that this would have reduced the total number of entering firms by 64% (with a comparable decline in the total capital stock) over the 1995-2004 period. This was a critical period in China's economic development, and given the network multiplier effect, the long-term consequences of shutting down the networks at this time would have been even more significant. Individual firms do not internalize the positive externality they generate for other members of the network, which implies that a credit subsidy to stimulate entry could be efficiency enhancing. Our second counter-factual experiment considers the effect of a one-time credit subsidy for entrants in the 1995-1999 period. This subsidy would have increased profits for infra-marginal firms (who would have entered regardless) but, more importantly, would have induced additional firms to enter. Our estimates indicate that the direct effect of the subsidy on profits in the 1995-1999 period would have been dwarfed by the indirect spillover effect in the subsequent, 2000-2004, period, particularly in higher population density birth counties.

If the government's objective was to maximize total profits, then these results indicate that the optimal policy would be to target subsidized credit to entrepreneurs from higher population density birth counties so

as to take advantage of the network externalities. The impact of such a targeted subsidy scheme is examined in a third counter-factual simulation. With the targeting, the bulk of the entrepreneurs who would have been induced to enter as a result of the subsidy would have been drawn from higher population density counties. Networks are relatively strong in those counties and, thus, these individuals would have had relatively low ability among all marginal entrepreneurs. They would not have been selected into entrepreneurship training programs or have been successful in business plan competitions where merit is currently the only criterion, underscoring the limitations of current strategies to boost entrepreneurship in developing economies.

In general, the optimal policy to stimulate entry and maximize profits in economies where networks are active would place weight on both individual ability and the potential spillover effect from individual entry. There are, however, two caveats to this policy prescription. First, a policy that places weight on both social affiliation and individual merit will only be effective in a population where community networks are already active or have the potential to be activated. In particular, the Chinese development experience will not be replicated in other countries by simply providing infrastructure and credit. This is relevant for Chinese overseas development assistance policy, which has largely focussed on infrastructure construction and industrial development (Zhang, 2016).[52] Chinese development assistance has grown exponentially in recent years (Lin and Wang, 2016), but our analysis indicates that the expected returns will only be realized if community networks in the recipient countries evolve in parallel with the infrastructure construction, just as they did in China. The second caveat is that even if the social structure is amenable to network-based growth, there are important consequences for inequality that must be considered. By bringing in less able entrepreneurs at the margin, community networks are redistributive within their populations. However, a policy that targets individuals from more socially connected populations to take advantage of the positive externalities that their stronger networks provide will only exacerbate existing inequalities across communities. Given the dynamic increasing returns that are generated by the networks, these inequalities will persist and, if anything, worsen over time. Absent other redistributive mechanisms, any policy that attempts to exploit network externalities must pay attention to the potentially enduring consequences for inequality.

[52]This policy is explicitly motivated by the Chinese domestic experience, and the belief that infrastructure construction is the key to development (see, for example, China's second Africa policy paper; Xinhua, December 4, 2015).

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Appendix A. Extension: Entry with Foresight

Consider the consequences of allowing entrepreneurs to look ahead and incorporate profits they would expect to make after the first period they enter. We suppose cohort t agents look ahead one additional period, i.e., make their entry decision based on anticipated present value profits in periods t and $t+1$. The equilibrium can no longer be computed recursively, owing to the need for entrants to coordinate their expectations of entry decisions of one another. We shall consider equilibria where these expectations are fulfilled. We continue to assume that incumbents are committed to their previous entry decisions.

Let ξ denote $\psi r^{-\frac{\alpha}{1-\alpha}}$, and $\delta \in (0,1)$ denote the common discount factor of agents. Then expected present value of entering B_i at t for a cohort t agent of talent ω is

$$P_{it}(\omega) = \omega \xi A_0^{\frac{1}{1-\alpha}} \exp(\theta p n_{i,t-1} \frac{1}{1-\alpha})[1 + \delta \exp(\theta(p) e_{it} \frac{1}{1-\alpha})] \tag{27}$$

while of staying in T is

$$N_{it}(\omega) = \omega^{\sigma}[1+\delta] \tag{28}$$

The agent will enter if

$$\log \omega > \frac{1}{1-\sigma}[-\log \xi - \frac{1}{1-\alpha}\log A_0 + \log(1+\delta) - \frac{1}{1-\alpha}\theta(p) n_{i,t-1} - \log\{1 + \delta \exp(\theta(p) e_{it} \frac{1}{1-\alpha})\}] \tag{29}$$

Define the function

$$\begin{aligned} g(e|s_{i,t-1}, n_{i,t-1}, A_{i0}) \quad &= k s_{i,t-1}\{1 + \tfrac{1}{1-\sigma}[\log \xi + \tfrac{1}{1-\alpha}\log A_0 - \log(1+\delta) \\ &\quad + \tfrac{1}{1-\alpha}\theta(p) n_{i,t-1} + \log\{1 + \delta \exp(\theta(p) e \tfrac{1}{1-\alpha})\}]\} \end{aligned}$$

Then equilibrium entry decisions form a fixed point of this function, i.e., $e_{it} = e(s_{i,t-1}, n_{i,t-1}, A_{i0})$ solves

$$g(e|s_{i,t-1}, n_{i,t-1}, A_{i0}) = e \tag{30}$$

The intercept of this function is exactly the entry that results in the myopic equilbrium with $\delta = 0$. The function is increasing in e, with a slope

$$g'(e|s_{i,t-1}, n_{i,t-1}, A_{i0}) = s_{i,t-1} \frac{\delta \exp(\frac{\theta(p)e}{1-\alpha})}{1 + \delta \exp(\frac{\theta(p)e}{1-\alpha})} \frac{k\theta(p)}{(1-\alpha)(1-\sigma)} \tag{31}$$

Hence if

$$\frac{k\theta\bar{p}}{(1-\alpha)(1-\sigma)} < 1 \tag{32}$$

where $\bar{p}$ is an upper bound for p, an equilibrium exists and is unique. Computing the equilibrium is easy, as it involves solving for fixed points of a contracting mapping defined recursively by past entry decisions. It can be easily verified that entry is rising in $s_{i,t-1}, \theta(p)$ and $n_{i,t-1}$, just as in the myopic entry case.

Appendix B. Derivation of the Adjusted HHI

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

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

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

Based on the general properties of the multinomial distribution,

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

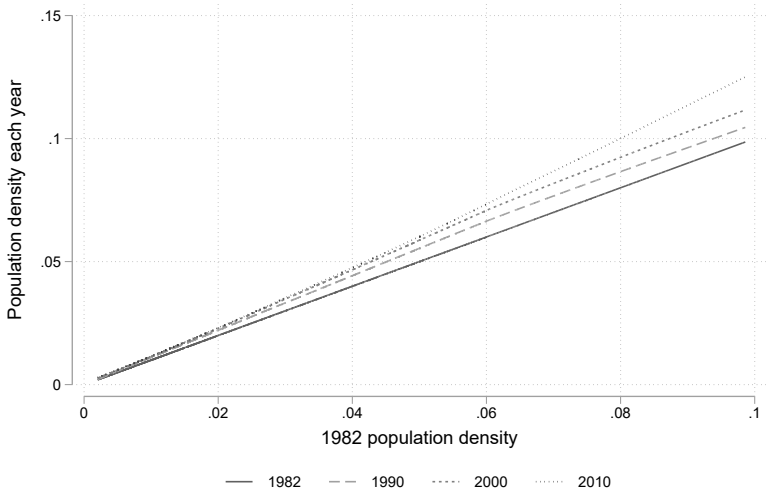
It follows that,

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

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

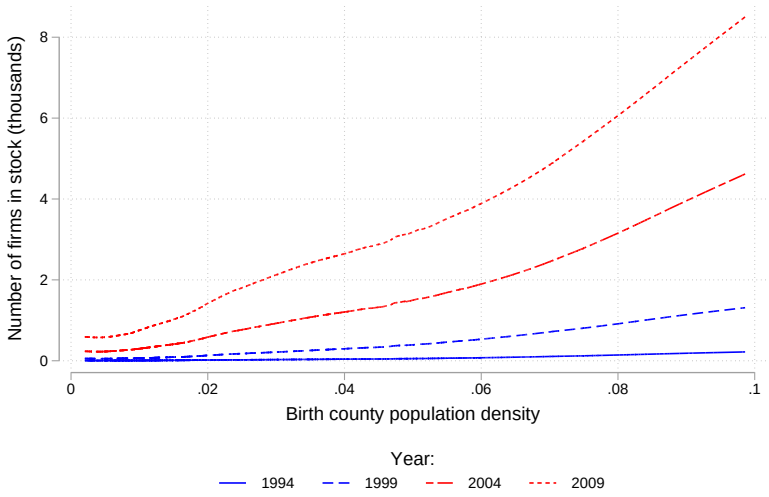
Appendix C. Figures

Figure C.1. Population Density over Time



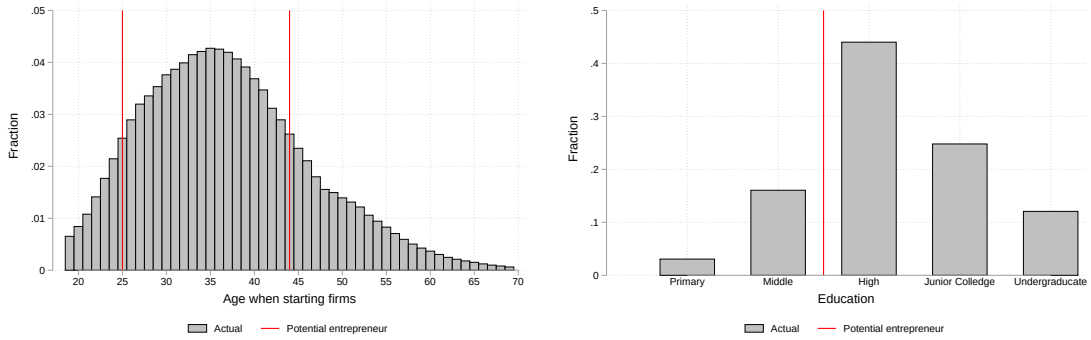
Source: Registration Database and 1982 population census.

Figure C.2. Stock of Firms and Population Density



Source: Registration Database and 1982 population census.

Figure C.3. Education and Age Distribution of Entrepreneurs



(a) Age **(b)** Education

Source: SAIC registration database.

Appendix D. Tables

Table D.1. Sectoral and Spatial Concentration and Population Density

Dependent variable:	adjusted HHI across sectors				adjusted HHI across destinations			
Year:	1994	1999	2004	2009	1994	1999	2004	2009
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth county population density	0.106***	0.417***	0.444***	0.574***	0.023**	0.052***	0.068**	0.110**
	(0.023)	(0.057)	(0.061)	(0.074)	(0.011)	(0.017)	(0.034)	(0.054)
Observations	1,622	1,624	1,624	1,624	5,479	15,132	23,753	26,784

Note: sectoral concentration measured by the Herfindahl Hirschman Index (HHI) across two-digit sectors, divided by the expected HHI that would be obtained by random assignment, given the number of entrants and the number of sectors at each point in time.
Spatial concentration, within one-digit sectors, is measured by the Herfindahl Hirschman Index (HHI) across destinations (outside the birth county), divided by the expected HHI that would be obtained by random assignment, given the number of entrants and the number of destinations at each point in time.
Control variables include population, education and occupation distribution in the birth county.
Sector fixed effects included in the regression with spatial HHI as the dependent variable.
Robust standard errors are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table D.2. Marginal Ability, Marginal Initial Capital and Population Density

Dependent variable:	marginal ability				marginal initial capital			
Time period:	1990-1994	1995-1999	2000-2004	2005-2009	1990-1994	1995-1999	2000-2004	2005-2009
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth county population density	-1.829	-2.685***	-3.570***	-1.435***	-0.100***	-0.118***	-0.134***	-0.041***
	(1.369)	(1.103)	(0.807)	(0.755)	(0.030)	(0.026)	(0.017)	(0.010)
Mean of dependent variable	66.07	52,47	40.79	40.15	-0.803	-1.093	-1.669	-2.225
Observations	4,079	6,595	10,354	11,137	15,601	46,877	83,276	99,877

Note: the entrepreneur's ability is measured by his percentile rank in his birth county-birth cohort education distribution.
The marginal entrepreneur is defined as the individual at the bottom one percentile of the ability distribution among entering entrepreneurs in a given birth county-sector-time period. Marginal initial capital defined as the bottom one percentile of the initial capital distribution at the birth county-sector-time period level.
Control variables include population, education and occupation distribution in the birth county.
Standard errors clustered at birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table D.3. The Effects of Initial Entry on Subsequent Entry (controlling for distance)

Dependent variable:	subsequent entrants from the birth county			
Time period:	2000-2004		2005-2009	
	(1)	(2)	(3)	(4)
Initial entrants from the birth county	5.239***	5.202***	5.796***	5.739***
	(1.065)	(1.063)	(1.356)	(1.351)
Initial entrants from the birth county × birth county population density	1.361**	1.371**	2.262**	2.276**
	(0.619)	(0.618)	(0.991)	(0.990)
Distance from the birth county to the destination	–	-0.002***	–	-0.002***
		(0.000)		(0.000)
Mean of dependent variable	3.065	3.065	3.128	3.128
Observations	413,452	413,452	804,918	804,918

Note: number of entrants is measured at the (two-digit) sector-destination level.
Initial entry is derived over the 1990-1994 period.
Distance, from the centroid of the birth county to the centroid of the destination, is measured in thousands of KM.
All specifications include birth place-sector fixed effects.
Number of entrants is obtained from the SAIC registration database and birth county population density is derived from the 1982 population census.
Standard errors clustered at birthplace-sector level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table D.4. Synthetic Entry (based on initial destinations) and Population Density

Dependent variable:	synthetic entry			
Time period:	1990-1994	1995-1999	2000-2004	2005-2009
	(1)	(2)	(3)	(4)
Birth county population density	-0.003*	0.007	0.010	0.001
	(0.002)	(0.005)	(0.010)	(0.013)
Constant	0.137**	0.523***	1.369***	1.750***
	(0.068)	(0.161)	(0.364)	(0.490)
Observations	15,694	15,694	15,694	15,694

Note: synthetic entry (in thousands) in each time period is measured by the weighted average of total entry (from all origins excluding the birth county) across all destinations for a given birth county-sector.
The weight on a given destination if the fraction of initial(1990-1994) entrants from the birth county-sector who located at that destination.
All specification include sector fixed effects.
Control variables include population, education and occupation distribution in the birth county.
Standard errors clustered at birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table D.5. Clan Concentration and Population Density

Dependent variable:	adjusted HHI across clan			
Year:	1990-1994	1995-1999	2000-2004	2005-2009
	(1)	(2)	(3)	(4)
Birth county population density	0.167***	0.535***	0.835***	0.873***
	(0.014)	(0.027)	(0.037)	(0.045)
Constant	0.730***	1.643***	3.283***	4.785***
	(0.010)	(0.022)	(0.033)	(0.042)
Observations	1,607	1,624	1,624	1,624

Note: clan is defined by the same surname group and the same birth county.
Clan concentration measured by the Herfindahl Hirschman Index (HHI) across surnames, divided by the expected HHI that would be obtained by random assignment, given the number of clans and the number of stock of firms from the birth counties at each point in time.
Control variables include population, education and occupation distribution in the birth county.
Robust standard errors are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table D.6a. Estimates based on Actual and Model Generated Data (In-Sample)

Dependent variable:	number of entrants				average initial capital			
Data:	actual	model generated (myopic)	model generated (forward looking)	model generated (with sector-level spillovers)	actual	model generated (myopic)	model generated (forward looking)	model generated (with sector-level spillovers)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth couunty population density	0.335***	0.215***	0.109***	0.171***	-0.010**	-0.002**	-0.003**	-0.003**
	(0.034)	(0.030)	(0.016)	(0.025)	(0.005)	(0.001)	(0.001)	(0.001)
Time period	0.476***	0.305***	0.095***	0.369***	-0.202***	-0.191***	-0.151***	-0.191***
	(0.020)	(0.021)	(0.011)	(0.019)	(0.009)	(0.002)	(0.003)	(0.002)
Observations	3,032	3,032	3,032	3,032	18,401	18,401	18,401	18,401

Table D.6b. Estimates based on Actual and Model Generated Data (Out of Sample)

Dependent variable:	number of entrants				adjusted HHI across sectors			
Data:	actual	model generated (myopic)	model generated (forward looking)	model generated (with sector-level spillovers)	actual	model generated (myopic)	model generated (forward looking)	model generated (with sector-level spillovers)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth county population density	0.920***	0.988***	0.426***	1.683***	0.268***	0.662***	0.569***	0.508***
	(0.083)	(0.132)	(0.086)	(0.189)	(0.018)	(0.028)	(0.026)	(0.025)
Constant	1.331***	1.228***	0.320***	2.060***	2.809***	2.847***	3.149***	3.706***
	(0.041)	(0.055)	(0.032)	(0.082)	(0.016)	(0.023)	(0.021)	(0.021)
Observations	1,516	1,516	1,516	1,516	1,516	1,516	1,516	1,516

Note: in-sample estimates based on two time periods, 1995-1999 and 2000-2004 and out of sample estimates based on the 2005-2009 period.
Firm entry (in thousands) measured at the birth county-time period level. Initial capital (in million Yuan) is measured in logs. Average initial capital is the average of the initial capital distribution at the birth county-sector-time period level. Sectoral concentration, across one-digit sectors, is adjusted for expected concentration due to random assignment.
Time period is a binary variable taking the value one for the 2000-2004 period and zero for the 1995-1999 period.
Actual firm entry, initial capital and HHI are obtained from the SAIC registration database and birth county population density is derived from the 1982 population census.
Standard errors clustered at the birth county level are reported in parentheses. * significant at 10%, ** at 5%, *** at 1%.