Industry Choices and Social Interactions of Entrepreneurs:

Identification by Residential Addresses

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Abstract:

This paper shows that industry choices of entrepreneurs are determined by their social networks. We establish the causality using *residential* addresses of entrepreneurs. In a large cross-section of London neighborhoods (about one squared mile each), we show that new generation of entrepreneurs are more likely to enter their *residential* neighbors' popular industries. We further show that industry composition of a neighborhood is more persistent when social interactions are more intensive, as proxied by higher ethnic homogeneity, more sociable housing structures, or higher entrepreneurial population density. The effect is also stronger in industries that require more informational interactions, as proxied by higher geographic agglomeration of entrepreneurs.

The separation of residential and business addresses helps us identify the impacts of social interactions because we can safely argue that residential addresses determine social networks but do not directly affect industry choices. The median home-business distances in our sample is nearly six kilometers, thus the persistence of industry specializations is unlikely to be driven by unobservable common product market conditions. We also control for sectoral composition at borough level (each borough contains around 20 neighborhoods), to further remove the effects of unobservable factors. Finally, we also use various sub-groups of entrepreneurs to test for a series of alternative hypotheses, and we do not find support for them.

We do not find failure rates to be significantly different for entrepreneurs who follow their neighbors' popular choices. Overall, the results suggest that entry of new entrepreneurs tend to reinforce agglomeration, while exits do not reverse it. These evidences (weakly) lend support to the existence of agglomeration economies.

Keyword: Social Interactions, Neighborhood Effects, Industry Choices

JEL: Z13, M13, J24, R12

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1. Introduction

1.1. Motivation

In London, entrepreneurs from certain neighborhoods, both the old generation and the new generation, dominate certain industries for a long period of time. For instance, a neighborhood called Garden Suburb supply disproportionate number of entrepreneurs in real estate businesses. Why is it so? Given the free and convenient mobility in London, why should neighbors and neighborhood matter? We suspect that social interactions matter and social interactions determined individuals' industry choices.

Individuals are not considered as isolated entities but rather as being part of networks of friends, relatives, neighbors, colleagues, that jointly provide cultural norms, economic opportunities, information flows, social sanctions and so on (Topa, 2001). As stated by Shiller (2000): "A fundamental observation about human society is that people who communicate regularly with one another think similarly". We suspect that such social interaction effects exist not only when people pick their stocks, but also when people make entrepreneurial decisions regarding which industries to enter. Residents living a same neighborhood are more likely to social with one another, and they are thus more likely to be familiar with what one another are working on.

There are two strands of literature both of which are compatible with such a prediction. First, human beings have intrinsic desires to behave like certain others. Hamilton (2000) and Moskovitz and Vissing-Jorgensen (2002) both show that entrepreneurial decisions can be motivated by non-pecuniary benefits, which are mainly acquired through social interactions. Social interactions may create social norms that make certain industries more respectful, associated with social status, esteem, and prestige and the like in some neighborhoods (Cole et al. 1992 and Bernheim 1994). An individual, when assessing alternative behavioral choices, will find a given behavior relatively more desirable if others have previously behaved or are currently behaving in the same way. For instance, Giannetti and Simonov (2004) show that in social groups where entrepreneurship is more widespread individuals are more likely to become entrepreneurs, even though their entrepreneurial profits are lower. This suggests that social norms create non-pecuniary benefits from entrepreneurial activities.

Second, agglomeration economy literature can also make the same empirical predictions that entrepreneurs are more likely to enter industries in which their residential neighbors are historically overrepresented. Individuals may learn how to run a business by observing their neighbors. Geographic economists have shown that easy flow of ideas explain why industries cluster into close quarters. Local accumulations of knowledge, enhanced by long-term relationships and histories of interactions, will create a stock of "local trade secrets" and informational externalities that benefit local firms and entrepreneurs. On the empirical side, a vast and growing literature[1] has attempted to provide a statistical estimate of the magnitude of local interactions and neighborhood effects.

1.2. Empirical Strategy and Summary of Findings

Manski (2000, pp. 128) (also known as "the Manski critique") argues that unobservable factors could create correlation of behaviors among members of a same social group, absent social interactions. This creates difficulty for empirical research. To address this problem, we use residential addresses of entrepreneurs to identify social networks. A residential address determines an entrepreneur's social network, but does not directly affect his choice of industry, which is more likely to be affected by the business location. Thus residential addresses become valid instrumental variables for the availability of social contacts as well as the contacts' industry backgrounds.

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[1] There are two sorts of externalities, as found by previous literature. The Marshall-Arrow-Romer (MAR) externality concerns knowledge spillover between firms within an same industry. A good example would be the Silicon Valley, where IT firms benefit from locating close to each other. Jacobs (1969), unlike MAR, believes that the most important knowledge transfers come from outside the core industry. He believes that, variety and diversity of geographically proximate industries rather than geographical specialization promote innovation and growth.Using city-industry data, Glaeser et al . (1992) show that local competition and urban variety , but not regional specialization, encourage employment growth in industries. Their evidences suggest that important knowledge spillovers might occur between rather than within industries, consistent with the theories of Jacobs. Henderson et al. (1995) however show that both MAR externalities and Jacobs externalities can affect industry growth positively. Jencks and Mayer (1990), Ioannides and Loury (2004) and Brock and Durlauf (2001) give excellent surveys of the empirical literature on agglomeration economy.

We implement our tests using government records of residential addresses of London entrepreneurs. The administrative nature of the data set allows us to track down the detailed location and industry background of virtually everyone in London. Our results are based on a cross-section of neighborhood-industry pairs. We find that entrepreneurs are more likely to enter industries in which their residential neighbors are historically over-represented. We also find that the effect is stronger in neighborhoods with more intensive social interactions, and in industries with higher agglomeration of entrepreneurs. This provides an extra level of identification. The effects we find are not likely to be driven by unobservable product market conditions (e.g., demand growth) which are supposed to be determined by business addresses. The reasons are as follows.

First, we are examining an entrepreneur's residential address rather than his business address, and these two addresses are usually distant away from each other. With the gazetteer dataset provided by the Royal Post, we find that, in our sample, the median distance between an entrepreneur's residential and business addresses is 5.45 kilometers, which is about one quarter of the radius of Greater London. More than 80 % of entrepreneurs have their businesses operated outside the neighborhoods where they reside, and nearly 70% outside the borough they reside. Furthermore, entrepreneurs from a same residential neighborhood do not usually locate their businesses close to one another[2]. We also run regressions based on sub-samples excluding entrepreneurs who operate their businesses in their own residential neighborhoods or boroughs, and our results remain robust. For these reasons, we argue that residential addresses only affect social interactions, but do not directly affect industry choices.

Second, in all of our regressions, we also control for industry specialization at borough level (each of which contains around 20 neighborhoods). This practice further

[2] A median neighborhood (in terms of the number of neighborhood where its residents have business presence) has businesses operated in 104 other neighborhoods in London, which by the way are not concentrated in a particular part of London but can be found in 24 boroughs (a higher level of geographic unit than neighborhood) dispersed around London. For this same neighborhood, the Herfindahl-Hirschman Index (at neighborhood level) for the geographic concentration of businesses belonging to its residents is 1288, which is usually not considered as concentrated. This suggests that entrepreneurs of a neighborhood venture everywhere in London and do not cluster in a particular place (i.e. , this is not that sort of "China Town" story), and they are thus supposed not to share common product market factors.

takes care of the omitted variable problems, because we are actually examining the within-borough variations across neighborhoods, which are mostly driven by difference in circles of social interactions rather than in product markets. Positive sorting is unlikely to happen in this context, as it is unlikely that entrepreneurs move to certain neighborhoods in order to find industry peers. Finally, we can think of very few residential neighborhood characteristics that can determine which neighborhoods must do which industries.

The remainder of the paper is organized as follows. In Section 1.3, we briefly review literature in relation to social interactions and individual choices. In Section 2, we explain how we construct the data set and how we create industry specialization indices for a large cross-section of neighborhood-industry pairs. In Section 3, we introduce the empirical strategy. In Section 4, we report how new entrepreneurs' industry choices are influenced by the established entrepreneurs in their own residential neighborhoods. In Section 5, we attempt to identify the channels through which established entrepreneurs influence new entrepreneurs. In Section 6, we test for the agglomeration economy hypothesis. We conclude in Section 7.

1. 3. Related Literature

Social interaction's impacts on individual choices are also documented in other lines of literature, mainly in relation to occupational choice and portfolio choice, among many others. Here I mainly review papers in relation to multiple choices, but some papers studying binary choices decisions are also covered when necessary.

The most relevant is on employees' occupational choices. Labor economics literature shows that workers' occupational choices are positively affected by their neighbors[3]. Bayer et al. (2004) find that neighbors in a same neighborhood block are 50% more likely to work in a same place, which indicates some sorts of information sharing

[3] Corcoran (1980), Montgomery (1991) and Granovertter (1995) show that from 24% to 74% of Americans found their jobs through friends, neighbors, and relatives. Bentolila et al. (2004) argue that people use personal contacts as referrals to find jobs, ending up working in the same occupations as their friends, but this usually create mismatch between occupations and their comparative productive advantage, and thus resulting in lower aggregate productivity.

among neighbors in the job searching process. Marmaros and Sacerdote (2002) find that Dartmouth students' occupational choice are heavily influenced by their randomly assigned freshmen roommates, hallmates, and dormmates. Bertrand et al. (2000) find that members of high welfare-using language groups are more likely to claim benefits if living in neighborhoods with many people speaking the same languages. They interpret this as a social interaction effect.

Literature on the portfolio choices of investors also suggests some sorts of "word-of-mouth" effects. Hong, Kubik and Stein (2003) find that a mutual fund manager is more likely to buy (or sell) a particular stock in any quarter if other managers in the same city are buying (or selling) that same stock. Gamble (2003) finds similar effects among individual investors. Lei and Seasholes (2004) find that purchases and sales are highly correlated when we divide retail investors geographically.

There are applications in other fields as well. In relation to social interaction's effects on consumption behavior, Grinblatt et al. (2004) show that consumers' purchase of automobiles are strongly influenced by the purchases of his neighbors, particularly those who are geographically most proximate. They also show that the choices on models of automobiles are also affected by neighbors' choices. In relation to social activities, Sacerdote (2001) find that Dartmouth roommates and dormmates are more likely to join the same fraternities or sororities. Glaeser, Sacerdote and Scheinkman (1996) show that criminal behaviors are strongly shaped by peer groups.

2. Construction of Data Set and Industry Specialization Index

2.1. Entrepreneurs

Our data set is based on administrative record of United Kingdom's incorporated companies. Companies Act of U.K. requires that every limited liability company or limited partnership must report to the Registrar of Companies House (the registration authority) within 14 days after it makes changes to its board of directors, and failing to do so will automatically result in penalties[4]. Thus we are able to collect information on almost the whole universe of directors for U.K. limited liability companies and limited partnerships for the past ten years.

We define entrepreneurs as those who are directors of limited liability companies registered in UK (including public and private companies). We do not have data for entrepreneurs who register as sole traders or unlimited partnerships. This exclusion however is irrelevant to our results since we do not use total entrepreneur numbers as regression variables. One assumption we need to make is that preference for incorporation (as opposed to other legal forms) is industry-specific or neighborhood-specific but not industry-neighborhood-pair –specific (that it is more popular to incorporate as limited companies in some industries, or some neighborhoods, but not some industry-neighborhood pairs). Under this assumption, we can measure industry specialization without data on entrepreneurs who register as sole traders or partners. Furthermore, given the low cost of incorporation in U.K., people undertaking truly entrepreneurial ventures are most likely to have registered as limited liability companies to take advantage of the limited liability protection.

Entrepreneurs in our sample are not likely to be those kind of non-entrepreneurial directors we see in big corporations who only meet several times a year for major decisions, as our sample are overwhelmed by small and micro enterprises[5] and presumably their directors personally should operate the businesses on a daily basis. Moreover, the turnover of directors is low (80% of directors joined within half a year since the companies' incorporations), which suggests that most directors follow the ventures from the beginning and can be safely defined as entrepreneurs. Last of all, outside directors are also able to provide information to their residential neighbors.

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[4] The Companies House actively inform entrepreneurs on her web site that "Being Late is a Criminal Offence", see www.companyhouse.gov.uk) . Certainly there are some companies which fail to update their information promptly. This however has minimal effects, because we do not see wide-spread incentives for which people would systematically provide false information on the identity of their directors. Thus we believe that these data are quite reliable (compared to accounting information).

[5] According to UK Inland Revenue Department's definition (43 Million GBP in total asset as a cut-off point), 98.2% of the companies in our sample are SMEs. As a matter of fact, among the SMEs, most are micro enterprises.

An entrepreneur is included in our sample if he meets the following two conditions: (1) His company is registered and/or operated in Greater London; (2) He resides in Greater London as well. By setting such restrictions, our results are cleaner as the location decisions are less likely to be affected by transportation frictions or local product market conditions. Greater London (the core of London Metropolitan Area) is a single Travel-To-Work area with extensive and convenient public transportation network, such that it is doable to commute within the area on a daily basis without substantial costs, and thus most people who work in this area also live in this area.

2.2 Neighborhoods

Although people can travel conveniently in London, we believe that people still interact more with neighbors in the same neighborhoods where they live. Our definition of a neighborhood is the "electoral ward" in UK. Ward is the lowest level of geographic and political unit for which representatives to local councils can be elected. In densely populated area such as London, each ward has a population of around 10,000, which is much smaller than electoral wards in the United States. In U.K. a ward is also unofficially called a community or a neighborhood, and we will use the name "neighborhood" throughout our paper, for convenience of presentation. There are more than 600 such neighborhoods in Greater London. A map of Greater London, with boundaries of boroughs and electoral wards is shown in Figure 1.

[insert Figure 1 about here]

The average area of a neighborhood is less than one square mile. The underlying assumption of our paper is that the development and maintenance of social contacts is limited to some extent by physical distance, and individuals are more likely to interact with people who live physically close. This is strongly supported by previous findings, which show that most social interactions happen within a one square mile area[6].

[6] Wellman (1996) using Toronto resident data finds that about 38% of yearly active contacts in all social networks take place between pairs of agents who live less than one mile apart. In a Detroit study, Connerly (1985) finds that 41% of the respondent had at least one third of their Detroit friends residing within one mile. Guest and Lee (1983) and Hunter (1974), using Seattle and Chicago data respectively, find that nearly half of the respondents say they have majority of their friends living in the same community (which actually have similar size as the electoral ward we use in this paper). Conley and Topa (2002) using

Furthermore, for political reasons, the boundaries of electoral wards are intentionally drawn in a way that residents within an electoral ward level generally share similar social-economic background as well as neighborhood identities, and are affected by the same set of public service (e.g., public schools)[7]. Thus, residents living in the same ward are more likely to meet, social, associate, and bond.

Thus, we sort entrepreneurs into their neighborhoods by using the a look-up table provided by the Census Dissemination Unit (CDU) which use electoral wards defined right before 2001 census, which is current with our base year 2000.

2.3. Industries

After matching entrepreneurs' home address with neighborhoods, we also match their industries with United Kingdom Standard Industrial Classification of Economic Activities (1992) codes. UKSIC codes are used because they are grouped according to the "similarity in the process used to produce goods or services", and thus the exchange of information and knowledge are presumably more valuable for entrepreneurs in the same industry divisions. We use two-digit SIC industry divisions. Three-digit and four-digit SIC industries may be distinct on the demand side, but less distinct in the operation side. Within a two-digit industry, knowledge and "trade secrets" are generally transferable. Furthermore, moving to a more finely disaggregated level creates substantial difficulties with small number of entrepreneurs in each neighborhood-industry pair.

In Table 1, we present the top twenty industries in London, in terms of their shares of entrepreneurs in London. Virtually all of them are service industries. Only

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Chicago data find that unemployment rates across census tract are weak, and suggest that most social interactions happen within census tracts (which correspond to our electoral wards). Rosenthal and Strange (2005) find that the amount of local employment in an entrepreneur's own industry has positive effects on births of new ventures in this industry, but this effect beyond one mile is an order of magnitude smaller than the effect of the more immediate environment. The average population of an electoral ward is 10,000 residents, which is also commonly accepted as the size of neighborhood/community, e.g., Project on Human Development in Chicago Neighborhoods (PHDCN) documented by Sampson, Raudenbush and Earls (2003). Durlauf (2003) provides a good survey of the economics literature on neighborhood effects.

[7] The criteria and guidelines for drawing neighborhood boundaries can be found on the website of U.K. government's Boundary Committee (www.boundarycommittee.org.uk).

"manufacturing of furniture and manufacturing not elsewhere classified"[8] narrowly makes into top twenty. The top twenty industries however already host 95% of London's entrepreneurs. Entry requirements are low for these industries. GBP 20,000 -30,000 of starting total asset is the norm for them, except "Real Estate Activities" industry which requires some GBP 150,000. This explains why they are so popular in terms of number. This also makes our later results more convincing, because financial constraints are not of secondary importance for entrepreneurs' industry choices. The top five industries in year 2000 is other businesses services, real estate activities, residents property management, computer and related activities, and other services. The industry composition of London entrepreneurs is quite stable. Comparing the industry composition of established entrepreneurs in year 2000 and that of the new entrants in the next four years, we find that the ranking of industry share barely changed.

[insert Table 1 about here]

Arguably, an SIC industry division whose name starts by "Other...." (e.g., "Other Business Activities" and "Other service activities") or whose name includes "not else classified" (e.g., "Manufacturing of Furniture and Manufacturing Not Else Classified") are less homogenous. This could affect our results. However, the results in this paper do not rely on inclusion or exclusion of these industries. As a matter of fact, we also estimate the model separately for each of the major industries, and find that our results are not driven by any particular ones.

2.4. Calculation of Industry Specialization Index For a Cross-Section of Neighborhood-Industry Pairs

[8] In this case, it is certainly inappropriate to define a collection of "not else classified" manufacturing businesses as a homogenous industry. Nevertheless, in our analysis, this group happens to be the only manufacturing "industry" in the top twenty industries, thus the entry into this two-digit SIC industry sufficiently proxy for an industry choice of manufacturing as opposed to service. For that matter, this group of businesses is sharply distinct from the other industries, and in this special case we can accept it as a homogenous group. Finally, our results are not driven by this particular industry.

Following Glaeser et al. (1992), with the following formula we will create "industry specialization (concentration) index" for each neighborhood-industry pair (i.e., industry i in neighborhood n), where i denotes industry and n denotes neighborhood. "# Entrepreneurs" is short for "Number of Entrepreneurs"

$$Specialization\_Index_{i,n} = \frac{\text{\# Entrepreneurs}_{\text{i, n}} \ / \ \text{\# Entrepreneurs}_{\text{i}}}{\text{\# Entrepreneurs}_{\text{n}} \ / \ \text{Total \# Entrepreneurs in London}}$$

This index is independent of the geographic distribution of total entrepreneurs, which are controlled for by the denominator of the formula. Very intuitively, index values greater than one indicate relative concentration/over-representation of industry i in neighborhood n.

Using the formula mentioned above, for a cross-section of neighborhood-industry pairs, we create industry specialization indices for two groups of entrepreneurs respectively: (1) Old generation of established entrepreneurs on our base date January 1, 2000; (2) New generation of entrepreneurs who entered businesses in the next four-year period between January 2, 2000 and January 1, 2004. For established entrepreneurs, we also create index based on specializations at borough level.

Established entrepreneurs are defined as current directors of active companies on the date of January 1, 2000. Constrained by data availability (company records which have not been active for the past five years are routinely removed from the data set[9]), year 2000 is the best choice if we want to obtain a complete snapshot of London entrepreneurs active at a certain point in time.

We choose to end our investigation in 2004 because for companies incorporated in most recent years UKSIC codes have not yet been assigned for them. We exclude entrepreneurs who enter businesses by joining companies incorporated before January 1,

[9] If a company can be located in the database, it is almost certain that it was still alive around year 2000. On the one hand, choosing earlier years would result in incomplete coverage, as those which ceased trading in 2000 (but still active before that) were dropped from the database already. On the other hand, choosing companies incorporated in later years would create another problem that we will not be able to identify whether a firm was active or not at a certain point in time, as the database only gives information on whether a company is active or not as of now (thus we may risk including directors for dead companies as active entrepreneurs).

2000, as that would create spurious correlation in our regressions (since replacement directors are more likely to be drawn from the same neighborhoods).

During the period, the number of entrepreneurial entries is unprecedented. The number of new entrepreneurs entering businesses in this merely four-year period is already about half of the number of existing ones in year 2000. This exogenous shock to the equilibrium provides us with a good opportunity to investigate the transition dynamics. The surge of entrepreneurship in U.K. is argued to be the result of rising prices of real estates, which can be used as collaterals to borrow against. Bank of England states in its February 2004 inflation report that: "self-employment may simply be more feasible than in the past, as sharp rises in house prices have increased the collateral at workers' disposal and so reduced the credit constraints they face." In the four-year period 2000-2004 we study, the house price in Greater London and Outer Metropolitan Area appreciated by more than 50%, according to the house index provided by Nationwide Co. The other favorable factors that contribute to the rise of entrepreneurship includes among others the economic booms, loose monetary polices, tax reform in 2002, and probably the drift of social norms toward entrepreneurship. We will also show later that the major tax reform in 2002 is not creating spurious correlation in our regressions.

2.5. Geography of London Entrepreneurs

Since we are using a new data set, it may be helpful to present a simple description of the data.

Entrepreneurs are not evenly distributed in London. Neighborhoods vary in terms of entrepreneurship. In Figure 2, we display a histogram of entrepreneurial densities in a cross section of neighborhoods. We measure entrepreneurial density of a neighborhood by the percentage of entrepreneurs in working age population. The median of entrepreneurial densities is 3.6%, but we also have quite a few extremely entrepreneurial neighborhoods with more than 30% of their working age residents running their own businesses. We would not exploit this dimension of variation to examine why some neighborhoods are more entrepreneurial because it is very difficult to address the omitted variables problems.

[insert Figure 2 about here]

Neighborhoods in our sample also vary greatly in their industry specializations. "Industry specialization" is defined on a relative term. A neighborhood will be defined as a specialist of industry X if this neighborhood has *disproportionate* share of entrepreneurs in industry X. In Figure 3, we present a histogram of "industry specialization index" for a cross-section of neighborhood-industry pairs. In Table 2, we also display the specialist industries by each of the top thirty most entrepreneurial London neighborhoods. For each neighborhood we only present its top three specialist industries. We notice that most of these neighborhoods specialize in real estate and financial intermediation activities, which is not surprising as they demand a lot of social interactions. Later we also show that these two industries are among the most geographically agglomerated in terms of entrepreneurs' residential addresses, and the persistence of agglomeration is stronger in these industries. This correlation may suggest to us the reason why entrepreneurs of certain industries crowd into a small number of neighborhoods, while doing so certainly drive up real estate prices.

[insert Table 2 and Figure 3 about here]

Most entrepreneurs start their business outside their own residential neighborhoods. In Table 1, we also present for each of the top twenty industries the percentage of entrepreneurs operating businesses in their own residential neighborhoods, as well as the median distance between their homes and their business sites. For the whole population of entrepreneurs, only 20% of them locate their businesses in their own residential neighborhoods, and the median distance between their homes and business sites is nearly six kilometers. There are some industries where the two addresses are relatively closer, such as residential management industry and computer industry, which is not surprising considering the way these industries are operated.

3. Empirical Strategy

In this paper, we begins by first establishing to presence of a robust, positive correlation between industry choices of old and new generations of neighbors. We then proceed through a series of steps to rule out alternative hypotheses and to provide stronger evidences in favor of the social interaction story.

In this section, I introduce how the correlation is established. Like most of the existing literature (among others, Giannetti and Simonov 2004, Betrand, Luttmer and Mullainathan 2000), we assume that social network are defined by administrative boundaries (in our case neighborhood boundary) and can thus test only indirectly how social interactions operate. For this reason, we base our analysis on a cross-section of neighborhood-industry pairs instead of letting social network to vary across every individual. I establish the correlation by testing whether, in a neighborhood, industry backgrounds of old generation of entrepreneurs in year 2000 affect industry choices of new entrepreneurs who start their businesses in the next four-year period. We estimate a model as specified below[10], with industry specializations of new entrepreneurs as dependent variables, which reflect aggregate outcomes of a neighborhood's industry choices. Used as explanatory variables are industry specializations of old generation of entrepreneurs in year 2000, which proxy for the industry background of a neighborhood's social network (i.e., for a would-be entrepreneur residing in neighborhood A, how likely it is for him to meet a neighbor with entrepreneurial background in industry I). Later we will also let the correlation to vary across neighborhoods and industries to provide more direct evidence that social interactions are driving the correlation.

Specialization Index (at neighborhood level) of new entrepreneurs

$=$ $\boldsymbol{\beta}_1$ [Specialization Index (at neighborhood level) of old entrepreneurs] $+$ $\boldsymbol{\beta}_2$ [Specialization Index (at borough level) of old entrepreneurs] + Constant

We estimate the model with Tobit regressions (truncated at zero) instead of OLS, because for substantial number of neighborhood-industry pairs we observe zero

[10] There are certainly alternative ways to test for our hypothesis. For instance, Brock and Durlauf (2003) already develop an econometric method to estimate multinomial choice with social interactions. Their complicated method however is not necessary in our context, where we have separation of home and business addresses, as well as variation of social interactions across neighborhoods

values (i.e., absence of industry i in neighborhood c). In our baseline sample of 600 neighborhoods by 20 industries, 15% of the observations are zero (and even higher in other samples).

We also run regressions separately for each of the individual industries, to make sure that our results are not driven by an individual or a sub-group of industries. We also use bootstrapping technique to address the concern that industry specialization index within a neighborhood is mechanically correlated. Finally, neighborhood- or industry-specific dummies are not necessary, as by construction the "industry specialization index" does not contain any neighborhood- or industry-specific components.

A statistically an economically significant β_1 would indicate the persistence of industry specialization over time. We also let β_1 to vary across neighborhoods or industries in order to detect the detailed channels through which social interactions impact entrepreneurs' industry choices. Theoretically, such effects should be stronger in neighborhoods with more scope for social interactions, as well as in industries more dependent on social interactions.

The specification is arguably very parsimonious. Undoubtedly, industry choice is also influenced by many other factors. However, so long as these unobservable factors are orthogonal to entrepreneurs' residential choices, we are always able to obtain unbiased estimates of the social interaction effects. Most importantly, we argue that our null hypothesis of "entrepreneurs from a same neighborhood make their industry choices independently" is very powerful, and it is hard to reject it unless there exist some sorts of information interactions among neighbors. Below we will explain it in details.

Arguably, residential addresses should only affect social interactions, but do not directly affect industry choices. First, entrepreneurs are facing a bigger market than their own neighborhoods, and most of them operate their businesses far enough away from where they reside and should not be affected by some unobservable common product market factors. Second, we are regressing flow variables against stock variables in the past, and we are not supposed to find correlations unless there exists word-of-mouth of observational learnings among neighbors. Third, our basic unit of analysis is neighborhood-industry pair, for which we can think of very few residential area characteristics such as life style that can potentially affect the dependent variable in such a systematic way (i.e., which neighborhoods must do which industries), although certain life style may increase the density of entrepreneurial activities at aggregate level.

Most importantly, we also control for industry specializations at borough level. Borough is the higher level of political/geographic unit than neighborhood. London is composed of 33 boroughs (including City of London and City of Westminster). There are around 20 neighborhoods within each borough. It is more convenient for people to travel within a borough (because of shorter distances) than travel across boroughs in London, thus entrepreneurs in the same borough may face similar product market conditions as well as common circle of social interactions. Controlling for industry specializations at borough level further restrict the scope for omitted variable problems, because the coefficients on industry specialization index (at neighborhood level) will now only catch the within-borough cross-neighborhood variations, which are not likely to be driven by common market factors.

4. Persistence of Industry Specialization Index in a Cross Section of Neighborhood-Industry Pairs

4.1. Is industry composition of a neighborhood persistent over time?

In Table 3 and Table 4, we report the results based on our basic regressions. We are interested in the signs of the coefficients on the "industry specialization index" at neighborhood level. If this coefficient turns out to be significantly positive, it indicates that sectoral composition of a residential neighborhood is very persistent over time, and that entrepreneurs are more likely to start businesses in industries where their neighbors are overrepresented.

[insert Table 3 and Table 4 about here]

From the 633 neighborhoods for which we have data, we exclude from the estimation the 33 least entrepreneurial ones, which account for less than 1% of all entrepreneurs in our sample[11]. Each of these neighborhoods has on average only fifty entrepreneurs (in all industries), and it is difficult to measure industry specialization with such small number of entrepreneurs (we will explain in more details below). In Table 3, readers can compare the regressions results in Row (1) which includes all 633 neighborhoods, and Row (2) which exclude the 33 least entrepreneurial ones. Two results are quantitatively similar. Later in Section 5 we also show that social interactions among entrepreneurial are the weaker in less entrepreneurial neighborhoods.

In the above regressions, we run regressions by pooling all industries together, while in Table 4, we also run regressions separately for each industries and report results of the top thirty industries. For regressions which pool all industries, we find that the coefficients of interest are highly significant and positive, which supports the presence of social interaction peer effects. The pseudo R^2 however are close to zero, which suggests that log-likelihoods for the full-model and the constant-only model are almost the same. This is not surprising after we examine the industry-by-industry regressions in Table 4, where we find that the persistence of a neighborhood's sectoral composition is mainly driven by the top twenty industries, which however already account for 95% of the entrepreneurial population. This suggests that the low explanatory power is caused by the outliers. The industry-by-industry regressions also address another concern: some industries may require certain endowment that only residents of certain neighborhoods possess, and as a result entrepreneurs of certain industries persistently come from certain neighborhoods. Nevertheless, it is very hard to argue that this is true for all of the twenty-three industries where we find very significant persistence of industry specializations.

London heavily specializes in a small group of industries. Though theoretically entrepreneurs have sixty SIC industries to choose from, nearly 95% of the entrepreneurs

[11] The choice of 600 as a cut-off point is certainly arbitrary, but our results are not affected by alternative choices. We choose 600 simply because (1) it is a round number; (2) we do not want to drop too many observations, but it is equally unwise not to drop those very obvious outliers.

are in the top twenty industries, and the top thirty industries already account for more than 98% of the entrepreneurs. Smaller industries outside top thirty attract so few entrepreneurs per industry (not enough for one entrepreneur in each neighborhood, let alone forming a social network) that specialization index will mechanically contain a lot of measurement errors. Ellison and Glaeser (1997)'s "Dartboard" theory suggests that simply by random chances small industries can be agglomerated geographically. For instance, for an industry with only 300 entrepreneurs in London, simple by random chance it is going to be agglomerated geographically because you can not divide one person into two and assign half to each neighborhood. This generates large measurement errors.

In Row (3) and Row (4) of Table 3, we report the regression results based on top thirty and top twenty industries respectively and readers can compare the results. The restriction to top twenty industries in analysis has minimal costs of sample selection (we already include 95% of the entrepreneurs) while minimize the influences of outliers' measurement errors. Bertrand et al. (2000) also adopt such a censoring by excluding languages spoken by less than 2000 people in their sample. The results in Row (5) are based on the "20 industries by 600 neighborhoods" sample. Using full sample would not change our results, though reducing the size of pseudo R^2. Unless otherwise indicated, the results presented later are based on this main sample[12].

By construction the values of industry specialization index within a neighborhood are mechanically correlated (if neighborhood A is a relative specialist of industry X, it is less likely to be a specialist in industry Y). This could inflate the t-statistics we obtain. We use bootstrapping to adjust for the standard errors. We re-sample the dependent variable for 10,000 times. The sample drawn during each replication is a bootstrap sample of clusters by neighborhood. We report the bootstrapping adjusted standard errors in brackets under Row (5). We find that the correlation of residuals is not very

[12] The choice is certainly arbitrary. One can always ask why top 600 communities, but not 599 or 601. But for the brevity of the presentation, we have to make a choice.

serious because the unadjusted standard errors previously reported are only biased downward by very small magnitude.

We also address this problem by reporting standard errors robust to potential clustering of residuals by neighborhoods. This adjustment produces an upper bound of the standard errors. Certainly the residuals can cluster by industries as well. This however has much smaller impacts asymptotically. We have more than 600 neighborhoods, and relative concentration of industry X in any one of them presumably should have minimal impact on the other neighborhoods. We cannot produce clustering-robust standard errors in Tobit regressions, but only in OLS regressions. In Row (6) of Table 3, we report the OLS results with standard errors robust to potential clustering of residuals by neighborhoods, as well as un-adjusted standard errors. The results still hold strongly, and by comparing the adjusted and unadjusted standard errors, we find that the correlation of residuals within a neighborhood is actually minimal.

The coefficients on the borough "industry specialization index" are significantly positive as well, which indicates that new entrepreneurs' industry choices are also correlated with those of the established entrepreneurs in the same borough. We are however less confident in whether the correlation is due to social interaction or common product market factors. The magnitude of the coefficients on neighborhood "industry specialization index" is also a little bit smaller than those on borough "industry specialization index". This however does not mean that agglomeration at borough level is more important, as we have to take into account the fact that standard deviation of "industry specialization index" at borough level is only half of that at neighborhood level.

4.2. Testing For Alternative Hypotheses Using Special Sub-Groups of Entrepreneurs

In this sub-section, we use various sub-sample of entrepreneurs to test for alternative hypotheses that may also explain our findings. We implement this by constructing industry specialization index with only a certain sub-group of new entrepreneurs, which is used to reflect aggregated choices of this sub-group of new entrepreneurs. The industry specialization index of established entrepreneurs, on the right hand side of the regression, remains the same because it is used to proxy for contact availability.

4.2.1. Sample of "Commuters"

[insert Table 5 about here]

With "Manski critique" in mind, a very natural question reader may ask is whether the correlation we find is the result of persistent and unobservable product market factors, which determine industry specializations of both the established entrepreneurs and the new entrepreneurs. We argue earlier that this is unlikely as we are examining the residential addresses rather than business addresses of entrepreneurs, and these two addresses are separate. In our sample, more than 80% of our entrepreneurs operate their businesses outside the residential neighborhoods where they live. However, it is still possible that our results are completely driven by the rest 20% who start business in their own residential neighborhoods.

In Row (1) of Table 5, we formally address this concern by estimating a same model but based on a sub-group of entrepreneurs who start businesses outside their residential neighborhoods. In Row (2), we further exclude entrepreneurs who start their businesses in the same boroughs where they live. The effects we find earlier are still found in these two sub-groups of entrepreneurs. This safely rule out the common product market factor concern, because it is hard to argue that entrepreneurs away from their boroughs are still subject to the same product market conditions as their residential neighbors.

4.2.2. Tax-Advantage-Induced Incorporations

There is concern that the tax reform in 2002 can cause the correlation we find. The Budget Plan of 2002 cut the starting rate of corporate tax by 1%, and for the first 10,000 GBP of profit the tax rate is reduced from 10% to 0%. Thus, if a sole trader or a partnership changes its legal form to an incorporated company and pay dividends to shareholders, it can benefit from this scheme. This can create some spurious correlation, if many of the newly incorporated companies have existed in a neighborhood for a long time (thus their industry choices are affected by the same set of unobservable variables that affects the existing companies). Critics attribute the unprecedented number of new incorporations in 2002-2003 to this tax reform. Our analysis in the footnote shows that tax-induced incorporations are not wide-spread[13]. Nevertheless, to directly address this concern, we also run a regression for entrepreneurs who incorporated their companies before April 2002 (when this drastic tax cut became effective). Between 2000 and 2002, there were no changes to corporate tax rates, and thus we can argue that taxation-induced incorporations are minimal. The results in Row (3) show that our results are not driven by the group of potentially taxation-driven incorporations.

4.2.3. Sample of Founders

There is also concern that the entry of entrepreneurs can be inflated simply by high turnover of directors. Some directors may join the businesses much later after incorporation and they are not entrepreneurs at all but experienced locals (from the same neighborhoods as the replaced directors) who get on board to help. In neighborhoods where an industry is overrepresented, you are more likely to find some neighboring friends who can help, i.e., the pool of talents are bigger, and thus either higher turnover or building up of bigger board is more feasible. This could also create

[13] For a company in our sample to incorporate for this incentive, it has to meet the following requirements. First, it has to be profitable, otherwise sole trader or partnership has better tax advantage as they can offset the loss against their personal income from other sources. The profit must also not be that high, as only the first 10,000 GBP of profit is eligible for tax relief. Second, the companies must pay dividends, otherwise the shareholders do not materially benefit from the schemes. U.K. corporation tax is an annual tax, which means it must be passed annually by parliament; otherwise there is no authority to collect it. The uncertainty on whether the scheme will be reversed is very high, and a company incorporated for tax purpose should pay back dividends as soon as possible. Third, such companies should not include non-shareholder directors. Generally, to prevent people from exploit this scheme, the taxman will require the dividends to be about equal to the salaries paid to directors, for businesses recently switch from other legal forms to corporations.
In our sample, less than 10% of newly incorporated companies pay any dividends, and this percentage did not go up after April 2002. If many companies are incorporated to exploit this tax advantage, we should observe sharp rise of newly incorporated companies paying dividends. The Longitudinal Labour Force Survey also provide counter-evidence to the tax-reform-induced-incorporations argument. Although there has strong increase of sole director (of limited companies) since Spring 2002, this seems to be part of the general phenomenon of rise of entrepreneurship because we also see strong increase in freelancing and agency work. Independent data from Inter Departmental Business Register, using VAT registration numbers, also show that the rise of self-employed is a general trend not only present among incorporated companies. Thus it is hard to argue that taxation advantage provide a major incentive for incorporations.

the correlation we found. In Row (4), we only include those directors who join the businesses within half a year since incorporation, and they are more likely to be entrepreneurs in a strict sense. Our results still hold strongly.

4.2.4. Young Entrepreneurs

In Row (5), we include only young people who are under age 30 when they start their ventures. There are two competing hypotheses as to whether young entrepreneurs are more or less influenced by their neighbors. The "new generations" hypothesis suggests that they would be less influenced by their neighbors. Residents of some neighborhoods specialize in certain industries because they have the expertise in doing so for historical reasons (for instance, immigrations), and since then stick to these trades. Young entrepreneurs under the age of 30 are more likely to have grown up more integrated with the world outside their neighborhoods, learn new skills and new information, and should be able to do something different from what their parents do. "Role model" hypothesis suggests the opposite. Young people may be less mature to make their own carefully-thought-out decisions, and thus are more likely to be influenced by their neighbors. This is called role model effects (Wilson, 1987), in which the behavior of one individual in a neighborhood is influenced by the characteristics and earlier behaviors of older members of his social group. Our results suggest that young entrepreneurs are also influenced by the established entrepreneurs in their neighborhoods.

4.2.5. Controlling For Board Size

It is also likely that residents of some neighborhoods prefer bigger boards of directors *for some industries*. This would also create the correlation we find in the data, as it constantly creates more entry of entrepreneurs in some neighborhood-industry pairs. We formally address this concern in Row (6) and (7) , where we only count as one observation if in a board there are multiple directors from the a same neighborhood or sharing a same full postcode respectively. These only exclude 15% of the entrepreneurs. Most directors who share a same neighborhood actually share a same postcode. They are more likely to be family members or very close neighbors, as a full postcode in London usually refer to one property or a very small group of dwellings. Our results are robust to this alternative measure of entrepreneurial population.

5. Establishing Causality by Identifying Detailed Mechanisms of Social Interactions

In Section 3 and 4, we establish that industry composition in a neighborhood is usually very persistent over time. Correlation of industry choices between new and old generations of entrepreneurs in a same neighborhood, however, is not necessarily the result of social interactions. In order identify the roles of social interactions in such correlation of industry choices, we need to document the detailed channels through which social interactions impact industry choices. If we can show that the effects we found are stronger in neighborhoods where social interactions are more intensive, we will establish strong support to our story of social interactions. This approach is similar to Bertrand et al. (2000), where they measure "Contact Availability" and examine whether correlation of benefit claims are stronger when "contact availability" is stronger. Furthermore, the role of social interactions will also be supported if the effects are found stronger in industries where social interactions are more important.

We do not have any data directly measuring the social interaction intensity at neighborhood level. But we find two proxies for it, the first is related to ethnic composition of residents, and the second is related to housing structures. We are also able to use Ellison-Glaeser index to proxy for industries' dependence on social interactions.

5.1. Ethnic Fragmentation and Social Interactions

Previous literature suggests that social interactions may be stratified along ethnic lines. Marsden (1988) using General Value Survey data, finds that the chance of observing a black-black friends tie is 4.2 times higher than that generated by pure random matching, given the relative proportions of the different racial and ethnic categories in the population. If people interact more with neighbors sharing similar ethnic background, then we would expect residents in neighborhoods with more homogenous ethnic background to interact more. Conley and Topa (2002) also find that measure of ethnic distance seems to be the most salient dimension along which neighborhoods exhibit spatial correlation.

We collect ethnic background data from UK Census 2001, which is the closest survey to our base year. We divide UK population into several major ethnic groups: (1) UK whites (British and Irish) (2) Other whites (Europeans) including mixed (3) South Asian (India, Pakistan, etc) (4) Black (5) Chinese (6) Other. Following commonly-accepted practice, we measure the ethnic fragmentation of a neighborhood by the probability that two randomly drawn households belong to two different ethnic groups.

In London, we find large variations of ethnic homogeneity across neighborhoods, from completely white-dominated ones, to neighborhoods not very different from a small United Nations. In a median neighborhood in terms of ethnic homogeneity, you have fifty percent chance of meeting people with different ethnic background than yours. Even in the top 10% neighborhoods in terms of ethnic homogeneity, a resident still has 20% chance of randomly meeting a neighbor from different ethnic background.

[insert Table 6 about here]

In Column (1) of Table 6, we run the same regression but also include as explanatory variables the ethnic fragmentation index as well as its interaction term with industry specialization index. The interaction term enters significantly negative, which suggest that persistence of industry specializations is stronger in neighborhoods where ethnic composition is more homogenous.

5.2. Housing Structure and Social Interactions

Social interactions can be determined by architecture structure of a neighborhood. Glaesser and Sacerdote (2000) examine the connection between housing structure and social interactions. They find that neighbors in large apartment buildings are more likely to be socially connected with one another, perhaps because distances between neighbors are shorter, and because public spaces (traditional squares, piazzas, coffer shops, bars, etc) create interactions between persons who don't have natural reasons to interact. This connection is not incompatible with the popular belief that neighbors in apartment buildings develop weaker ties. Although they do not develop very deep relationship with their neighbors as rural inhabitants do, they interact with a larger set of neighbors because such neighborhoods are more densely populated. In our context, what matters is how many neighbors you get to know, i.e., the scope of social interactions, but not how well you know them, because you only need to know someone a little bit to know something about his industry.

From UK 2001 Census data, we know the composition of accommodation type in each neighborhood. We create a urbanization index by measuring the log difference between the number of "Flat, maisonette or apartment" and the number of "Whole house or bungalow" in a neighborhood. London neighborhoods are among the most urbanized ones in U.K. However, within London, there is still a great deal of variations of urbanization across neighborhoods.

We explore this variation to test for our hypothesis. In Column (2), we interact the urbanization index with industry specialization index of established entrepreneurs. We find that persistence of industry specializations is indeed stronger in neighborhoods where the number of apartment buildings dominates that of detached houses.

5.3. Entrepreneurial Density and Social Interactions with Entrepreneurs

If there are very few entrepreneurs among residents of a neighborhood, a potential entrepreneur is still less likely to meet and know an established entrepreneur even when social interactions are very intensive. In these neighborhoods, industry choices of start-up entrepreneurs are less likely to be influenced by neighbors, because not many of them are entrepreneurs. In Column (3), we interact entrepreneurial density of a neighborhood with industry specialization index of old generation of entrepreneurs. We find that persistence of industry specializations is indeed weaker in neighborhoods where people are less likely to meet an established entrepreneur.

5.4. Agglomeration of industries and information flows

Presumably, start-up entrepreneurs imitate their established counterparts because they think they may benefit from information flows. As a result, we should expect such herding to be stronger in industries where information interactions look more important. We cannot directly quantify which industries require more information interactions, although some previous research (e.g., Gordon and McCann 2000) make subjective judgments by employing a panel of experts to evaluate the dependence on social network for a small cross-section of industries. We instead measure it based on outcomes. If based on residential addresses an industry's entrepreneurs are historically agglomerated geographically, we define that information interactions are more important in this industry.

With the methodology proposed by Ellison and Glaeser (1997, page 899), we create Ellison-Glaeser index (short as EG index) for industries in London. The EG index was originally used to measures how much a certain industry's employment is agglomerated geographically, controlling for the agglomeration of total employment in all industries, as well as the industrial organization of the industry (i.e., how competitive the industry is). In other words, it measures, to what extent the geographic distribution of employment deviate from randomness ("throwing darts toward a dartboard"). In our context, the index however measures how much an industry's *entrepreneurs* (not plants) are relatively agglomerated based on their residential addresses, controlling for industry size (in terms of entrepreneur population) and geographic agglomeration of the whole entrepreneur population.

We present the indices in Table 1 for each of the top twenty industries. The unit of analysis Ellison and Glaeser (1997) use is state in the U.S, while ours is neighborhood in London, thus the absolute value of the indices are not comparable. Also, since we are measuring the concentration of entrepreneurs in terms of where they live (which is quite a "city-wide tradable goods", we do not need to follow Ellison and Glaeser (1997) to restrict the sample to manufacturing industries. Among the top twenty industries, the most agglomerated industries are real estate activities industry and financial intermediation industry. These industries act as intermediaries in business activities, and thus naturally depend on social interactions and extensive exchange of information. The least agglomerated industries are other services industry, and retail trade industry. Rosenthal (2001) discuss why some industries are more agglomerated than others.

In Column (4), we interact Ellison-Glaeser index with industry specialization index of established entrepreneurs. We find that persistence of geographic agglomeration is indeed stronger among these geographically agglomerated industries. This may suggest that geographic agglomeration is self-reinforcing.

5.5. Industry Specialization Based on Business Addresses

In Column (5), we formally address the question whether businesses set up in a neighborhood can also influence local resident's industry choice, and whether this effect dominates the social interaction effect we find. Residents living in a neighborhood will certainly get familiar with the businesses set up in their neighborhoods (which although may be operated by residents from other neighborhoods). Although the residents generally do not interact with these "immigrant" entrepreneurs as much as they interact with their residential neighbors, we still expect there exist some sort of interactions of information. To formally address this concern, we also create industry specialization based on the business addresses of companies in our database. In Column (5), we control for this as well in our regression. Indeed, start-up entrepreneurs are also influenced by these "immigrant" entrepreneurs. The effects however are in a much smaller order of magnitude. Thus our results suggest that entrepreneurs mainly imitate their residential neighbors, not businesses established in their residential neighborhoods.

6. Testing for Agglomeration Economy Hypothesis

We are interested to know whether social interactions produce valuable information to new entrepreneurs and create agglomeration economies. If an entrepreneur who starts a business in his neighborhood's specialized industry does fare much better, this would suggest that the persistence of industry specialization we observe in the data are the results of wise economic considerations (e.g. agglomeration economies). For instance, Dumais et al. (2002) shows that plants in industry centers are less likely to close, controlling for plant's age and size. Even if these entrepreneurs do only equally better compared with others, this will still be weak evidence in favor of agglomeration economies, if we assume that: when a neighborhood is overrepresented in a certain industry, the match between talent and industry is worse because the distribution of industry talents are similar across neighborhoods. Finally, if the failure rate is higher for them, we would say that these entrepreneurs make their industry choices out of behavioral biases because their interactions with neighbors increase their overconfidence in the odd of successes in their neighborhoods' specialized industries, which may even creates mismatch of talents across industries.

We collect data on a cohort of London entrepreneurs whose businesses got started during year 2000. There are more than 50,000 of them. The first question we have to address is how to measure the performance of the start-ups. A natural answer would be to measure their profitability. However, UK law exempts small and medium businesses from filing detailed Profit and Loss accounts to the Registrar of Companies House. Furthermore, those which did not survive the first year certainly did not report either. This will create large sample selection problems if we only examine those who report.

To solve this problem, we find an alternative measure: the failures of start-ups. The database provides information on whether a company is still alive, which are available for each company without exception. Thus we are able to create a binary variable "failure" for each entrepreneur, based on the fate of the businesses he keeps. The reason why we only examine companies started in year 2000 is that from the database we only know whether a company is alive or not by now, but do not know the exact date when they started to cease trading. A safe decision is to include only companies started 4-5 years ago, as we believe that if a company started then would fail (because of lower quality), it should have failed now. The reason we examine start-up companies is also that we want to achieve better comparability and initial homogeneity across companies in our sample.

The failure rate for start-ups is very high. Five years from incorporation, more than 40% of these entrepreneurs are not in active trading any more. Such high rate of exit is not unusual, but is consistent with comparable studies[14].

The model is specified as follows, with failures of entrepreneurs as (binary) dependent variable.

Failure = $\boldsymbol{\beta}_1$ [Specialization Index (at neighborhood level) of established entrepreneurs] + $\boldsymbol{\beta}_2$ [Specialization Index (at borough level) of established entrepreneurs] + Individual entrepreneur characteristics + Industry dummies + neighborhood (or borough) dummies + Constant

Based on a large cross-section of individual entrepreneurs, we estimate the model using Probit. As explanatory variables we use industry specialization index at both neighborhood and borough level, to examine whether entrepreneurs who choose to follow their neighbors' industry choices benefit from information spillovers (which presumably will be evidenced by lower failure rate or at least equal failure rate), or entered the trade by over-optimism encouraged by neighbors (which presumably will be evidenced by higher failure rate). We include industry dummies to correct for the fact that companies in some industries are naturally more risky, and have higher odds of failures. We also include neighborhood dummies to control for lower quality of entrepreneurs in some neighborhoods as well as other unobservable factors. Estimation of Probit regressions with fixed effects is known to be problematic when there is small number of observations for each fixed effect group. For this reason, we also use borough dummies to replace neighborhood dummies in alternative specifications because the numbers of entrepreneurs per borough are much higher.

We also control for entrepreneurs' individual characteristics. We include the age of the entrepreneurs (when they started their businesses) to control for their experiences (more experienced ones are less likely to fail), their substantial shareholder status to

[14] Scarpetta et al. (2002) using OECD data show that, leaving profitability aside, only half of all startups survive more than three years. Landier and Thesmar (2004) documented the same pattern in France. Both Cooper et al. (1998) and Landier and Thesmar (2004) show that the over-optimism of entrepreneurs at the beginning contributes to such high failure rates.

control for agency problems (entrepreneurs with small shares may act like employees and prefer less risky projects), and their genders to control for differences of risk-aversion (females are more risk averse and may pick less risky projects). The standard errors we report are also robust for potential clustering of residuals at firm level, as many firms have more than one entrepreneur from the same neighborhoods.

[insert Table 7 about here]

In Column (1) of Table 7, we control for neighborhood fixed effects, while in Column (2) we control for borough fixed effects. The results do not favor the agglomeration economy hypothesis, which should be reflected by a negative coefficient value of β_1. Entrepreneurs starting businesses in their neighbors' popular sectors do not have lower odds of failures. One reason we do not find imitators doing better could be that: When there are something wrong with a company, new directors from where this industry is overrepresented (and presumably who are equipped with better industry expertise according to agglomeration economy theory) may join as "fire fighters", and this would offset the negative correlation between industry specialization and odds of failure. To address this concern we use a sub-group of entrepreneurs who were appointed as directors within half a year since the companies' incorporations. They are more likely to be "founders" than "fire fighters". In Column (3) and (4), we run regressions for "founders" who incorporate their companies during year 2000, controlling for neighborhood and borough fixed effects respectively. We still do not find any significant relationship between specialization and failure rates.

Although entrepreneurs who imitate their neighbors do not have lower failure rates, they do not do significantly worse either. If we assume that (1) industry talents are distributed similarly in populations of different neighborhoods; and (2) entrepreneurs of lower quality (in terms of match of talents with industry) are also tempted into their neighborhoods' popular industries as a result of social interactions, then the fact that the average failure rates do not significantly go up may suggest that agglomeration economies are working in the opposite direction to offset the negative effects. This indicates that social interactions promote entry in a neighborhood's traditional specialty without causing higher failure rates. In the future, we can shed more light on this research question by controlling for observable quality of individual entrepreneurs. For instance, we can control for individual-specific characteristics by using a special sub-group of entrepreneurs who used to start more than two businesses in different industries.

Overall, the results suggest that entry of new entrepreneurs tend to reinforce agglomeration, while failures do not change the geographic concentration. This is in contrast to Dumais et al. (2002)'s study on the dynamic process of geographic concentration based on business addresses. Using U.S. manufacturing industries data, they show that location choices of new firms play a de-agglomerating role, whereas plant closures have tended to reinforce agglomeration. The two findings however are not conflicting. When it comes to choosing locations to set up businesses, agglomeration always results in rising costs for new entrants due to limited supply of commercial sites, and entrepreneurs would have incentive to locate their businesses in new places. When it comes to making decisions merely regarding which industries to enter, however, entrepreneurs can choose any industries (e.g., industries that their neighbors specialize in) without competing for resources with neighbors, because there are no known constraints on how many people living in a residential neighborhood can enter certain industries, so long as they do not go to the same places.

7. Conclusions

Why do entrepreneurs from certain neighborhoods consistently dominate certain industries? In this paper, utilizing separations of home and business addresses, we find evidences in support of social interactions' impacts on entrepreneurs' industry choices. Based on a cross-section of neighborhood-industry pairs, we find that, new entrepreneurs are more likely to enter their residential neighbors' popular industries. This persistence of industry specialization is stronger in neighborhoods with more intensive social interactions, and stronger in industries which are more agglomerated geographically. This effect is not likely to be driven by product market factors, as we are examining the residential addresses but not business addresses of the entrepreneurs, and the two addresses are generally distant from each other. We are able to identify the causality because residential addresses only determine social interactions but do not directly affect industry choices. Finally, we admit that, by aggregating our data from individual level to neighborhood level, we remain somewhat agnostic as to the actual mechanism linking neighborhoods to individual outcomes. Alternative strategies, especially those that allow causal inferences to be drawn about particular channels and for broader populations, have the potential to increase our understanding of the impact of neighborhoods on individual outcomes.

References

Bayer, Patrick; Stephen L. Ross; Giorgio Topa. 2004. Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes. *Working Paper*

Bentolila, Samuel; Claudio Michelacci; Javier Suarez. 2004. Social contacts and occupational choice. *Working Paper, CEMFI*

Bernheim, B. Douglas (1994), A Theory of Conformity, *The Journal of Political Economy* 102, 841-877.

Bertrand, Marianne; Sendhil Mullainathan and Erzo Luttmer. 2000. Network Effects and Welfare Cultures, *The Quarterly Journal of Economics*, August

Brock, William A. and Steven N. Durlauf. 2003. Multinomial Choice with Social Interactions. NBER technical Working Paper No. 288.

Brock, William A. and Steven N. Durlauf. 2001. Interactions-based model. In *Handbook of Econometrics*, Volume 5, Chapter 54, pp. 3297-3380, Edited by J.J. Heckman and E. Leamer, Elsevier Science B.V., 2001.

Cole, Harold L., George J. Mailath, and Andrew Postlewaite 1992. Social Norms, Saving Behavior, and Growth, *The ournal of Political Economy* Vol. 100, 1092-1125.

Conley, Timothy G; Giorgio Topa. 2002. Socio-economic distance and spatial patterns in unemployment. *Journal of Applied Econometrics*. Vol. 17: 303-327

Connerly, Charles E. 1985. The neighborhood question: an extension of Wellman and Leighton. *Urban Affairs Quarterly*. Vol.20: 537-556

Cooper, Arnold C., Carolyn Y. Woo, and William C. Dunkelberg. 1988. Entrepreneurs' perceived chances of success. *Journal of Business Venturing* 3: 97-108

Corcoran, M., L. Datcher and G. Duncan. 1980. "Information and Influence Networks in Labor Market" in G. Duncan and J. Morgan (eds.) *Five Thousand American Families: Patterns of Economic Progress*. Vol. 7, 1-37.

Dumais, Guy; Glenn Ellison; Edward L. Glaeser. 2002. Geographic concentration as a dynamic process. *The Review of Economics and Statistics*. May: 193-204

Durlauf, Steven N. 2003. Neighborhood Effects. In *Handbook of Regional and Urban Economics*. Volumn 4, Economics, J.V. Henderson and J.-F. Thisse, eds.

Ellison, Glenn; Edward L. Glaeser. 1997. Geographic concentration in U.S.: manufacturing industries: a dartboard approach. *Journal of Political Economy*. Vol. 105(5)

Feng, Lei and Mark S. Seasholes, 2004, "Correlated Trading and Location," *Journal of Finance*, LIX, 5, October, 2117-2144.

Gamble, Keith. 2003. Word-of-Mouth Influence on the Stock Holdings of Individual Investors. *Working Paper, UC Berkeley*

Giannetti, Mariassunta and Andrei Simonov. 2004. Social interactions and entrepreneurial activities. *Working paper, Stockholm School of Economics*.

Glaeser, Edward L.; Hedi D. Kallal; Jose A. Scheinkman; Andrei Shleifer. 1992. Growth in cities. *The Journal of Political Economy*. Vol. 100. No. 6.

Glaeser, Edward L.; Bruce I. Sacerdote and Jose A. Scheinkman. 1996. Crime and social interactions. *Quarterly Journal of Economics*. May

Glaesser, Edward L. and Bruce I. Sacerdote. 2000. The Social Consequences of Housing. *Journal of Housing Economics*. Vol. 9

Gordon, Ian R. and Philip McCann. 2000. Industrial clusters: complexes, agglomeration and /or social networks? *Urban Studies*. Vol. 37 (3): 513-532

Granovetter, Mark 1995. Getting a Job: a Study on Contacts and Careers (2nd Ed).Chicago, Chicago University Press.

Grinblatt, Mark; Matti Keloharju; Seppo Ikaheimo. 2004. Interpersonal effects in consumption: evidence from the automobile purchase of neighbors. *Working Paper. Helsinki School of Economics.*

Guest, Avery M. and Barrett A. Lee. 1983. The social organization of local areas. *Urban Affairs Quarterly*. Vol. 19-217-240

Hamilton, Barton H. 2000. Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*. Vol. 108: 604-631

Henderson, Vernon; Ari Kuncoro; Matt Turner. . 1995. Industrial Development in Cities. *Journal of Poltiical Economy*. Vol. 105. No. 5

Hong, Harrsion; Jeffrey D. Kubik and Jeremy C. Stein. 2005. "Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers," *Journal of Finance*, forthcoming.

Hunter, Albert. 1974. Symbolic neighborhoods: the persistence and change of Chicago's local neighborhoods. The University of Chicago Press: Chicago

Ioannides, Yannis M. and Datcher Loury. 2004. Job information networks, neighborhood effects and inequality. *Journal of Economic Literature*. Vo. 42(4)

Jacob, Jane. 1969. The Economy of Cities. New York: Vintag

Jencks, Christopher and Susan Mayer. 1990. "The Social Consequences of Growing Up in a Poor Neighborhood." In Laurence Lynn, Jr., and Michael G.H. McGeary (eds) *Inner City Poverty in the United States*. Oxford: University Press.

Landier, Augustin, and David Thesmar. 2004. Financial contracting with optimistic entrepeneurs: theory and evidence. *NYU Stern working paper*

Manski, Charles F. 2000. Economic Analysis of Social Interactions. *Journal of Economic Perspective*. Vol. 14, No. 3, pp. 115-136.

Marsden Peter V. 1988. Homogeneity in confiding relations. *Social Networks*. Vol. 10: 57-76

Montgomery, James D. 1991. Social Network and labor-market outcomes: toward an economic analysis. *The American Economic Review* Vol. 81(5)

Moskowitz, Tobias J. and Annette Vissing-Jorgensen. 2002. The private equity premium puzzle. *American Economic Review*. Vol. 92: 745-778

Rosenthal, Stuart S. and William C. Strange. 2005. The geography of entrepreneurship in the New York Metropolitan Area. *Working Paper, Syracuse University and University of Toronto*

Rosenthal, Stuart S. 2001. The determinants of agglomeration. *Journal of Urban Economics*. Vol. 50: 191-229

Sacerdote, Bruce I. 2001. Peer effects with random assignment: results for Dartmouth roommates. *Quarterly Journal of Economics*. May

Sampson, Robert J.; Stephen W. Raudenbush; Felton Earls. 2003. Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science.* Vol. 277: 918-24

Scarpetta, Stefano, Philip Hemmings, Thierry Tressel, and Jaejoon Woo. 2002. The role of policy and institutions for productivity and firm dynamics: evidence from micro and industry data. *OECD paper*.

Shiller, Robert J. 2000. Irrational Exuberance. Broadway Books: New York

Topa, Giorgio; 2001. Social interactions, local spillovers and unemployment. *Review of Economic Studies*. Vol. 68: 261-95

Wellman, Barru 1996. Are personal neighborhoods local? A dumptarian reconsideration. *Social Networks*. Vol. 18: 347-354

Wilson, William J. 1987. The truly disadvantaged: the inner city, the underclass, and public policy (Chicago: University of Chicago Press)

Table 1 : Top Twenty Industries in London

SIC codes and industry names	industry share in year 2000 (%)	industry share among new entrants (%)	% of entrepreneurs operating businesses in their own residential neighborhoods	median distance between residential and business addresses (KM)	EG Index X 10^{-3}
74. Other business activities	21.32	36.57	17.8	6.10	0.46
70. Real estate activities	12.15	10.62	14.9	5.57	2.34
98. Residents property management	11.45	3.47	48.1	0.22	1.26
72. Computer and related activities	6.33	7.63	42.7	1.39	0.78
93. Other service activities	6.2	3.05	14.8	6.21	0.09
92. Recreational, cultural and sporting activities	5.7	6.08	12.0	5.74	0.79
51. Wholesale trade and commission trade	4.91	3.15	11.9	7.54	0.81
45. Construction	4.3	4.39	20.2	5.77	1.63
52. Retail trade	3.72	3.75	12.9	6.44	0.31
85. Health and social work	3.48	2.3	9.7	5.13	0.45
65. Financial intermediation, except insurance and pension funding	3.08	2.03	6.1	7.69	1.86
55. Hotels and restaurants	2.53	3.45	11.4	6.93	0.64
22. Publishing, printing and reproduction of recorded media	2.18	1.1	8.9	7.76	0.52
91. Activities of membership organizations not elsewhere classified	1.5	2.28	6.6	7.34	0.52
63. Supporting and auxiliary transport activities; activities of travel agencies	1.47	0.93	11.5	7.74	0.43
80. Education	1.34	1.54	12.4	4.94	0.42
66. Insurance and pension funding, except compulsory social security	1.1	0.42	5.5	9.10	1.50
50. Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	0.88	0.74	12.1	6.82	1.73
36. Manufacture of furniture and not else classified	0.59	0.3	9.2	8.36	0.62
60. Land transport; transport via pipelines	0.58	0.81	14.5	7.59	1.73

Notes:

1. This table provides summary descriptive of the top thirty industries in London sorted by their shares of entrepreneurs in London. SIC codes and industry names are shown in the first column.
2. The second column reports the industry share of established entrepreneurs in year 2000 while the third column the industry share of new entrepreneurs during the next four-year period.
3. In the forth column is the percentage of an industry's entrepreneurs operating businesses in their own residential neighborhoods, while in the fifth column is the median distance between residential and businesses addresses of entrepreneurs.

4. The sixth column reports the Ellison-Glaeser index for each industry, scaled by 10^{-3}. Higher values of this index indicate higher geographic agglomeration of entrepreneurs.

Table 2 : Specializations of the top thirty most entrepreneurial neighborhoods

Neighborhoods	First Specialty	Second Specialty	Third Specialty
Garden Suburb	Real Estate	Wholesale Trade	Financial Intermediation
Edgware	Other Business Activities	Wholesale Trade	Retail Trade
Frognal and Fitzjohns	Real Estate	Financial Intermediation	Property Management
Knightsbridge and Belgravia	Financial Intermediation	Real Estate	Insurance and pension
Abbey Road	Real Estate	Financial Intermediation	Wholesale Trade
Hampstead Town	Real Estate	Recreational and Cultural	Financial Intermediation
Finchley Church End	Real Estate	Wholesale Trade	Manufacture
Holland	Financial Intermediation	Real Estate	Supporting Transport
Totteridge	Wholesale Trade	Real Estate	Manufacture
Childs Hill	Real Estate	Wholesale Trade	Health and Social Work
Village	Financial Intermediation	Insurance and pension	Education
Swiss Cottage	Real Estate	Property Management	Financial Intermediation
Hendon	Real Estate	Wholesale Trade	Manufacture
Regent's Park	Real Estate	Wholesale Trade	Financial Intermediation
Golders Green	Real Estate	Wholesale Trade	Manufacture
Queen's Gate	Financial Intermediation	Insurance and pension	Hotels and Restaurants
Stanmore Park	Real Estate	Wholesale Trade	Retail Trade
Little Venice	Property Management	Recreational and Cultural	Supporting Transport
Brompton	Financial Intermediation	Hotels and Restaurants	Retail Trade
Highgate	Real Estate	Financial Intermediation	Property Management
Belsize	Property Management	Real Estate	Recreational and Cultural
Cockfosters	Wholesale Trade	Insurance and pension	Sales of Motor Vehicle
Mill Hill	Wholesale Trade	Real Estate	Retail Trade
Marylebone High Street	Real Estate	Recreational and Cultural	Hotels and Restaurants
West End	Real Estate	Financial Intermediation	Hotels and Restaurants
Campden	Financial Intermediation	Insurance and pension	Supporting Transport
Hyde Park	Hotels and Restaurants	Real Estate	Publishing and Printing
Royal Hospital	Financial Intermediation	Insurance and pension	Real Estate
Chislehurst	Insurance and pension	Sales of Motor Vehicle	Construction
Hans Town	Insurance and pension	Financial Intermediation	Real Estate

Note:
This table reports the industry specializations of the top thirty most entrepreneurial neighborhoods in London. Neighborhood names are shown in the first column. In the second, third, and forth column we report the top three specialist industries of each neighborhood based on the "industry specialization index" we calculate.

Table 3: Persistence of industry specializations over time

Dependent variable: industry specialization index of new entrepreneurs
Unit of analysis: neighborhood-industry pair

		"industry specialization" at neighborhood level	"industry specialization" at borough level	Pseudo R^2	Obs.
(1)	All 633 neighborhoods	0.053 (0.014)***	1.220 (0.061)***	0.00	37,980
(2)	Top 600 neighborhoods	0.058 (0.015)***	1.182 (0.063)***	0.00	36,000
(3)	Top thirty industries	0.236 (0.013)***	0.725 (0.028)***	0.03	18,357
(4)	Top twenty industries	0.318 (0.012)***	0.513 (0.023)***	0.07	12,660
(5)	Top 20 Ind. / Top 600 Neighborhoods	0.356 (0.012)*** [0.023]***	0.469 (0.022)*** [0.038]***	0.07	12,000
		Bootstrapping adjusted standard errors are reported in brackets			
(6)	OLS, robust to clustering by neighborhoods	0.329 (0.020)*** [0.022]***	0.440 (0.031)*** [0.036]***	0.20	12,000
		Standard errors robust to potential clustering of residuals at neighborhood level are reported in brackets			

Notes:
1. The regression is specified as follows and estimated with Tobit unless otherwise indicated:
Specialization (at neighborhood level) of new entrepreneurs
= β1 [Specialization (at neighborhood level) of established entrepreneurs] + β2 [Specialization (at borough level) of established entrepreneurs] + Constant
2. The regressions are based on a cross section of neighborhood-industry pairs. On the left hand side is the neighborhood c's specialization index in industry i of new entrepreneurs entering businesses between 2000 and 2004. On the right hand side we have two independent variables regarding the industry specializations of established entrepreneurs in year 2000. One variable is neighborhood c's specialization index in industry i, while the other is borough b's specialization in industry i, both are based on the established entrepreneurs in year 2000.
3. We present results based on varied sub-samples, to address the problem that industry specializations are estimated with large errors when there are too few entrepreneurs in a certain neighborhood or in a certain industry. Our full sample is consisted of 633 neighborhoods and 60 industries. Our main sample however is only consisted of 600 neighborhoods and 20 industries. This nevertheless does not affect our results. Top 600 neighborhoods already account fro 99% of the entrepreneurs, while top 20 industries account for 95%. Cut-off points for "top" neighborhoods and industries: Top 30 industries: >=595 entrepreneurs, Top 20 industries: >=1931 entrepreneurs, Top 600 neighborhoods: >=91 entrepreneurs.

4. In Row (5), bootstrapping (cluster by neighborhoods) adjusted standard errors are reported in brackets.
5. In Row (6), regression is estimated by OLS, with un-adjusted standard errors reported in parentheses. Standard errors robust to clustering by neighborhoods are reported in brackets

Table 4: Regression results for each of the top thirty industries respectively

Dependent variable: industry specialization index of new entrepreneurs
Unit of analysis: neighborhood-industry pair

SIC code	Industry	Number of entrepreneurs in year 2000	Coefficient on "industry specialization at neighborhood level"	Standard errors	Significance of the coefficient	LR Chi-Squared
74	Biz Services	70527	0.242	0.035	***	124.16
70	Real Estate	40184	0.862	0.036	***	479.23
98	Prop. Magt.	37860	0.540	0.059	***	152.55
72	Computer	20929	0.343	0.029	***	215.65
93	Services	20519	0.250	0.072	***	13.89
92	Recreational	18858	0.546	0.034	***	444.65
51	Wholesale	16248	0.366	0.062	***	128.84
45	Construction	14222	0.542	0.037	***	644.66
52	Retail Trade	12305	0.406	0.058	***	122.48
85	Health	11501	0.123	0.055	**	38.36
65	Financial	10198	0.820	0.066	***	225.53
55	Hotel & Res	8367	0.423	0.039	***	147.72
22	Publishing	7215	0.202	0.071	***	35.19
91	Mem. Org.	4960	0.149	0.039	***	81.21
63	Aux. Tran.	4862	0.231	0.067	***	40.44
80	Education	4445	0.198	0.050	***	21.53
66	Insurance	3635	0.956	0.122	***	134.69
50	Motor Sales	2913	0.289	0.062	***	162.43
36	Manufacturing	1959	0.303	0.139	**	17.67
60	Land Tran.	1931	0.322	0.040	***	164.40
18	Apparel	1810	0.596	0.110	***	135.24
67	Aux. Finan.	1750	0.318	0.060	***	148.69
64	Post. Tele.	1704	0.055	0.036		12.03
28	Fab. Metal	1415	0.322	0.201		35.73
15	Food & Bev.	862	-0.186	0.171		7.77
71	Rent Mach.	842	0.023	0.084		2.06
73	R&D	750	-0.160	0.149		21.08
31	Ele. Mach.	659	0.325	0.575		14.11
11	Petro.	597	0.453	0.164	***	55.97
24	Chemical	595	0.414	0.457		1.4

Notes:
1. The regressions are specified as follows and estimated with Tobit:
Specialization (at neighborhood level) of new entrepreneurs
= β1 [Specialization (at neighborhood level) of established entrepreneurs] + β2 [Specialization (at borough level) of established entrepreneurs] + Constant
2. The regression in each row is based on a cross section of neighborhoods for an individual industry i. On the left hand side of the regression is the neighborhood c's specialization index in industry i of new entrepreneurs entering businesses between 2000 and 2004. On the right hand side we have two independent variables regarding the industry specializations of established entrepreneurs in year 2000. One variable is neighborhood c's specialization index in industry i,

while the other is borough b's specialization in industry i, both are based on the established entrepreneurs in year 2000. For the brevity of presentation, we do not report in the table the coefficients on “borough industry specialization index”.

3. There are 600 neighborhoods in the sample. We run regressions for all the 60 industries but only report the results of the top thirty industries. We do not find significant results in the smaller industries. The SIC codes and abbreviation names for the industries are displayed in the first and second column.

4. *** indicates that the coefficients on “industry specialization index” is significantly different from zero at 1% level, ** denotes 5%, * denotes 10%

Table 5: Testing for alternative hypotheses using special sub-samples

Dependent variable: industry specialization index of new entrepreneurs
Unit of analysis: neighborhood-industry pair

		"industry specialization" at neighborhood level	"industry specialization" at borough level	Pseudo R^2	Obs
(1)	Commuters (outside own neighborhoods)	0.370 (0.013)***	0.492 (0.026)***	0.06	12000
(2)	Commuters (outside own boroughs)	0.393 (0.015)***	0.476 (0.029)***	0.05	12000
(3)	Before 2002 tax reform	0.377 (0.016)***	0.538 (0.030)***	0.05	12000
(4)	Founders only	0.365 (0.013)***	0.447 (0.025)***	0.06	12000
(5)	Young People Only	0.386 (0.054)***	0.696 (0.101)***	0.01	12000
(6)	Same-neighborhood directors count only once	0.354 (0.011)***	0.469 (0.022)***	0.08	12000
(7)	Same-postcode directors count only once	0.360 (0.012)***	0.476 (0.022)***	0.08	12000

Notes:
1. The regression is specified as follows and estimated with Tobit:
Specialization (at neighborhood level) of new entrepreneurs
= β1 [Specialization (at neighborhood level) of established entrepreneurs] + β2 [Specialization (at borough level) of established entrepreneurs] + Constant
2. The regressions are based on a cross section of neighborhood-industry pairs. On the left hand side is the neighborhood c's specialization index in industry i of new entrepreneurs entering businesses between 2000 and 2004. On the right hand side we have two independent variables regarding the industry specializations of established entrepreneurs in year 2000. One variable is neighborhood c's specialization index in industry i, while the other is borough b's specialization in industry i, both are based on the established entrepreneurs in year 2000.
3. We present results based on varied sub-samples, to test for alternative hypotheses. Our sample is consisted of 600 neighborhoods and 20 industries. In Row (1) and Row (2), we exclude entrepreneurs who operate businesses in their own neighborhoods or boroughs respectively. In Row (3), we only include entrepreneurs who enter businesses before the April 2002 tax reform. In Row (4), we only include entrepreneurs who join the businesses within half year after incorporation. In Row (5), we only include entrepreneurs under age 30. In Row (6) and Row (7), we only count as one entry for companies with multiple directors from the same neighborhood or the same full postcode block.

Table 6: The mechanisms of social interactions

Dependent variable: industry specialization index of new entrepreneurs
Unit of analysis: neighborhood-industry pair

	(1)	(2)	(3)	(4)	(5)
"industry specialization" at neighborhood level	0.409 (0.026)***	0.362 (0.013)***	0.314 (0.015)***	0.163 (0.023)***	0.328 (0.013)***
"industry specialization" at borough level	0.457 (0.023)***	0.461 (0.022)***	0.448 (0.022)***	0.449 (0.022)***	0.454 (0.022)***
ethnic fragmentation	0.056 (0.078)				
interacted with Specialization	-0.118 (0.050)**				
urbanization		-0.119 (0.026)***			
interacted with Specialization		0.044 (0.019)**			
entrepreneurial density			-0.016 (0.003)***		
interacted with Specialization			0.012 (0.002)***		
EG index				-0.217 (0.022)***	
interacted with Specialization				0.159 (0.017)***	
industry specialization of business addresses					0.073 (0.009)***
Pseudo R^2	0.07	0.07	0.07	0.08	0.07
observations	12000	12000	12000	12000	12000

Notes:
1. The regression is specified as follows and estimated with Tobit:
Specialization (at neighborhood level) of new entrepreneurs
= β1 [Specialization (at neighborhood level) of established entrepreneurs] + β2 [Specialization (at borough level) of established entrepreneurs] + β3 Proxy for Social Interaction Intensity + β4 Proxy for social interaction intensity X Industry Specialization Index + Constant
2. The regressions are based on a cross section of neighborhood-industry pairs. On the left hand side is the neighborhood c's specialization index in industry i of new entrepreneurs entering businesses between 2000 and 2004. On the right hand side we have two independent variables regarding the industry specializations of established entrepreneurs in year 2000. One variable is

neighborhood c's specialization index in industry i, while the other is borough b's specialization in industry i, both are based on the established entrepreneurs in year 2000.

3. In Column (1), we test whether persistence of industry specialization is stronger in neighborhoods with more homogeneous ethnic composition, by including on the right hand side of the regression the ethnic fragmentation index of a neighborhood as well as its interaction term with "industry specialization index" of the established entrepreneurs. In Column (2), we instead use housing structure as a proxy for intensity of social interactions. In Column (3), we test whether persistence is stronger in neighborhoods with higher entrepreneurial population density. In Column (4), we test whether persistence is stronger in industries which are more agglomerated geographically. In Column (5), we control for industry specialization based on business addresses.

Table 7: Determinants of entrepreneurs' failures.

Dependent variable: an entrepreneur's failure
Unit of analysis: entrepreneur

	(1)	(2)	(3)	(4)
	Full Sample		Founders only	
Fixed Effects	Neighborhood	Borough	Neighborhood	Borough
Industry Specialization (at neighborhood level)	0.002 (0.017)	0.017 (0.016)	-0.020 (0.020)	0.028 (0.017)
Industry Specialization (at borough level)	-0.008 (0.031)	-0.035 (0.030)	0.033 (0.034)	-0.050 (0.032)
Log of Ages	-0.445 (0.030)***	-0.451 (0.030)***	-0.702 (0.037)***	-0.531 (0.034)***
Substantial Shareholder	0.450 (0.017)***	0.452 (0.017)***	0.827 (0.021)***	0.407 (0.018)***
Male	0.022 (0.017)	0.028 (0.017)	-0.015 (0.020)	0.026 (0.019)
Industry Fixed-Effects	Y	Y	Y	Y
Location Fixed-Effects	Y	Y	Y	Y
Pseudo R^2	0.102	0.083	0.150	0.078
Obs.	49149	49171	35904	36405

Notes:
1. The regression is specified as follows and estimated with Probit:
Failure = β1 [Specialization (at neighborhood level) of established entrepreneurs] + β2 [Specialization (at borough level) of established entrepreneurs] + individual entrepreneur characteristics + industry dummies + neighborhood (or borough) dummies + Constant
2. The regressions are based on a cross section of entrepreneurs who start their businesses during year 2000. On the left hand side is a binary variable with 1 indicating that the entrepreneur is out of business. On the right hand side we have two independent variables regarding industry specializations of established entrepreneurs in year 2000, as well as entrepreneur's individual characteristics. Regarding industry specialization, one independent variable is neighborhood c's specialization index in industry i, while the other is borough b's specialization in industry i, both are based on the established entrepreneurs in year 200. Individual characteristics include age, shareholder status and gender.
3. In all regressions, we control for industry fixed-effects. In the meantime, in Column (1) and (3), we control for neighborhood fixed-effects, while in Column (2) and (4), we control for borough fixed-effects.
4. Standard errors are robust for clustering of entrepreneurs around firms

Figure 1: Maps of Greater London and Inner London

Borough boundaries (Greater London)

Ward Boundaries (Inner London only)

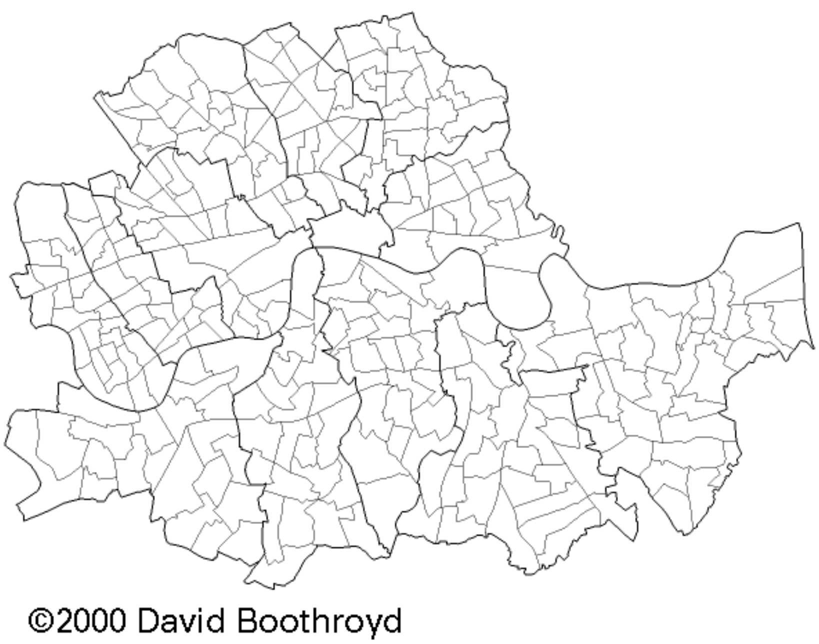

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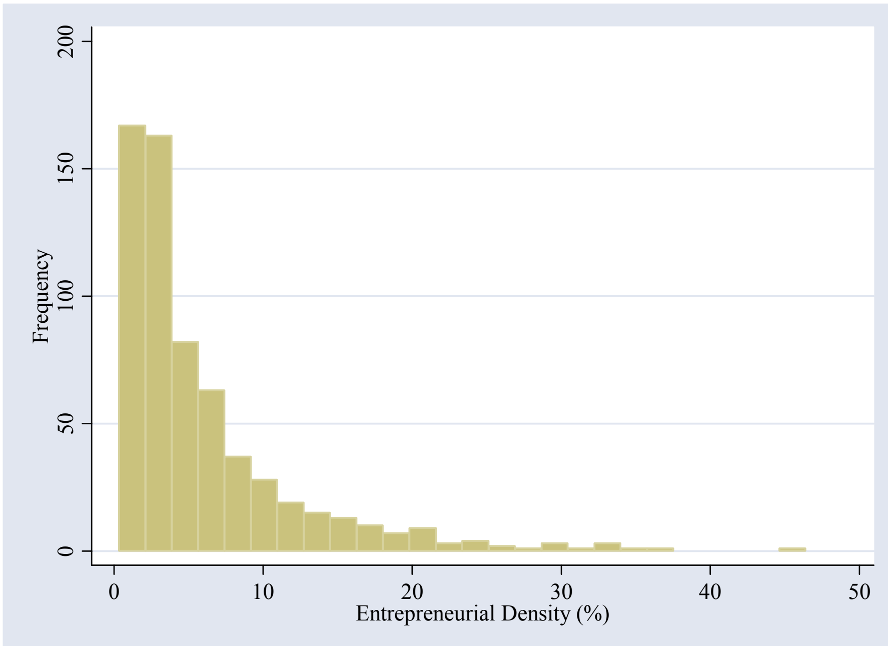
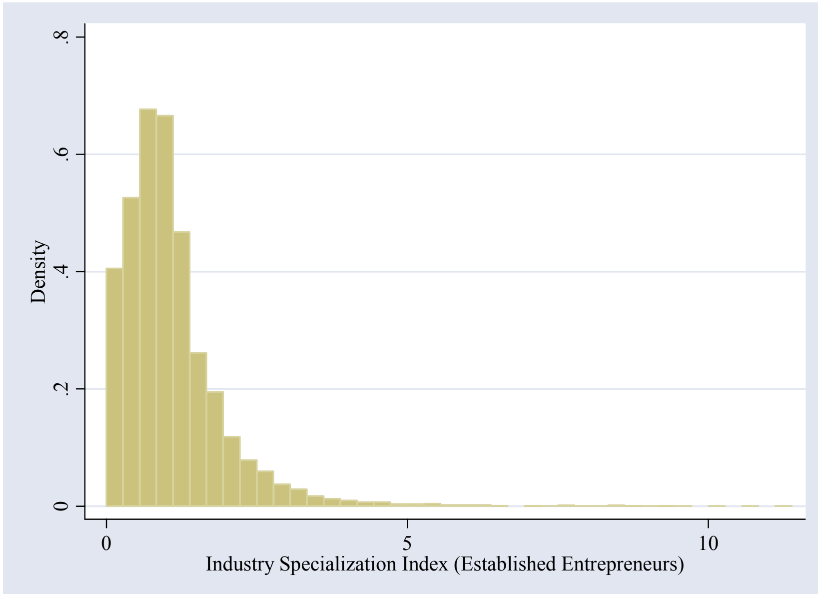
Figure 2: Histogram of entrepreneurial population density

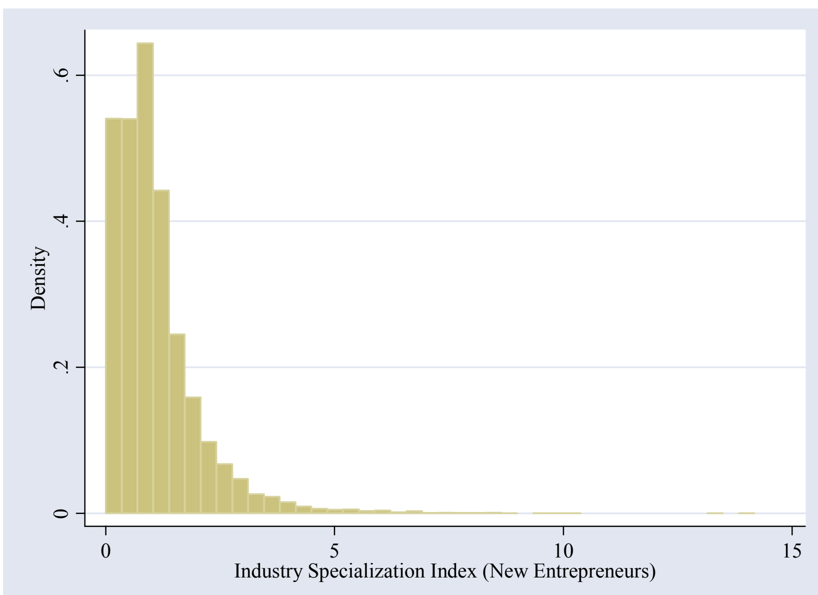


Note:
This frequency histogram shows the entrepreneurial population density in a cross section of neighborhoods in London. Entrepreneurial population density is defined as the percentage of current entrepreneurs in working age population as of year 2000.

Figure 3: Histogram of “industry specialization index”



Based on established entrepreneurs in Year 2000



Based on new entrepreneurs between January 2000 and January 2004

Notes:

1. “Industry specialization index” is as defined in section 2. 3.

2. These two density histograms show the distributions of “industry specialization index” in a cross-section of neighborhood-industry pairs (top 20 industries in top 600 neighborhoods)

3. The upper histogram is based on established entrepreneurs in year 2000, while the bottom chart is based on new entrepreneurs who enter businesses in the next four years.