View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Institutional Knowledge at Singapore Management University

Singapore Management University
Institutional Knowledge at Singapore Management University

Research Collection School Of Economics School of Economics

4-2017

Why form business partnerships?

Jungho LEE
Singapore Management University, jungholee@smu.edu.sg

Follow this and additional works at: https://ink.library.smu.edu.sg/soe_research

Part of the Entrepreneurial and Small Business Operations Commons, and the Finance Commons

Citation
LEE, Jungho. Why form business partnerships?. (2017). 1-76. Research Collection School Of Economics.
Available at: https://ink.library.smu.edu.sg/soe_research/2071

This Working Paper is brought to you for free and open access by the School of Economics at Institutional Knowledge at Singapore Management University. It has been accepted for inclusion in Research Collection School Of Economics by an authorized administrator of Institutional Knowledge at Singapore Management University. For more information, please email libIR@smu.edu.sg.

Why Form Business Partnerships?*

Jungho Lee†

April 14, 2017

Abstract

I estimate a matching model of partnerships among startup owners to quantify the relative importance of productivity gain, financing gain, and moral hazard to business-partnership formation. The productivity gain accounts for 85% of the gain from the observed partnerships. For partners in the first quintile of the wealth distribution, however, financing accounts for 85% of the gain. The moral hazard cost corresponds to 39% of the entire gain from partnerships. A government-guaranteed loan program specifically targeting partnership firms does not increase the number of partnership firms, and is ineffective in improving match quality among partners.

JEL Classification: D23, D24, L22, L26, M13

Keywords: partnership, productivity, financial constraints, moral hazard, entrepreneurship, matching

*This paper is based on the first chapter of my PhD dissertation at Washington University in St. Louis. I am greatly indebted to Barton H. Hamilton for his guidance and advice. I am also very grateful to Tat Chan, George-Levi Gayle, and Carl Sanders for their help and feedback on this project. I thank Mariagiovanna Baccara, Kyoung Jin Choi, Ignacio Esponda, Yumi Koh, Takashi Kunimoto, Gea M. Lee, Patrick Legros, Sunha Myong, JungJae Park, Thomas Sargent, Bernardo Silveira, and Aloysius Siow for helpful comments. All errors are my own.

†School of Economics, Singapore Management University, 90 Stamford Road, Singapore 178903; Email: jungholee@smu.edu.sg.

1 Introduction

Finding a partner is one of the most important decisions for potential startup owners. Successful business owners often argue that finding the right partner is the key for a firm's success.[1] Indeed, many successful companies started as partnerships. Examples include Hewlett-Packard, Procter & Gamble, and Ben & Jerry's. Yet, despite successful examples, only 16% of non-family-owned businesses began as partnerships.[2] Who forms business partnerships, and why? Answering these questions can be valuable not only for potential startup owners, but also for policy makers who try to boost entrepreneurship via partnerships.

Theoretical studies have identified gains and losses from business partnerships. Working with a partner may increase a firm's productivity by a knowledge transfer between partners. Financially constrained entrepreneurs can increase financing capacity by finding a wealthy partner. The gains, however, can be offset by moral hazard, that is, the problem of inducing optimal effort by partners when the private return to effort is smaller than the marginal product of effort. The overall impact on entrepreneurs of the option to form a partnership will depend on the magnitude of productivity gain, financing gain, and moral hazard.

In this paper, I quantify the relative importance of productivity gain, financing gain, and moral hazard in business-partnership formation by developing and estimating a model of partnership formation. The estimated model implies productivity gain between partners is the major driving force behind a partnership formation. For low-wealth partners, however, financing gain accounts for the major gains from partnerships. The moral hazard cost is high among the observed partnerships. A government-guaranteed loan program that specifically targets partnership firms is in general ineffective in that it does not increase the number of partnership firms, and its role in improving match quality among partners is less effective than a loan program targeting any startup firm.

Using the Survey of Income and Program Participation (SIPP), a nationally representative household-based survey of the US population, I first document the pattern of partnership choice of startup owners. First, business earnings of partners are significantly greater than those of measurably similar single owners. Second, the predicted probability of becoming a partner

[1] See, for example, Cohen and Eisner (2010) and Kawasaki (2004).

[2] The Survey of Income and Program Participation (SIPP). See section 2 in this paper.

is higher in the lower and upper percentile of the wealth distribution than in the middle. Third, despite the high earnings among the observed partners, only 16% of startup owners form partnerships. The high earnings of a partner may be driven either by productivity gains or by the increased investment from the other partner. The second observation may support the view that partnerships are driven by a financial motive, because low-wealth individuals are more likely to be financially constrained (Evans and Jovanovic (1989)). Moral hazard could be a reason behind the small proportion of partnerships among startup owners.

To disentangle the effect of financing and productivity motives and to quantify the cost of moral hazard, I develop a simple model of partnership formation. The model is an extension of Evans and Jovanovic (1989), an occupational choice model between a worker and an entrepreneur with collateral constraint. I incorporate into their model an option to form a partnership. By forming a partnership, financially constrained agents can increase borrowing capacity. I also allow for the possibility that working with a partner requires an additional ability, such as collaborative skills. A partnership can be formed if mutual gains in productivity exist or if one partner gains in productivity and the other partner gains in financing despite the cost of moral hazard. Who is matched with whom is determined in a stable matching in which no partner would prefer to be a single owner or a worker, and one cannot find two partners who would both rather form a partnership with each other than remain with their current partners. The model is estimated by the method of simulated moments.

The estimated model implies the increase in productivity accounts for the major gains from partnerships among those who choose to be partners: 85% of the aggregate gains for all partners are attributed to the productivity gains. The key feature in the data driving this result is that relatively more partners are observed in the upper percentile than in the lower percentile of the wealth distribution. Given that most of the financially constrained agents are estimated to be concentrated below 20th percentile of the wealth distribution, the fact that we observe more partners in the upper part of the wealth distribution implies many partnerships are formed by two relatively wealthy agents. Because they are not financially constrained, the only way we rationalize their behavior in the model is by the mutual gains in productivity.

However, the gains from financing are the major gains for low-wealth partners. For the partners in the first quintile of the wealth distribution, financing accounts for 85% of the entire gain from partnerships. The moral hazard cost is high among the observed partnerships. This cost corresponds to 39% of the entire gain from partnerships.

The estimated model enables me to quantify the extent to which financial friction generates "mismatch" among partners. The welfare loss associated with the mismatch is 3.16% of the aggregate welfare losses due to financial friction. However, a group of people − mostly agents with enough wealth − exist who gain from the mismatch. The welfare gain for these agents corresponds to 2.14% of the aggregate welfare losses due to financial friction.

Finally, I compare the effectiveness of two government-sponsored funding programs, one for any startup firm and the other for only partnership firms. The former is more effective both in helping financially constrained startup owners to create businesses and in improving the match quality among partners.

This paper is related to the literature on business partnership. Extensive theoretical studies have examined a reason behind business partnership formation. In the presence of complementarity between partners, a partnership arises as the optimal contract if the knowledge or a tacit human capital between partners is not observable or not contractible (e.g., Teece (1980); Garicano and Santos (2004); Morrison and Wilhelm (2004); Bar-Isaac (2007)).[3] On the other hand, Legros and Newman (1996) show that agents' wealth can play an important role in partnership formation in the presence of financial friction. Regarding the cost of partnerships, moral hazard between partners has been the primary theoretical concern since Holmstrom (1982).[4] I contribute to this line of literature by quantifying mechanisms discussed in theoretical studies using a parsimonious equilibrium model of partnership formation. Gaynor and Gertler (1995) and Lang and Gordon (1995) also empirically examine business partnership. They show the extent of moral hazard among partners in the professional industry depends on the degree to which the partners spread risk. This paper complements their studies by examining different motives for partnership formation that are particularly relevant to startup firms in general industries.[5]

[3] Related to this line of literature, Jensen and Meckling (1992) and Becker and Murphy (1992) point out that a firm's productivity can *decrease* due to difficulties in coordination and communication between partners.

[4] The papers that study moral hazard in teams include Radner (1986), Rasmusen (1987), Legros and Matsushima (1991), Legros and Matthews (1991), Miller (1997), Strausz (1999), Battaglini (2006), and Rahman and Obara (2010).

[5] Another difference is that I focus on the formation of business partnerships among startup owners, whereas Gaynor and Gertler (1995) and Lang and Gordon (1995) examine already established partnerships.

This paper also contributes to the literature on financial friction and new firm formation. In a seminal paper, Evans and Jovanovic (1989) suggest financial constraint hinders the optimal allocation of entrepreneurial talent. The subsequent studies show financial constraint is an important factor for starting a business (Evans and Leighton (1989); Holtz-Eakin et al. (1994); Paulson et al. (2006); Cagetti and De Nardi (2006); Adelino et al. (2015); Schmalz et al. (2016)).[6] Related to this paper, Basaluzzo (2006) and Ševčík (2015) quantify to what extent the option to find a partner can help financially constrained agents create a business, and hence increase the aggregate outcome. This paper differs from theirs in two important ways. First, Basaluzzo (2006) does not allow mutual gains in productivity, and therefore a partnership is formed only if a complementarity exists between one partner's gain in productivity and the other partner's gain in financing. Similarly, Ševčík (2015) focuses on the efficient resource allocation between two separate establishments in the presence of financial friction, and therefore does not allow a possibility that a partnership is formed due to the increase in the productivity.[7] By allowing gains in mutual productivity as another source of partnership formation, I show a potential role for financing is relatively small compared to two previous studies. For example, the number of partners increases only marginally when financial friction is introduced in the economy. Second, by allowing a match solely driven by gains in mutual productivity, I can quantify how much financial friction changes the sorting pattern among startup owners, and how much mismatch due to financial friction drives the welfare loss.[8]

This paper is also related to the literature on estimating a one-sided matching model (e.g., Gordon and Knight (2009); Weese (2015)). In attempting to overcome a challenge − we do

[6]Hurst and Lusardi (2004) challenge this view by showing a nonlinear relationship between the probability of becoming a business owner and household wealth.

[7]Ševčík (2015) defines the outcome from a partnership between two separate establishments as the sum of each establishment's outcome, which has a decreasing returns-to-scale technology with respect to capital. Because a financially constrained establishment has higher marginal returns to capital, forming a partnership with an unconstrained establishment can increase efficiency by allocating capital within a partnership. Without financial friction, however, this incentive disappears and no establishment forms a partnership.

[8]In a related paper, Åstebro and Serrano (2015) show independent inventors having a partner can significantly increase the probability of commercialization success. Different from Åstebro and Serrano (2015), I allow heterogeneous productivity gains (or losses) across agents induced by a matching equilibrium, and use the estimated model to address welfare and policy analyses. Another related paper is Eeckhout and Munshi (2010), who present a model of competitive matching in which potential borrowers and lenders are sorted into groups to exploit gains from trade in the presence of financial friction. Like this paper, they also examine how financial friction and government regulation affect the matching outcome, but the subject of interest is quite different. They are interested in an informal financial institution in India called Chit funds, whereas I focus on the business-partnership formation.

not observe who is matched with whom in the data, especially with respect to net worth − I exploit the aggregate moments, notably the outcome from the matching. For example, I use the proportion of partners and the first moment of partners' earning distribution conditional on net worth to identify the extent of financial friction.

The paper is organized as follows. Section 2 describes the data. A model of partnership formation is presented in section 3. Section 4 discusses the estimation of the matching model. The main results are presented in section 5. Section 6 presents a welfare analysis. Policy experiments are discussed in section 7. Section 8 concludes.

2 Data

The Survey of Income and Program Participation (SIPP) is used for this study. The SIPP is a nationally representative household-based survey of the United States population designed to collect information for income and program participation. I chose the SIPP for several reasons. First, the sample size is large and the survey is nationally representative. The sample size and the time periods of each panel range from approximately 14,000 to 36,000 households and from 3 to 4 years, respectively. I use panels including the years 1996, 2001, 2004 and 2008, and hence the time periods spans more than 10 years. Thanks to a large number of respondents, I can observe a relatively large number of individuals at the time they become business owners. Second, the SIPP contains information on the respondent's equity share of the business. Using this information, I can define partners versus single owners. Finally, the SIPP provides information on the net worth at the household level, so I can see the relationship between the probability of becoming a partner and household net worth *before* starting a business.[9]

[9] Two other sources provide information on ownership choice by startup owners. The Kauffman Firm Survey (KFS), a panel study of 4,928 businesses founded in 2004, provides detailed information on firm financing, but does not provide startup owners' wealth information. Another data source is the Panel Study of Entrepreneurial Dynamics (PSED). The PSED provides information on two cohorts of startup owners, the one starting a business in 1998 and the other in 2005. The PSED provides the household net-worth information by respondents, but it is collected *after* they start a business. Thus, the net-worth information in the PSED may reflect activities during the startup process, and the first-year performance of the startup. On the other hand, the SIPP provides the household net-worth information before a respondent starts a business, which is more informative in capturing financing capacity when the respondent decides whether to start a business. Moreover, the SIPP provides the information not only on startup owners but also on workers, so I can observe the aggregate proportion of startup owners as well as the income distribution conditional on worker and on startup owners. This information is required to estimate the model developed in this paper. Finally, the number of observations on startup owners in the SIPP is *more* than the one in the PSED. For example, the

Using the SIPP data, I construct a two-year panel. To limit the influence of the labor market participation, I focus on males ages 18 to 65 who are employed before they start their businesses. I drop family businesses because forming a partnership among household members does not increase the total value of household net worth, a mechanism this paper investigates. In the first year, all agents are workers. In the second year, some of the first-year workers choose to be business owners. I call the first year the base year and the second year the subsequent year. I present a detailed sample construction procedure in Appendix A.

2.1 Descriptive Analysis

A business partnership is characterized as a group that divides its profit among its members (equity holders).[10] A partner is defined as a business owner whose share of business equity is greater than or equal to 25% and less than or equal to 75%. Similarly, a business owner whose equity share is greater than 75% is defined as a single owner.[11]

Table 1 reports the summary statistics for characteristics of workers, single owners, and partners. Excluding family businesses, about 16% of startup owners chose to form partnerships. The years of education and the years of experience are similar for both types of owners. Partners are more likely to be white. They are also more likely to be married than single owners.

Figure 1 depicts the density of equity shares for those who have positive but less than 100% equity shares. Most of the equity shares are around 50%. This finding may suggest two-owner partnerships with the same equity share are the most common ownership structure among startup partnerships.[12] Bitler et al. (2005) report the same observation.

Table 2 reports the summary statistics for incomes of workers, single owners, and partners. Figure 2 depicts the density of log incomes for each group. The median income of

total number of startup owners in all cohorts of the PSED is 2,044, whereas the total number of startup owners in all cohorts of the SIPP is 3,809 as shown in Table 18. For these reasons, I choose the SIPP as the main data set for this study.

[10]The literature offers a similar definition (e.g., Holmstrom (1982); Farrell and Scotchmer (1988); Levin and Tadelis (2005)).

[11]Given that most business owners have either 50% or 100% equity share, the results in this paper are not sensitive to this particular definition of partners versus single owners.

[12]Consistent with Figure 1, in the KFS, 70% of multi-owner firms are two-owner firms, and 84% of two-owner firms that reported equity share have either 49% to 51% or 50% to 50% equity share.

startup owners is less than that of workers as is well-documented in the literature (e.g., Hamilton (2000); Pugsley (2013)). Among business owners, median income and mean income of partners are greater than those of single owners. To determine whether the same pattern is observed after controlling for other observables, I conduct a regression analysis for log incomes among startup owners. Table 3 reports the estimates for the regression of log incomes on the partnership dummy and other covariates. I first start with the typical Mincer regression in the regression equation (1) and add various controls for other regressions. For all cases, the partnership dummy is significant and indicates partners earn about 1.5 times more than the single owners.

Table 4 shows the summary statistics for the net worth of workers, single owners, and partners. Figure 3 depicts the density of net worth for each group. The wealth distribution of partners is more dispersed than that of single owners. To further investigate the relationship between the net worth and the probability of becoming a partner conditional on business ownerships, I conduct a Probit regression of partnership choice among startup owners on a fifth-order polynomial in net worth and other covariates. Table 5 reports the estimates from the Probit analysis. The predicted probability of becoming a partner is higher in the lower and upper percentile of the wealth distribution than in the middle.

Table 6 reports the number and the proportion of partners for different industries. Partnerships are observed in all industries. Based on the National Survey of Small Business Finances (NSSBF) in 1987, Hurst and Lusardi (2004) categorize construction and services as low-starting capital industries. They categorize the following as high-starting-capital industries: mining; manufacturing; transportation and public utilities; wholesale and retail trade; and finance, insurance and real estate. The partnership proportion for high-starting capital industries is greater than for low-starting capital industries (p-value 0.10).

Discussion

Two hypothesis could explain the fact that the partners earn 1.5 times more than single owners even after controlling for other observables. The first hypothesis is that the high earnings stem from productivity gains through the partnership. The second hypothesis is that the high earnings stem from the investment by a wealthy partner in a highly productive but financially constrained partner.

The fact that the predicted probability of becoming a partner is higher in the lower percentile of the wealth distribution than in the middle may support the view that startup owners' financial motives drive the partnerships. Furthermore, the fact that relatively more partners are observed in the high-starting capital industries may also support this finance-based hypothesis. One aspect of the partnership is similar to equity financing: financially constrained potential startup owners may give up some portion of equity in exchange for financing from a partner. Therefore, partnerships can be particularly attractive for low-wealth individuals who are more likely to be financially constrained.

Extensive theoretical studies identify moral hazard as a primary concern for working with a partner. Moral hazard costs may, to some extent, explain the fact that only 16% of startup owners choose to form partnerships, despite the high earnings among the observed partners.

Among lawyers and physicians, risk sharing is considered the main motive for joining a partnership (Gaynor and Gertler (1995); Lang and Gordon (1995)). However, certain features of the data are not consistent with the risk-sharing-hypothesis predictions. First, most partnerships are formed by two partners. If the motivation behind finding a partner is to share risk, the number of partners within a firm would vary depending on the partners' heterogenous risk preference. For example, if an agent is highly risk averse, he would find not just one but many partners who have a similar risk preference. Indeed, Gaynor and Gertler (1995) and Lang and Gordon (1995) report sufficient variation on the group size for physicians and law partnerships.[13] Second, as Figure 4 shows, the predicted probability of becoming a partner increases with wealth level after a certain threshold. The opposite relation is predicted if risk sharing is the main motive for forming partnerships and a decreasing absolute risk-aversion preference is assumed.[14]

Although the data pattern is consistent with several hypotheses regarding partnerships, quantifying each one is difficult without further explanation of the data-generating process. In the next section, I present a simple model of partnership formation. I use this model as a

[13]For example, Gaynor and Gertler (1995) report the average and standard deviation for the number of partners in law partnerships are 21.13 and 8.76, respectively.

[14]Consider a choice between forming a partnership and being a single owner conditional on deciding to start a business. Suppose forming a partnership generates a certain payoff, whereas being a single owner generates a risky payoff. Cressy (2000) shows the probability of becoming a single owner increases as individual wealth increases, if agents' preference exhibits a decreasing absolute risk aversion.

measurement tool to quantify the productivity gain, the financing gain, as well as the cost of moral hazard. The model is also used for welfare and policy analyses.

3 A Model of Partnership Formation

Agents make decisions in two stages. In the first stage, called the matching stage, agents decide whether to form a partnership, start a business alone, or become a worker. A partnership is formed by no more than two agents.[15] In the second stage, called the production stage, agents produce the outcome. I solve the model backwards. In section 3.1, I first introduce the environment in the production stage. In section 3.2, I present the environment in the matching stage.

3.1 The Production Stage (The Second Stage)

The environment in the production stage is an extension of Evans and Jovanovic (1989). I incorporate effort and heterogeneous partnership productivity into their model.

Preference

The utility is linear in consumption. The effort is incorporated to capture moral hazard between partners. Under the quadratic form, I can derive an analytic value function, which significantly reduces the computational burden in the estimation. The marginal rate of substitution between consumption and effort is captured by κ:[16]

$$u(c, z) = c - \kappa \frac{z^2}{2}, \quad c\text{: consumption, } z\text{: effort}$$

[15] This assumption is based on the fact that a majority of business partnership are formed by two owners. Although allowing a partnership with more than two agents is more realistic, characterizing and simulating the model would be too costly.

[16] Based on the empirical evidence discussed in section 2.1, I abstract the risk-sharing motive from the model. Basaluzzo (2006) finds that the ratio of business wealth to total wealth is on average higher among partners than single owners from the Survey of Consumer Finance (SCF), and conclude portfolio diversification does not appear to be the main reason for business-partnership formation. As a theoretical point of view, Newman (2007) argues risk-based explanations for entrepreneurship are not consistent with the tendency for entrepreneurs to be richer than workers. Allowing a convex utility can be more general, but the analytic solution for value functions will not be available, which in turn makes the computation too costly.

Technology

Income as a worker is determined by worker productivity (θ_w) and efforts. Income as a single owner is determined by solo productivity (θ_s), capital investment (k), and efforts:

$$w = \theta_w z^{1-\alpha}\epsilon_w \qquad \text{if} \quad d=1 \quad \text{(worker)}$$

$$y = \begin{cases} \left\{\theta_s k^{\alpha} z^{1-\alpha} - rk\right\}\epsilon_s & \text{if} \quad d=2 \quad \text{(single owner)} \quad \alpha \in (0,1) \\ \\ \left\{\theta_p k^{\alpha}(z+z')^{1-\alpha} - rk\right\}\epsilon_p & \text{if} \quad d=3 \quad \text{(partner)} \end{cases}$$

The partnership output is determined by partnership productivity (θ_p), the joint capital investment, and the efforts from both partners. Under this partnership production function, the efficient outcome from two identical partners is the same as the sum of each partner's outcome if the solo and partnership productivity are the same (Corollary 1 in section 3.1.2). Moreover, the value from single ownership is the same as the value from hiring the potential partner as an employee if we interpret hiring an agent as a situation in which (1) the productivity does not change from the solo productivity, (2) the wage contract is set to eliminate moral hazard of the worker, and (3) the wage is equal to the marginal benefit of hiring the agent. I allow the earning shocks to workers (ϵ_w), to single owners (ϵ_s), and to partners (ϵ_p) with the assumption that the expectation of the shocks is equal to 1.[17]

Financial Market

Without financial friction, agents can borrow any amount of money for the risk-free gross interest rate r. A financial friction is modelled as a limited commitment between borrowers and lenders. The fact that lenders cannot force borrowers to repay a loan limits the maximum amount of borrowing. I assume the maximum borrowing amount depends on the borrowers' net worth. More specifically, a single owner can borrow up to $(\lambda-1)A$. λ is a constant that is greater than or equal to 1. Therefore, the maximum amount of investment by the single owner is $(\lambda-1)A + A = \lambda A$. If he forms a partnership with another agent with net worth A',

[17] Business owners in SIPP were asked to report their profits as business earnings. To make the model consistent with the data, I specified a random shock as a shock to a firm's profit.

the partnership can invest up to $\lambda(A + A')$.

3.1.1 Value Functions and Earned Incomes

I first consider the value function and earned incomes for partners. The occupational choice made in the first stage is assumed to be irreversible, and therefore the outside option for each partner when the partnership dissolves is zero. The equity share is assumed to be determined as the symmetric Nash bargaining solution. The solution is equal sharing.[18] In the matching stage, however, agents may use an ex-ante transfer to attract a better partner. I discuss this issue more in section 3.2.2.

Effort in an entrepreneurial team is spent on activities such as generating an idea, validating the business idea, and developing a business model. Effort in these types of activities is hard to observe or monitor. For this reason, I assume effort is not observable.

Suppose agent i and agent j are matched and their partnership productivity is given as θ_p. The partners choose $\{z_i, z_j, k\}$, their effort levels and the joint investment. $\{z_i, z_j, k\}$ is determined as the Nash equilibrium of a simultaneous-move game between two partners.

Given $\{z_j, k\}$, the best-response function for z_i solves

$$\max_{z_i} \mathbb{E}\Big[\frac{1}{2}\big\{\theta_p k^{\alpha}(z_i + z_j)^{1-\alpha} - rk\big\}\epsilon_p\Big] - \kappa\frac{z_i^2}{2}$$

Likewise, given $\{z_i, k\}$, the best response of z_j solves

$$\max_{z_j} \mathbb{E}\Big[\frac{1}{2}\big\{\theta_p k^{\alpha}(z_i + z_j)^{1-\alpha} - rk\big\}\epsilon_p\Big] - \kappa\frac{z_j^2}{2}$$

Finally, given $\{z_i, z_j\}$, k solves

$$\max_{k} \mathbb{E}\Big[\big\{\theta_p k^{\alpha}(z_i + z_j)^{1-\alpha} - rk\big\}\epsilon_p\Big]$$

[18] Equal sharing is a defining feature of partnerships. For example, Farrell and Scotchmer (1988) define a partnership as "a group that divides its output equally among its members." Indeed, many data sources, including the sample in this paper, indicate two owners with equal shares are the most common partnership structure. Many studies investigate theoretical implications of equal sharing in partnerships (e.g., Farrell and Scotchmer (1988); Sherstyuk (1998); Levin and Tadelis (2005)). Others provide a rationale for equal sharing among partners (e.g., Bartling and von Siemens (2010); Espino et al. (2015)). Moreover, under the production technology in section 3.1, the equal sharing is the sharing rule that maximizes the aggregate outcome from a partnership.

The earned incomes and value function *per* partner are given as

$$\pi_p(\theta_p, A_p) = \frac{1}{2}\Big[\theta_p k^{*\alpha}(2z^*)^{1-\alpha} - rk^*\Big]\epsilon_p$$

$$= \begin{cases} a_1\theta_p^{\frac{2}{1-\alpha}}\epsilon_p & \text{if} \quad \lambda A_p \geq \hat{a}\theta_p^{\frac{2}{1-\alpha}} \\ \\ \Big\{a_8\Big(\frac{\lambda A_p}{2}\Big)^{\frac{2\alpha}{1+\alpha}}\theta_p^{\frac{2}{1+\alpha}} - \frac{r\lambda A_p}{2}\Big\}\epsilon_p & \text{if} \quad \lambda A_p < \hat{a}\theta_p^{\frac{2}{1-\alpha}} \end{cases}$$

$$V_p(\theta_p, A_p) = \mathbb{E}[\pi_p(\theta_p, A_p)] - \kappa\frac{z^{*2}}{2}$$

$$= \begin{cases} a_3\theta_p^{\frac{2}{1-\alpha}} & \text{if} \quad \lambda A_p \geq \hat{a}\theta_p^{\frac{2}{1-\alpha}} \\ \\ a_4\Big(\frac{\lambda A_p}{2}\Big)^{\frac{2\alpha}{1+\alpha}}\theta_p^{\frac{2}{1+\alpha}} - \frac{r\lambda A_p}{2} & \text{if} \quad \lambda A_p < \hat{a}\theta_p^{\frac{2}{1-\alpha}} \end{cases}$$

where

$$A_p = A_i + A_j, \quad \hat{a} = \Big(\frac{1-\alpha}{\kappa}\Big)\Big(\frac{\alpha}{r}\Big)^{\frac{1+\alpha}{1-\alpha}}, \quad a_3 = \hat{a}r\Big(\frac{1-\alpha}{\alpha}\Big)\Big(\frac{3}{8}\Big),$$
$$a_4 = \Big(\frac{1-\alpha}{2\kappa}\Big)^{\frac{1-\alpha}{1+\alpha}}\Big(\frac{3+\alpha}{4}\Big), \quad a_1 = \hat{a}r\Big(\frac{1-\alpha}{2\alpha}\Big), \quad a_8 = \Big(\frac{1-\alpha}{2\kappa}\Big)^{\frac{1-\alpha}{1+\alpha}}$$

Given the worker productivity θ_w, workers choose effort to maximize their utility. The earned incomes and value function as a worker aregiven as

$$\pi_w(\theta_w) = a_6\theta_w^{\frac{2}{1+\alpha}}\epsilon_w$$

$$V_w(\theta_w) = a_2\theta_w^{\frac{2}{1+\alpha}}$$

where

$$a_2 = \Big(\frac{1-\alpha}{\kappa}\Big)^{\frac{1-\alpha}{1+\alpha}}\Big(\frac{1+\alpha}{2}\Big), \quad a_6 = \Big(\frac{1-\alpha}{\kappa}\Big)^{\frac{1-\alpha}{1+\alpha}}$$

Single owners optimally choose the amount of investment and efforts, and the earned incomes and value function are given as

$$\pi_s(\theta_s, A) = \begin{cases} 2a_1\theta_s^{\frac{2}{1-\alpha}}\epsilon_s & \text{if} \quad \lambda A \geq \hat{a}\theta_s^{\frac{2}{1-\alpha}} \\ \\ \left\{a_6(\lambda A)^{\frac{2\alpha}{1+\alpha}}\theta_s^{\frac{2}{1+\alpha}} - r\lambda A\right\}\epsilon_s & \text{if} \quad \lambda A < \hat{a}\theta_s^{\frac{2}{1-\alpha}} \end{cases}$$

$$V_s(\theta_s, A) = \begin{cases} a_1\theta_s^{\frac{2}{1-\alpha}} & \text{if} \quad \lambda A \geq \hat{a}\theta_s^{\frac{2}{1-\alpha}} \\ \\ a_2(\lambda A)^{\frac{2\alpha}{1+\alpha}}\theta_s^{\frac{2}{1+\alpha}} - r\lambda A & \text{if} \quad \lambda A < \hat{a}\theta_s^{\frac{2}{1-\alpha}} \end{cases}$$

To summarize, the individual choice (d) and the corresponding conditional income (π) are

$$d = \arg\max\left\{V_w(\theta_w), V_s(\theta_s, A), V_p(\theta_p, A_p)\right\}$$

$$\pi = \begin{cases} \pi_w(\theta_w) & \text{if} \quad d = 1 \quad \text{(worker)} \\ \\ \pi_s(\theta_s, A) & \text{if} \quad d = 2 \quad \text{(single owner)} \\ \\ \pi_p(\theta_p, A_p) & \text{if} \quad d = 3 \quad \text{(partner)} \end{cases}$$

3.1.2 Decomposing Benefits and Costs of Partnerships

Before further discussions, I derive the value for each partner from the first-best allocation. In doing so, I assume the aggregate production from the efficient allocation is distributed equally among partners.

Proposition 1. *The value function for each partner from the efficient allocation under financial friction is given as (1)*

$$V_p^E(\theta_p, A_p) = \begin{cases} a_1\theta_p^{\frac{2}{1-\alpha}} & \textit{if} \quad \frac{\lambda A_p}{2} \geq \hat{a}\theta_p^{\frac{2}{1-\alpha}} \\ \\ a_2\left(\frac{\lambda A_p}{2}\right)^{\frac{2\alpha}{1+\alpha}}\theta_p^{\frac{2}{1+\alpha}} - \frac{r\lambda A_p}{2} & \textit{if} \quad \frac{\lambda A_p}{2} < \hat{a}\theta_p^{\frac{2}{1-\alpha}} \end{cases} \tag{1}$$

Proof See Appendix C.1.

With Proposition 1 in hand, it is straightforward to prove the following corollaries:

Corollary 1. $V_p^E(\theta_s, 2A) = V_s(\theta_s, A)$

Suppose two identical agents form a partnership and the solo and partnership productivity are the same. Corollary 1 says the sum of each partner's value as a single owner is equal to the aggregate value of the partnership. Three channels make the value from partnerships different from the value from single ownership.

Corollary 2. $V_p^E(\theta_p, 2A) = V_s(\theta_p, A) > V_s(\theta_s, A)$ *if and only if* $\theta_p > \theta_s$

Suppose $A = A'$. The first-best value from partnerships is greater than the value from single ownership if and only if the partnership productivity is greater than the solo productivity. The value difference in Corollary 2 captures the value generated by the partnership productivity.

Corollary 3. $V_p^E(\theta_s, A_p) > V_s(\theta_s, A)$ *if and only if* $A' > A$ *and* $\lambda A < \hat{a}\theta_s^{\frac{2}{1-\alpha}}$

Although the partnership productivity and the solo productivity are the same, if an agent is financially constrained as a single owner and his partner's net worth is greater than his net worth, the value from the partnership is strictly greater than the value from single ownership if no moral hazard exists. The value difference in Corollary 3 captures the value generated by financing. Notice that if no financial friction exists, the value difference induced by financing would be zero.

Corollary 4. $V_p(\theta_s, 2A) < V_p^E(\theta_s, 2A) = V_s(\theta_s, A)$

Finally, the moral hazard cost is captured by the value difference in Corollary 4.

To summarize,

$$V_p(\theta_p, A_p) - V_s(\theta, A) = \underbrace{V_p^E(\theta_p, 2A) - V_s(\theta_s, A)}_{\Omega_1} + \underbrace{V_p^E(\theta_p, A_p) - V_s(\theta_p, A)}_{\Omega_2}$$

$$+ \underbrace{V_p(\theta_p, A_p) - V_p^E(\theta_p, A_p)}_{\Omega_3} \tag{2}$$

where Ω_1 represents gains from productivity, Ω_2 represents gains from financing, and Ω_3 captures the moral hazard cost.

3.2 The Matching stage (The First Stage)

In this section, I describe the environment for the matching stage. Section 3.2.1 describes how the partnership productivity is determined if two agents are matched, and section 3.2.2 describes the environment for the matching market.

3.2.1 Matching Function and Complementarities

First, I model partnership productivity as a function of the solo productivity of each partner. More specifically,

$$\theta_p(i,j) = \sqrt{\tilde{\theta}_i \tilde{\theta}_j} \quad \text{where} \quad \tilde{\theta}_i = g_i \theta_{si}, \quad \tilde{\theta}_j = g_j \theta_{sj}, \quad g_i, g_j > 0 \tag{3}$$

Knowledge transfer has been considered the key mechanism through which teamwork increases productivity (Lazear (1998); Argote and Ingram (2000)). However, knowledge transfer is hard and it can be costly due to difficulties in coordination and communication (Arrow (1969); Teece (1977); Becker and Murphy (1992); Jensen and Meckling (1992); Haas and Hansen (2005); Jones (2009)). "Collaborative skill" (Hamilton et al., 2003) and "willingness to cooperate" (Kosfeld and von Siemems, 2011) are necessary to facilitate the knowledge transfer. More importantly, such characteristics are heterogenous across individuals independent of the quality of their business idea. g captures this additional element for teamwork. I call this additional element "collaborative skill." Depending on individual skills for collaborating, it can enhance ($g > 1$) or reduce ($g < 1$) the solo productivity when partners work together. As a result, the productivity as a partner ($\tilde{\theta}$) can be different from the solo productivity (θ_s).

To model the partnership productivity in a tractable way, I impose a couple of assumptions in (3). First, the collaborative skill (g) interacts with the solo productivity (θ_s). Second, the contribution to partnership productivity by each partner is the same. Moreover, if two identical partners are matched, the partnership productivity is the same as their individual productivity as a partner. In particular, if we shut down the additional productivity channel by making g equal to 1, the partnership productivity is the same as the solo productivity when two identical agents are matched.

To explain how a partnership can be formed, I introduce the following two definitions.

Definition 1. *There exists complementarity between two partners' solo productivities in a partnership by Agent i and Agent j if* $\theta_p(i,j) \geq \max\{\theta_{si}, \theta_{sj}\}$.

Definition 2. *There exists complementarity between one partner's solo productivity and the other partner's wealth in a partnership by Agent i and Agent j if (1) one partner, say, Agent i, is financially constrained as a single owner, and (2) the other partner, Agent j, has more net worth than the financially constrained partner and* $\theta_p(i,j) > \theta_{sj}$.

Suppose no borrowing constraint exists. Then $V_p^E(\theta_p(i,j), A_p) \geq \max\{V_s(\theta_{si}, A_i), V_s(\theta_{sj}, A_j)\}$ if and only if $\theta_p(i,j) \geq \max\{\theta_{si}, \theta_{sj}\}$ by Corollary 2 in section 3.1.2. Therefore, without financial friction, a partnership is formed only if there exists complementarity between two partners' solo productivities.

If a borrowing constraint exists, a partnership is formed even without the complementarity between two partners' solo productivities. The intuition is found in Corollary 3. If a partner is financially constrained as a single owner, he may be willing to sacrifice his productivity for financing. Definition 2 captures this situation.

The complementarity between two partners' solo productivities and the complementarity between one partner's solo productivity and the other partner's wealth are not mutually exclusive. For example, a financially constrained agent may be matched with a more productive and wealthier agent if his productivity as a partner is high enough. To determine an equilibrium, who is matched with whom, I impose another structure on the matching market.[19]

3.2.2 Matching Market

I model the matching market as a frictionless roommate matching problem. Unlike the marriage matching market, I cannot separate market participants into two groups. I consider a market without search friction as a benchmark environment. As a robustness check, I re-estimated the model under the assumption that two agents in the population are randomly matched to each other, and are not allowed to form a partnership with any other agent except for the randomly matched agent. The result is discussed in Appendix E.

[19] Under the joint production technology defined in section 3.1, which is multiplicatively separable between the matching function and the joint effort, a concern about moral hazard does not affect the sorting pattern (Vereshchagina (2016)). Nevertheless, the moral hazards affect the matching outcome by decreasing the joint value from any partnership, and hence by decreasing the incentive for individuals to form a partnership.

Although equal sharing of equity is the most common ownership structure for partnership firms, some of those partnerships may be involved with ex-ante cash transfers. Before choosing between a non-transferable and transferable utility setup, I simulate two identical economies and compare the selection pattern – the number of agents for each occupation – and the sorting pattern under two different assumptions: one under non-transferable utility and the other under transferable utility. A detailed explanation for this analysis is found in Appendix D. Overall, both the selection and the sorting pattern are very similar under two assumptions. On the other hand, the computational time is much more costly for finding a stable matching with allowing ex-ante transfers. For these reasons, I choose the non-transferable utility with the equal sharing as the benchmark for estimation.

N agents exist. Let I denote the set of agents. An agent $i \in I$ is characterized by $\{g_i, \theta_{si}, A_i\}$. I assume θ_{si} is drawn from a continuous distribution, and therefore every agent has a different value of θ_s. A *matching* Γ is a one-to-one mapping from I onto itself such that for all $\{i, j\} \subset I$, $\Gamma(i) = j$ if and only if $\Gamma(j) = i$. A matching is *stable* if (i) no partner would prefer to be a single owner or worker, and (ii) one cannot find two partners who would both rather form a partnership with each other than remain with their current partners.

Proposition 2. *A unique stable matching exists.*

Proof With 50% to 50% equity share, the value per partner from any partnership is symmetric. Moreover, for any agent $i \in I$, the value from partnership with $k \in I$ – including to remain single – is different for all k because every agent has a different value of θ_s. In other words, every agent has a strict preference over I. Under these two conditions, a unique stable matching exits according to Gordon and Knight (2009). ■

Without a borrowing constraint, characterizing a stable matching is straightforward by the matching function in (3). For expositional purposes, assume g is so large that every agent wants to form a partnership rather than remain as either a worker or single owner. Sort agents in I with respect to $\tilde{\theta}$ and denote the agent with the highest $\tilde{\theta}$ be 1 and so on. With (3), every agent wants to be matched with Agent 1. Choosing his partner is then Agent 1's decision. Again, under (3), Agent 1 wants to form a partnership with Agent 2. By iterating this procedure, we can find a stable matching. The stable matching exhibits a positive assortative matching with respect to $\tilde{\theta}$.

With a borrowing constraint, however, the stable matching under no borrowing constraint can alter because of the financial motive for financially constrained agents. For example, consider a partnership formed by Agent 1 and Agent 2 in the above example. If financial friction is introduced, Agent 1 and Agent 2 may not be able to finance the optimal amount of capital, and the value from their partnership may decrease. Suppose Agent 3 has a marginally lower productivity but has a much higher net worth than Agent 2. With financial friction, Agent 1 may prefer to be matched with Agent 3 because he can increase financing capacity with Agent 3 without sacrificing much productivity.

3.3 Computational Algorithm

Before characterizing the stable matching with and without financial friction, I introduce a computational algorithm to find the stable matching:

```
STEP1

  - Count the number of agents in the matching market, and call it N.
  - Pick any agent in the matching market and call him 'i1.'
  - Find the most preferred agent, including himself, for agent 'i1.'  Call the
    chosen agent 'i2.'

STEP2

  - If 'i2' is equal to 'i1,' that is, if the agent 'i1' prefers to be either a
    worker or a single owner to forming a partnership with the best agent in the
    market, 'i1' goes out of the matching market and become either a worker or
    a single owner.  Go to STEP1 and pick an remaining agent in the market and
    call him 'i1.'  Replace the number of agents in the matching market with N−
    1.
  - If 'i2' is not equal to 'i1,' go to STEP3.

STEP3

  - Find the most preferred agent, including himself, for agent 'i2.'  Call the
    chosen agent 'i3.'
  - If 'i3' is equal to 'i2,' 'i2' goes out of the matching market and become either
    a worker or a single owner.  Go to STEP1 and pick an remaining agent in the
```

```
market and call him ‘i1.’  Replace the number of agents in the matching market
with N − 1.
```

```
- If ‘i3’ is equal to ‘i1,’ then ‘i2’ and ‘i1’ form a partnership and go out
  of the matching market together.  Go to STEP1 and pick a remaining agent in
  the market and call him ‘i1.’  Replace the number of agents in the matching
  market with N − 2.
- If ‘i3’ is not equal to either ‘i1’ or ‘i2,’ go to STEP1 and call ‘i3’ ‘i1.’
```

Starting with the entire sample, the computational algorithm terminates when no agent is left in the matching market. Note this algorithm is not guaranteed to terminate if a stable matching does not exist. For example, consider a matching market with three agents. Suppose Agent 1's best option is to form a partnership with Agent 2, Agent 2's best option is to form a partnership with Agent 3, and Agent 3's best option is to form a partnership with Agent 1. The above algorithm never terminates in this example. Thanks to the uniqueness result proven in section 3.2.2, however, the algorithm always terminate with the current model, and the computation time is quite fast even with more than 10,000 observations. Practically, if I sort the entire sample with respect to their ability as a partner, and start the algorithm with the agent with the highest ability as a partner, the computation time is the shortest.

3.4 Characterization

A simple example

I first present a simple example that can clearly show how financial friction changes the stable matching. Suppose four agents are in the market. The outside option value for workers is assumed to be zero and hence the relevant characteristics for matching is $\{g_i, \theta_{si}, A_i\}$. Assume g_i is 1.2 so that we can focuss on $\{\theta_{si}, A_i\}$. Assume

$$\{\theta_{s1}, A_1\} = \{2.1, 0\}, \quad \{\theta_{s2}, A_2\} = \{2, 0\}, \quad \{\theta_{s3}, A_3\} = \{1.1, \infty\}, \quad \{\theta_{s4}, A_4\} = \{1, \infty\}$$

For convenience, let $a_1 = 1$, $\alpha = 0.5$.

First, I consider a situation in which no borrowing constraint exists. The outside option value as a single owner for each agent is the following:

$$V_{s1} = \theta_{s1}^4 = 19.45, \quad V_{s2} = \theta_{s2}^4 = 16, \quad V_{s3} = \theta_{s3}^4 = 1.46, \quad V_{s4} = \theta_{s4}^4 = 1$$

It is easy to check that Agent 1 is matched with Agent 2 and Agent 3 is matched with Agent 4 in the stable matching. The value from the matching is

$$V_p(1,2) = \frac{3}{4}\Big(\theta_p(1,2)^4\Big) = 27.43, \quad V_p(3,4) = \frac{3}{4}\Big(\theta_p(3,4)^4\Big) = 1.88$$

Note $\theta_p(1,2) \geq \max\{\theta_{s1}, \theta_{s2}\}$ and $\theta_p(3,4) \geq \max\{\theta_{s3}, \theta_{s4}\}$, and hence both partnerships are driven by the complementarity between two partners' solo productivities.

Suppose now a borrowing constraint exists. The outside option value as a single owner changes:

$$V_{s1} = 0, \quad V_{s2} = 0, \quad V_{s3} = \theta_{s3}^4 = 1.46, \quad V_{s4} = \theta_{s4}^4 = 1$$

In this situation, it is easy to check that Agent 1 is matched with Agent 3 and Agent 2 is matched with Agent 4 in the stable matching. The value from the matching is

$$V_p(1,3) = \frac{3}{4}\Big(\theta_p(1,3)^4\Big) = 8.3, \quad V_p(2,4) = \frac{3}{4}\Big(\theta_p(3,4)^4\Big) = 6.22$$

Note $\theta_p(1,3) < \max\{\theta_{s1}, \theta_{s2}\}$ and $\theta_p(2,4) < \max\{\theta_{s3}, \theta_{s4}\}$, and hence both partnerships are driven by the complementarity between one partner's solo productivity and the other partner's wealth, not by the complementarity between two partners' solo productivities.

Financial Friction, Number of Partners, and Sorting Pattern

To see how financial friction affects the sorting pattern across individuals, I parameterize an economy as below, and simulate 10,000 individuals:

$$\{\kappa, \alpha\} = \{1, 0.3\}, \quad \theta_w = 1, \quad \log\theta_s \sim N(1,1), \quad \log g \sim N(0,1), \quad \log A \sim N(0,10)$$

Then by using the computational algorithm developed in section 3.3, I find the stable matching. I first find the stable matching without financial friction. The sorting pattern with respect to an individual's ability as a partner, $\log(g \cdot \theta_s)$, is shown at the upper panel in Figure 5. As illustrated in section 3.2.2, the positive assortative matching is clearly observed, and the correlation is 1. The sorting pattern with respect to individual log wealth is shown in the upper panel in Figure 6. If no financial friction exists, wealth does not affect a match between two partners, and as a result, we observe no relationship between two partners' wealth levels. The correlation is zero.

With the same simulated individuals, I next solve the stable matching by assuming λ is equal to 1. Before discussing the sorting pattern, I first show how the number of workers, single owners, and especially partners change. As Table 7 shows, the number of partners increases almost 20% when the financial constraint is imposed. When financial friction is introduced, additional gains from forming a partnership arise due to complementarity between one partner's ability and the other partner's wealth, as described in Definition 2. As a result, some agents who could have been single owners choose to form a partnership, and the total number of partners increases.

This simulation suggests the impact of financial friction on the extensive margin of business ownership could be overstated if we ignore the option to form a partnership. In the current simulation, the proportion of business owners decreases less than 2% even with the severe financial constraint ($\lambda = 1$). In section 5.3, I quantify the extent to which the option to form a partnership alleviates the barrier to becoming a business owner in the presence of financial friction by using the estimated model.

Financial friction not only changes the number of partners, but also changes the sorting pattern among partners. The sorting pattern with respect to an individual's ability as a partner is shown in the lower panel in Figure 5. Comparing the sorting pattern without financial friction, the extent of positive assortative matching is reduced. The correlation between two partners' ability becomes 0.76 as opposed to 1 in the case without financial friction.

The sorting pattern with respect to wealth is shown in the lower panel in Figure 6. Contrary to the case without financial friction in which the correlation between two partners' wealth is zero, a clear negative assortative matching pattern is observed when the financial constraint is imposed. The correlation between two partners' wealth when $\lambda = 1$ is -0.67.

In sum, financial friction may increase the number of partners, decrease the extent of positive assortative matching with respect to an individual's ability, and induce a negative assortative matching with respect to an individual's wealth. In section 6, I quantify the welfare implication from these changes in detail.[20]

4 Estimation

4.1 Specification

Before estimation, I specify wage equation, solo productivity, and the collaborative skill. The specification is similar to the one in Evans and Jovanovic (1989), Xu (1998), and Paulson et al. (2006).

Wage Equation

Remember log earnings for workers are characterized by $\log \pi_w = \log a_6 + \frac{2}{1+\alpha} \log \theta_w + \log \epsilon_w$ where $a_6 = (\frac{1-\alpha}{\kappa})^{\frac{1-\alpha}{1+\alpha}}$. I assume log earnings for workers are a function of education (x_1) and experience (x_2), by setting $\log \theta_w = \gamma_1 \log x_1 + \gamma_2 \log x_2$:

$$\log \pi_w = \log a_6 + \hat{\gamma}_1 \log x_1 + \hat{\gamma}_2 \log x_2 + \log \epsilon_w$$

where $\hat{\gamma}_1 = \frac{2\gamma_1}{1+\alpha}$ and $\hat{\gamma}_2 = \frac{2\gamma_2}{1+\alpha}$. The earning shock follows a log normal distribution with the expected value being equal to 1 (i.e., $\log \epsilon_w \sim N(-\frac{1}{2}\sigma_w^2, \sigma_w^2)$) following Evans and Jovanovic (1989).

Solo Productivity

The solo productivity is assumed to be a function of education, experience, net worth, and an unobserved component:

$$\log \theta_s = \beta_0 + \beta_1 \log A + \beta_2 \log x_1 + \beta_3 \log x_2 + \eta, \quad \text{where} \quad \eta \sim N(0, \sigma_\eta^2)$$

[20] In Appendix F, I characterize and discuss two more matching outcomes, one allowing a correlation between the solo productivity and net wealth, and the other allowing a correlation between the collaborative skill and the worker ability.

Similar to Evans and Jovanovic (1989) and Paulson et al. (2006), I allow a possible relationship between an agent's net worth and his value as a single owner even without financial friction.

Collaborative Skill

I specify g as a function of an observable and unobservable component:

$$\log g = g_0 + g_1 \log x_1 + g_2 \log x_2 + u, \quad u \sim N(0, \sigma_u^2) \tag{4}$$

As explained in section 3.2.1, g represents an additional ability as a partner, such as collaborative skill. Education and work experience are inevitably involved with social interaction, and therefore may help to develop the collaborative skill.

A critical assumption is that g is not a function of net worth. As explained in section 4.2, this assumption is required for identification of λ. Note that even if g is not a function of net worth, the partnership productivity is a function of net worth because it is also affected by θ_s, which is a function of net worth. Also note that even if the solo productivity θ_s and the collaborative skill g are independent, solo productivity and an individual's ability as a partner are not because ability as a partner is specified as $\tilde{\theta} = g \cdot \theta_s$ in section 3.2.1.

In reality, those who have high collaborative skill may earn more as a wage worker. With the current data, however, identifying the correlation between the worker productivity and the collaborative skill is difficult. As a robustness check, I allow a correlation between an unobserved heterogeneity in worker productivity and the collaborative skill, and discuss the implication for my main results in Appendix F.

Earning Shocks for Business Owners

As Figure 2 shows, the distribution of conditional income for business owners looks similar to a log-normal distribution with a possible realization of a zero or negative income. To capture this stylized feature of the data, I assume the expected value of an earnings shock for business owners is equal to 1, and allow its realization can be a negative value:

$$\epsilon_s = \tilde{\epsilon}_s - P_s, \quad \log \tilde{\epsilon}_s \sim N(\mu_s, \sigma_s^2), \quad \mathbb{E}[\epsilon_s] = 1, \quad P_s \text{ is a positive constant.}$$

$$\epsilon_p = \tilde{\epsilon}_p - P_p, \quad \log \tilde{\epsilon}_p \sim N(\mu_p, \sigma_p^2), \quad \mathbb{E}[\epsilon_p] = 1, \quad P_p \text{ is a positive constant.}$$

4.2 Identification

The unique stable matching generates the proportion of workers, single owners, and partners as well as the distribution of earnings conditional on each choice as an equilibrium outcome. The analytic representations of these aggregate outcomes are not feasible, and I provide an informal argument for how a given set of aggregate moments can identify the model parameters.

Given the assumption of lognormality, the distribution of the solo productivity is characterized by the mean ($\{\beta_0, \beta_1, \beta_2, \beta_3\}$) and the standard deviation (σ_η). Also, the distribution of the collaborative skill is characterized by the mean ($\{g_0, g_1, g_2\}$) and the standard deviation (σ_u). I will first explain the moments that can be informative to identify the mean parameters. Suppose β_0 increases. The average quality of a business idea among the entire population will be higher, and more people will start a business. Therefore, the proportion of startup owners among the entire population can identify β_0. Likewise, the proportion of startup owners among the entire population conditional on net worth, on education, and on experience can identify β_1, β_2, and β_3, respectively. We can apply a similar argument to identify $\{g_0, g_1, g_2\}$. Suppose g_0 has increased. More people can generate a high value as a partner, and the number of partners will increase in the stable matching. As a consequence, the proportion of partners among startup owners will increase. Therefore, the proportion of partners among startup owners can identify g_0. Likewise, the proportion of partners among startup owners conditional on education and on experience identify g_1 and g_2, respectively.

Note that observed log incomes by single owners reflect a truncated distribution of the solo productivity. Given the solo productivity, the observed log incomes by partners reflect a truncated distribution of the collaborative skill. Therefore, σ_η and σ_u will change the average log income for observed single owners and for observed partners, respectively. In particular, as σ_η becomes higher, the average log income for single owners conditional on either education or experience will be higher, and therefore these moments can be used to identify σ_η. Likewise, the average log income for partners conditional on either education or experience can be used to identify σ_u.

Given the independence of the worker productivity from the solo productivity and from the collaborative skill, the average income for workers conditional on education and on experience can identify γ_1 and γ_2, respectively. With the conditional mean of log income for workers, for single owners, and for partners being used to identify other parameters, the unconditional mean of log income for workers, for single owners, and for partners can be used to identify κ and α.

A couple of data moments identify λ. First, the proportion of partners among business owners conditional on net worth is only affected by λ given β_1. Consider, for example, business owners with a small net worth in which the measure of constrained single owners is positive. As λ becomes smaller, the value of those constrained single owners also decreases. As a result, those owners whose value as a single owner is marginally higher than their value as a worker or as a partner will change their choice either to workers or to partners. In either case, the proportion of partners among business owners conditional on the small net worth will increase. Second, λ also affects the average income both for single owners and for partners conditional on net worth, by affecting the income for financially constrained business owners.

Finally, the variance of log incomes for workers identifies σ_w. The variance of log incomes for single owners identifies σ_s given P_s. Given σ_s, the proportion of zero- or negative-income single owners identifies P_s. Likewise, the variance of log incomes for partners and the proportion of zero- or negative-income partners identify σ_p and P_p.

4.3 Method of Simulated Moments

The model is estimated by the method of simulated moments. To estimate the model, the unique stable matching is solved for each parameter value and for each simulation using the computational algorithm developed in section 3.3. To compare the data with the model-simulated moments, I use the moments calculated from the 2004 SIPP panel, which exhibits the most observations for both single owners and partners.[21]

[21] In other words, I consider the entire United States in a particular year as the relevant matching market for estimation. The same assumption is used in Choo and Siow (2006) when they estimate a model of the marriage market. By combining information from all industries, an industry-specific effect is more likely to be

The criterion function is given in (5):

$$M(\psi) = \Big[\sum_{i=1}^{n} Z_i\big(K_i - \tilde{K}_i(\psi)\big)\Big]' \hat{\Sigma}^{-1} \Big[\sum_{i=1}^{n} Z_i\big(K_i - \tilde{K}_i(\psi)\big)\Big] \tag{5}$$

$$\text{where} \quad \tilde{K}_i(\psi) = \frac{1}{ns}\sum_{s=1}^{ns} k_i^s(\psi)$$

Z_i represents a vector of instruments and K_i represents a vector of data moments. $\tilde{K}_i(\psi)$ represents a vector of moments simulated by the model given a set of parameters ψ. ns is the number of simulations.[22] $k_i^s(\psi)$ represents a vector of moments given ψ derived per simulation.

The moments choice is guided by the identification argument in section 4.2. In particular, I use the proportion of single owners and partners and the first and second moment of the conditional income. I also include the proportion of zero- or negative-income single owners and that of zero- or negative-income partners. Net worth, education, and experience are used as instruments.[23] I choose $\hat{\Sigma}$ to be a diagonal matrix that contains variances of the data moments. The number of parameters and the number of moments are 19 and 32, respectively.

Log value of net worth is required for estimation, and I replace negative net worth with \$1. Before estimation, I normalize one unit of net worth and income as \$10,000 in 2011.[24] The gross risk-free interest rate, r, is assumed to be 1.1 following the literature (e.g., Evans and Jovanovic (1989); Xu (1998); Paulson et al. (2006)). The standard errors are calculated following Gourieroux and Monfort (1996).

4.4 Model Fit

The full set of simulated and targeted moments are shown in Tables 16 and 17 in the Appendix. All moments are matched quite well, especially moments related to ownership choice. Some predicted moments related to single-owner income are a little bit higher than actual moments. First investigated by Hamilton (2000), low earnings for business owners have been explained by

washed out. The SIPP over-samples low-wealth individuals, but the over-sampled individuals are more likely to be dropped during the sample-construction process as explained in Appendix B.

[22] I set $ns = 3$ for estimation.

[23] Because net worth is an important state variable in the model, I use an interaction between net worth and the other covariates as additional instruments.

[24] Evans and Jovanovic (1989) used \$1,000 in 1976 as one unit.

a non-pecuniary benefit (Hamilton (2000); Pugsley (2013)). Abstracting from such a benefit makes perfectly matching the earnings differential difficult for the current model, especially for single owners.

5 Results

5.1 Estimates

Table 8 shows the estimates for log worker productivity ($\log \theta_w$) and log solo productivity ($\log \theta_s$). It shows a 10% increase in the years of education leads to approximately a 4% increase in worker productivity and a 3.3% increase in solo productivity. Likewise, a 10% increase in the years of experience leads to approximately a 1% increase in worker productivity and a 0.4% increase in solo productivity. The education and experience affect both worker productivity and solo productivity significantly, but their impacts are greater for worker productivity.

Table 8 also shows the relationship between net worth and solo productivity is estimated to be insignificant. This result is quite different from Evans and Jovanovic (1989). They find a significant and negative relationship between net worth and entrepreneurial productivity. Their model does not take into account the fact that an individual who could start a business with a partner despite a very low wealth level is more likely to have a very high ability as a partner. As a result, this additional mechanism may be absorbed as a relationship between net worth and entrepreneurial productivity.

Table 9 shows the estimates for log value of the collaborative skill. It indicates a 10% increase in the years of education leads to roughly an additional 2.5% increase in productivity as a partner. The coefficient for the years of experience is estimated to be insignificant. This finding implies the individual skill for collaborating with a partner is fostered more in schools than in workplaces. The constant term is estimated at -1.3726, suggesting a large productivity loss from working with a partner compared to working alone.

Table 10 reports the estimates for $\{\lambda, \alpha, \kappa\}$ and the outcome shocks. The collateral constraint parameter (λ) is estimated at 2.1541, suggesting agents can invest up to about twice their net worth. α is estimated at 0.1964, implying a 10% increase in investments leads to approximately a 2% increase in outputs for a given effort level.

To understand the relationship between the solo and partnership productivity, I project a simulated $\log\theta$ on a simulated $\log\tilde{\theta}$. The regression coefficient for $\log\theta$ is 1.22 and its p-value is less than 0.001. This finding suggests agents with better solo productivity tend to have better productivity as a partner. However, the collaborative skill, g, is estimated to be so low on average that only a small portion (3.4%) of the agents have greater productivity as a partner than alone. This finding is shown in Figure 7.

Note that I explicitly control for the cost of moral hazard in business partnerships. The moral hazard cost is not enough to explain the fact that only about 16% of agents choose partnerships conditional on business ownership. This finding supports the view that the cost of knowledge transfer outweighs the benefit for most individuals. The finding also supports the view that a productivity loss results from "collective decision making," in addition to the loss from moral hazard in business partnerships. Hansmann (1996) points out that the owners in a partnership firm often make important decisions, and this decision process can be costly due to heterogeneous interests among the owners.[25]

5.2 Decomposing Aggregate Gains

With the estimates of structural parameters, I use equation (2) to measure the benefits and the costs of the partnerships. More specifically, I use the following metric:

$$\begin{aligned}&\mathbb{E}_{(\eta,u)}\Big[\sum_{i=1}^{n}\big\{V_{pi}(\theta_{pi},A_{pi})-V_{si}(\theta_i,A_i)\big\}\mathbb{I}_i(d=3)\Big]\\=&\mathbb{E}_{(\eta,u)}\Big[\sum_{i=1}^{n}\Omega_{1i}\mathbb{I}_i(d=3)\Big]+\mathbb{E}_{(\eta,u)}\Big[\sum_{i=1}^{n}\Omega_{2i}\mathbb{I}_i(d=3)\Big]+\mathbb{E}_{(\eta,u)}\Big[\sum_{i=1}^{n}\Omega_{3i}\mathbb{I}_i(d=3)\Big]\end{aligned}\tag{6}$$

Equation (6) decomposes the benefits and the costs of business partnerships for those who choose to be partners. For each simulation, I calculate Ω_1 (gains from productivity), Ω_2 (gains from financing), and Ω_3 (losses from moral hazard) in equation (2) for every partner and then sum them up. After 1,000 simulations, I average the aggregate value of Ω_1, Ω_2, and Ω_3 for

[25] Merges between firms are similar to forming business partnerships in that the mergers are often thought to be driven by the gains in productivity. The low estimated g is also in line with the fact that most mergers – even *conditional on being merged* – are not successful and are often being divested. (see, e.g., Banal-Estañol and Seldeslachts (2011) and references therein.)

partners.

A graphical representation is shown in Figure 8. Most aggregate gains − before subtracting the losses from moral hazard − are explained by gains from the partnership productivity: 85% of the aggregate gains are explained by the partnership productivity; the remaining 15% is explained by the gains from financing.[26]

To investigate the variation between gains from two sources across the wealth distribution, I conduct the same exercise for those whose net wealth is below and above the 20th percentile of the wealth distribution. Figure 9 presents the results. Most gains from financing are generated by the low-wealth group and it is the major benefit for them: 85% of the aggregate gains for the low-wealth group is explained by financing. By contrast, most gains from partnership productivity are generated by the high-wealth group. For them, almost all of the gains are generated by the partnership productivity.

Note that a partnership is formed only if complementarity exists between the two partners' solo productivities or between one partner's solo productivity and the other partner's wealth. Looking at Figure 8, we cannot tell whether the large gains in productivity are driven by a pure productivity motive between partners or by the case in which wealthy but unproductive partners are matched with poor but productive partners due to a financial motive.

Figure 10 depicts the decomposition in equation (6) with respect to two complementarities. The gains generated by partnerships solely driven by the complementarity between two partners' solo productivities explain 73% of the gains from productivity and 62% of the entire gain from partnerships. This result is primarily because 63% of partnerships are driven solely by the complementarity between two partners' solo productivities. The remaining 37% of partnerships are involved with the complementarity between one partner's productivity and the other partner's wealth. Only a small portion (less than 1%) choose a partnership solely due to the complementarity between one partner's solo productivity and the other partner's wealth.

[26]I calculate the gains from financing, conditional on partnership productivity. I could have instead calculated it conditional on solo productivity. The difference between two decompositions matters in the following situation. Suppose an agent is not financially constrained as a single owner with his solo productivity, but is financially constrained as a single owner with the partnership productivity. Moreover, his partner's net worth is greater than his. With the current decomposition, the agent's gains from the partnership are captured both by the productivity gains and the financing gains. By contrast, all the gains from the partnership are attributed to the productivity gains with the alternative decomposition. As a result, the gains from financing with the alternative decomposition are smaller than the gains under the current decomposition.

The key feature in the data driving this result is the following: relatively more partners are observed in the upper percentile than in the lower percentile of the wealth distribution. For example, 64% of partners are located above the median of the wealth distribution and 45% of partners are located above the 70th percentile of the wealth distribution. The relationship between solo productivity and wealth is estimated to be insignificant; therefore, most of the financially constrained agents are concentrated in the lower percentile of the wealth distribution. The fact that we observe more partners in the upper part of the wealth distribution implies partnerships must exist that are formed by two relatively wealthy agents. Gains such partnerships generate explain major aggregate gains from business partnerships.

Finally, the cost of moral hazard among partners is estimated as 39% of the aggregate gains from partnerships (Figure 8). As Figure 9 shows the moral hazard cost is less for the low-wealth group (29%) than for the high-wealth group (41%).[27]

5.3 Financial Friction vs. Partnership Friction

Evans and Jovanovic (1989) do not allow an option to form business partnerships. As shown in section 3.4, however, most financially constrained single owners could find a business partner to overcome financial constraints, and the number of business owners does not change much even after a severe financial friction is imposed. Therefore, Evans and Jovanovic (1989) may over-emphasize the negative impact of financial friction on the transition into business ownership. To examine this issue, I simulate an economy without financial friction and compare the number of business owners to the estimated economy.

Table 11 shows the result. The total number of business owners without financial friction is normalized as 100. After the estimated financial constraint is imposed, the number of single owners decreases substantially from 84.17 to 73.69, but the number of partners increases only marginally from 15.83 to 15.88. The financially constrained single owners choose not to find a partner and instead to become a worker. As a result, the total number of business owners decreases more than 10% even if the option to form a partnership is allowed. This is because only a small portion of the agents is assigned the productivity as a partner greater than their

[27] The moral hazard cost increases as the partnership productivity increases. Some of the low-wealth partners sacrifice the gains from productivity for the gains from financing. As a result, the moral hazard cost is less for the low-wealth group than for the high-wealth group.

solo productivity as shown in Figure 7. The moral hazard cost is also high as shown in section 5.2. Overall, despite the potential gains from financing, the constrained agents do not choose to form partnerships due to the moral hazard cost and the potential productivity loss associated with working with a partner.

6 Welfare Analysis

This section analyzes the welfare implication of financial friction. Unlike most of the previous models with financial friction, the current model features an additional distortion due to financial friction: the efficiency loss from mismatch. I address an intuition using a simple example in section 3.4. Because of financial friction, a productive agent with low wealth can be matched with a less productive agent than the partner with whom he would have been matched if no financial friction were present.

Table 12A decomposes the welfare losses for each transition group.[28] I first normalize the aggregate welfare losses due to financial friction as 100: $\sum_{i=1}^{N}(V_i - V_i^f)\mathbb{I}_{\text{Loss}} = 100$. V_i^f and V_i represent the value of agent i with and without financial friction, respectively. $\mathbb{I}_{\text{Loss}}$ represents the indicator function for $V_i - V_i^f$ being positive. Most of the welfare losses come from the single owners who are constrained to become business owners. The welfare loss from this group accounts for 85.40% of the aggregate welfare losses due to financial friction. The second biggest source of welfare losses is single owners who remain single owners but with constrained borrowing. The welfare loss from this group accounts for 11.44% of the aggregate welfare losses due to financial friction.

Before further discussion, note that in my model, I define the following three situations as mismatches driven by financial friction: a partner changes his ownership either to being a worker or a single owner, a worker or a single owner become a partner, and a partner changes his partner.

Table 12A shows the welfare losses from mismatch account for 3.16% of the aggregate welfare losses due to financial friction. Of 3.16%, single owners who become partners due to a financial motive explain 0.49%. Partners who become workers or single owners explain

[28]I simulated the economy 1,000 times and averaged the results from all simulations.

0.32%. The remaining 2.35% is due to partners who remain partners, but are matched with less productive agents than the partners with whom they would have been matched if no financial friction were present.

The financial friction generates welfare *gains* for a certain group of people. Table 12B decomposes the welfare gains for each transition group. Workers who become partners benefit from financial friction. Their gains correspond to 0.23% of the aggregate welfare losses due to financial friction. Partners and a small proportion of single owners also benefit from financial friction. The welfare gains for these business owners correspond to 1.91% of the aggregate welfare losses due to financial friction. Again, an intuition is shown in section 3.4. Some partners, workers, and single owners with high wealth can have an opportunity to meet with more productive agents than the partners with whom they would have been matched if no financial friction were present.

In Table 13, I further investigate welfare losses and gains due to mismatch with respect to wealth level. Most welfare losses due to mismatch are generated by individuals whose net worth is less than the 20th percentile of the wealth distribution. These welfare losses account for 74.61% of the entire welfare loss from mismatch. This finding is a sharp contrast to the fact that only 2.55% of the gains from mismatch are generated by low-wealth individuals.

7 Policy Experiments

Financial friction is often a concern for policy makers who try to strengthen entrepreneurship. The model developed here can be used to evaluate the impact of loan programs not only on startup owners in general, but also on the formation of business partnerships.[29]

7.1 Policy 1: Loans for All Startup Firms

To reduce inefficiency from financial friction, I experiment with a policy in which a government lends startup businesses up to \$25,000 at the market interest rate r. I assign \$25,000 per business regardless of the number of owners.

[29] I simulated the economy with each policy 1,000 times and averaged the results from all simulations.

Given that the interest rate is the same as the market interest rate, only financially constrained startup owners will apply to the loan program as long as a small amount of costs associated with the application exist. The marginal benefit of additional investment is strictly greater than the market interest rate for financially constrained agents, and only those agents apply to the loan program.

The left column of Table 14 shows the welfare gain by Policy 1 for each transition group. About 97.7% of the aggregate welfare losses from financial friction disappear. Workers who could have become single owners without financial friction enter business ownership as single owners thanks to the government loans. The number of single owners increases more than 10% after the loan program is applied (Table 15). Most financially constrained single owners also benefit from the loan program and increase investments.

Policy 1 also alleviates mismatch by partners. In doing so, some partners – who can be matched with more productive partners due to financial friction – are worse off by the loan policy. The value of their wealth in the presence of financial friction reduces once other partners can access the loans provided by the government. Despite the gains from alleviating mismatch, the aggregate number of partners is almost identical before and after the loan program is applied (Table 15).

7.2 Policy 2: Loans Targeted for Business Partnerships

I experiment with a loan policy in which a government lends only business partnerships up to \$25,000 at the market interest rate r. As in Policy 1, only financially constrained partnership firms apply to the program.

The Small Business Technology Transfer (STTR) program sponsored by the US government provides funds only for partnerships between small businesses and nonprofit research institutions. The goal is to promote commercialization of innovations in science by encouraging partnership between the public and private sector. Although the firms targeted by the STTR program may be quite different from the firms in the sample for this paper, Policy 2 can be helpful to understand an equilibrium impact of the STTR program.

The number of partners remains almost identical before and after the implementation of the policy (Table 15). Moreover, although the program specifically targets business partnerships, the welfare gains generated by improving match quality is smaller than Policy 1: the gains from alleviating mismatch by Policy 2 are about 43% of the gains from alleviating mismatch by Policy 1. The key difference is that under Policy 2, partners who would have become single owners without financial friction still remain as partners. By contrast, under Policy 1, these partners switch their ownership choice to single ownership and generate welfare gains.

7.3 Discussion

The loan program targeted for general businesses is more effective than the loan program targeted only for business partnerships. The loan program for general businesses increases welfare for workers who would have been single owners without financial friction and for single owners who face borrowing constraints. Moreover, it improves the match quality more than the loan program specifically targeted for business partnerships.

One caveat of the policy analyses in this section is that I did not take into account applicants' default decisions. Endogenizing agents' default decisions can be valuable for analyzing small business loan programs, but is outside the scope of this paper.

8 Conclusion

I empirically investigate the formation of partnerships among startup owners. I first document that partners earn significantly more than single owners. In addition, relatively more partners are observed in the lower and upper percentile of the wealth distribution than in the middle. Despite the high earnings among observed partners, the proportion of partners is much smaller than single owners. To further investigate the decision to form a partnership, I develop and estimate a matching model based on Evans and Jovanovic (1989).

Using the estimated model, I first show the gains from the increase in productivity explain most gains from the observed partnerships. The gains from financing are the major benefit to individuals with low net worth. Financial friction generates inefficiency due to mismatch among partners. A government-sponsored funding program for all startup firms is effective both in helping financially constrained startup owners create businesses and in improving the match quality among partners.

This study focuses on the role of partnerships on the business formations. A limitation is that I only use the first-year business earnings as a measure of the business's outcomes. Although the first year's earnings are highly predictive of future earnings (e.g., Hamilton (2000)), they cannot fully capture the dynamics of businesses, especially their failure rate. Many new businesses fail within a few years. A further investigation into whether and how partnerships are related to business dissolution would shed light not only on business partnerships, but also on business failures.

References

M. Adelino, A. Schoar, and F. Severino. House prices, collateral and self-employment. *Journal of Financial Economics*, 117:288–306, 2015.

T. Andersson, J. Gudmundsson, D. Talman, and Z. Yang. A competitive partnership formation process. *Games and Economic Behavior*, 86:165–177, 2014.

L. Argote and P. Ingram. Knowledge transfer: A basis for competitive advantage in firms. *Organizational Behavior and Human Decision Processes*, 82:150–169, 2000.

K. J. Arrow. Classificatory notes on the production and transmission of technological knowledge. *American Economic Review*, 59:29–35, 1969.

T. Åstebro and C. J. Serrano. Business partners: Complementary assets, financing, and invention commercialization. *Journal of Economics & Management Strategy*, 24:228–252, 2015.

A. Banal-Estañol and J. Seldeslachts. Merger failures. *Journal of Economics & Management Strategy*, 20:589–624, 2011.

H. Bar-Isaac. Something to prove: Reputation in teams. *RAND Journal of Economics*, 38: 495–511, 2007.

B. Bartling and F. A. von Siemens. Equal sharing rules in partnerships. *Journal of Institutional and Theoretical Economics*, 166:299–320, 2010.

G. Basaluzzo. Entrepreneurial teams in financially constrained economies. *working paper*, 2006.

M. Battaglini. Joint production in teams. *Journal of Economic Theory*, 130:138–167, 2006.

G. S. Becker and K. M. Murphy. The division of labor, coordination costs, and knowledge. *Quarterly Journal of Economics*, 107:1137–1160, 1992.

M. P. Bitler, T. J. Moskowitz, and A. Vissing-Jørgensen. Testing agency theory with entrepreneur effort and wealth. *Journal of Finance*, 60:539–576, 2005.

M. Cagetti and M. De Nardi. Entrepreneurship, frictions, and wealth. *Journal of Political Economy*, 114:835–870, 2006.

E. Choo and A. Siow. Who marries whom and why. *Journal of Political Economy*, 114:175–201, 2006.

A. Cohen and M. D. Eisner. *Working Together: Why Great Partnerships Succeed*. New York: Happer Business, 2010.

V. P. Crawford and E. M. Knoer. Job matching with heterogeneous firms and workers. *Econometrica*, 49:437–450, 1981.

R. Cressy. Credit rationing or entrepreneurial risk aversion? an alternative explanation for the evans and jovanovic finding. *Economic Letters*, 66:235–240, 2000.

J. Eeckhout and K. Munshi. Matching in informal financial institutions. *Journal of the European Economic Association*, 8(5):947–988, 2010.

E. Espino, J. Kozlowski, and J. M. Sanchez. Too big to cheat: Efficiency and investment in partnerships. *working paper*, 2015.

D. S. Evans and B. Jovanovic. An estimated model of entrepreneurial choice under liquidity constraints. *Journal of Political Economy*, 97:808–827, 1989.

D. S. Evans and L. S. Leighton. Some empirical aspects of entrepreneurship. *American Economic Review*, 79:519–535, 1989.

J. Farrell and S. Scotchmer. Partnerships. *Quarterly Journal of Economics*, 103:279–297, 1988.

L. Garicano and T. Santos. Referrals. *American Economic Review*, 94:499–525, 2004.

M. Gaynor and P. Gertler. Moral hazard and risk spreading in partnerships. *RAND Journal of Economics*, 26:591–613, 1995.

N. Gordon and B. Knight. A spatial merger estimator with an application to school district consolidation. *Journal of Public Economics*, 93:752–765, 2009.

C. Gourieroux and A. Monfort. *Simulated-Based Econometric Methods*. New York: Oxford University Press, 1996.

M. R. Haas and M. T. Hansen. When using knowledge can hurt performance: The value of organizational capabilities in a management consulting company. *Strategic Management Journal*, 26:1–24, 2005.

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

B. H. Hamilton, J. A. Nickerson, and H. Owan. Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation. *Journal of Political Economy*, 111:465–497, 2003.

H. Hansmann. *The Ownership of Enterprise*. Cambridge: Harvard University Press, 1996.

B. Holmstrom. Moral hazard in teams. *Bell Journal of Economics*, 13:324–340, 1982.

D. Holtz-Eakin, D. Joulfaian, and H. S. Rosen. Sticking it out: Entrepreneurial survival and liquidity constraints. *Journal of Political Economy*, 102:53–75, 1994.

V. J. Huggins and K. E. King. Evaluation of oversampling the low income population in the 1996 survey of income and program participation (sipp). *Proceedings from the Survey Research Methods Section of the American Statistical Association*, pages 501–506, 1997.

E. Hurst and A. Lusardi. Liquidity constraints, household wealth, and entrepreneurship. *Journal of Political Economy*, 112:319–347, 2004.

M. C. Jensen and W. H. Meckling. *Specific and General Knowledge and Organizational Structure, a Chapter in Contract Economics*. Blackwell, 1992.

B. F. Jones. The burden of knowledge and the death of the renaissance man: Is innovation getting harder? *Review of Economic Studies*, 76:283–317, 2009.

G. Kawasaki. *The Art of the Start*. New York: Penguin Group, 2004.

M. Kosfeld and F. A. von Siemems. Competition, cooperation, and corporate culture. *RAND Journal of Economics*, 42:23–43, 2011.

K. Lang and P.-J. Gordon. Partnerships as insurance devices: Theory and evidence. *RAND Journal of Economics*, 26:614–629, 1995.

E. P. Lazear. *Personnel Economics for Managers*. New York: Wiley, 1998.

P. Legros and H. Matsushima. Efficiency in partnerships. *Journal of Economic Theory*, 55: 296–322, 1991.

P. Legros and S. A. Matthews. Efficient and nearly-efficient partnerships. *Review of Economic Studies*, 60:599–611, 1991.

P. Legros and A. F. Newman. Wealth effects, distribution, and the theory of organization. *Journal of Economic Theory*, 70(2):312–341, 1996.

J. Levin and S. Tadelis. Profit sharing and the role of professional partnerships. *Quarterly Journal of Economics*, 120:131–171, 2005.

N. H. Miller. Efficiency in partnerships with joint monitoring. *Journal of Economic Theory*, 77:285–299, 1997.

A. D. Morrison and W. J. Wilhelm. Partnership firms, reputation, and human capital. *American Economic Review*, 94:1682–1692, 2004.

A. F. Newman. Risk-bearing and entrepreneurship. *Journal of Economic Theory*, 137(1): 11–26, 2007.

A. L. Paulson, R. M. Townsend, and A. Karaivanov. Distinguishing limited liability from moral hazard in a model of entrepreneurship. *Journal of Political Economy*, 114:100–144, 2006.

B. Pugsley. Selection and the role of small business owners in firm dynamics. *working paper*, 2013.

R. Radner. Repeated partnership games with imperfect monitoring and no discounting. *Review of Economic Studies*, 53:43–57, 1986.

D. Rahman and I. Obara. Mediated partnerships. *Econometrica*, 78:285–308, 2010.

E. Rasmusen. Moral hazard in risk-averse teams. *RAND Journal of Economics*, 18:428–435, 1987.

M. C. Schmalz, D. A. Sraer, and D. Thesmar. Housing collateral and entrepreneurship. *The Journal of Finance*, 2016.

P. Ševčík. Financial frictions, internal capital markets, and the organization of production. *Review of Economic Dynamics*, 18(3):505–522, 2015.

K. Sherstyuk. Efficiency in partnership structures. *Journal of Economic Behavior & Organization*, 36:331–346, 1998.

R. Strausz. Efficiency in sequential partnerships. *Journal of Economic Theory*, 85:140–156, 1999.

D. J. Teece. Technology transfer by multinational firms: The resource cost of transferring technological know-how. *Economic Journal*, 87:242–261, 1977.

D. J. Teece. Economies of scope and the scope of the enterprise. *Journal of Economic Behavior & Organization*, 1:223–247, 1980.

G. Vereshchagina. The impact of moral hazard and budget balancing on sorting in partnerships. *working paper*, 2016.

E. Weese. Political mergers as coalition formation: an analysis of the heisei municipal amalgamations. *Quantitative Economics*, 6(2):257–307, 2015.

B. Xu. A reestimation of the evans-jovanovic entrepreneurial choice model. *Economics Letters*, 58:91–95, 1998.

Tables and Figures

Table 1: Summary Statistics

	Workers	Single Owners	Partners
Obs.	48,869	946	181
Experience (Year)	19.91	20.50	19.76
Education (Year)	13.76	14.05	14.16
Race (White)(%)	85.36	85.16	92.00
Married (%)	62.93	61.60	72.78

NOTE: This table reports the summary statistics for characteristics of workers, single owners, and partners. Mean is reported unless otherwise indicated. The survey weight is applied.

Table 2: Income

	Workers	Single Owners	Partners
Obs.	48,869	833	165
Mean	52,053	43,101	61,948
10%	15,095	3,362	7,503
50%	41,053	23,038	37,515
90%	95,990	100,108	136,107

NOTE: Dollar in 2011. This table shows the summary statistics for incomes of workers, single owners, and partners given that they reported a positive income.

Table 3: Income Regression for Business Owners

VARIABLES	(1) ln(Income)	(2) ln(Income)	(3) ln(Income)	(4) ln(Income)
Partnership	0.586	0.529	0.527	0.461
	(0.118)	(0.115)	(0.114)	(0.114)
Education	0.0855	0.0383	0.0351	0.0342
	(0.0161)	(0.0170)	(0.0182)	(0.0180)
Experience	0.0277	0.0132	0.0137	0.00568
	(0.0145)	(0.0143)	(0.0142)	(0.0145)
Experience^2	-0.000618	-0.000378	-0.000397	-0.000228
	(0.000319)	(0.000313)	(0.000312)	(0.000315)
Previous income		0.00574	0.00539	0.00489
		(0.000821)	(0.000818)	(0.000811)
Net worth		0.000212	0.000186	0.000229
		(0.000103)	(0.000103)	(0.000102)
Industry dummy	No	No	Yes	Yes
Other dummies	No	No	No	Yes
Observations	998	998	998	998
R-squared	0.055	0.108	0.136	0.169

NOTE: This table shows the estimates for regression of log incomes on partnership dummy, years of education, years of experience and its square, previous income, net worth, and industry and other dummies. Partnership means the partnership dummy. Previous income indicates the wage income in the base year. One unit is 10,000 USD in 2011. Other dummies include race, marital status, and year dummies. Standard errors are in parentheses.

Table 4: Net Worth

	Workers	Single Owners	Partners
Obs.	48,869	946	181
Mean	182,789	243,826	329,822
10%	-5,509	-7,263	-4,138
50%	76,039	90,849	139,875
90%	499,301	698,750	830,313

NOTE: Dollar in 2011. This table shows the summary statistics for net worth of workers, single owners, and partners.

Table 5: Net Worth and Partnership Choice

VARIABLES	Partnerships
Net worth/100,000	-0.0324
	(0.0619)
(Net worth/100,000)^2	0.0392
	(0.0200)
(Net worth/100,000)^3	-0.00530
	(0.00240)
(Net worth/100,000)^4	0.000236
	(0.000113)
(Net worth/100,000)^5	-3.26e-06
	(1.79e-06)
Education	-0.0221
	(0.0186)
Experience	-0.0107
	(0.00450)
Previous income	0.000352
	(0.000870)
Race	0.358
	(0.160)
Married	0.386
	(0.108)
Constant	-1.166
	(0.310)
Observations	1,127
Pseudo R-squared	0.0423

NOTE: This tables reports the estimates for a Probit regression of becoming a partner on wealth variables among business owners. Previous income is normalized by 10,000 USD in 2011. Race is the dummy variable for white. Standard errors are in parentheses. The coefficients for wealth variables are jointly significant (p-value 0.0115).

Table 6: Industry Decomposition

Industry	Single owners	Partners	Partners (%)
Agriculture, forestry, fishing, and hunting	56	18	24
Construction	263	46	15
Manufacturing	30	8	21
Wholesale trade	31	4	11
Retail trade	65	19	23
Transportation, warehousing, and utilities	48	4	8
Information	16	1	6
Finance, insurance, real estate, and rental and leasing	50	16	24
Professional, scientific, management, administrative, and waste management	204	32	14
Services	183	33	15
High−starting capital industry	224	51	19
Low−starting capital industry	446	79	15

NOTE: This table reports the number and the proportion of partners for different industries. Services include Business and repair services; Personal services; Educational, health and social service; Arts, entertainment, recreation, accommodations, and food service; Public administration; and other services. High-starting capital industry includes Manufacturing; Wholesale and Retail trade; Transportation, warehousing, and utilities; and Finance, insurance, real estate, and rental and leasing. Low-starting capital industry includes Construction and Services.

Table 7: Financial Friction and Sorting Pattern

	Economy w.o Financial Friction	Economy with $\lambda = 1$
# of workers	2,870	3,057
# of single owners	3,364	2,465
# of partners	3,766	4,478
Corr(P1.ability, P1.ability)	1	0.76
Corr($\log A1$, $\log A2$)	0	-0.67

NOTE: This table reports the selection and the sorting pattern from two simulated economies. I simulate 10,000 individuals from the economy characterized as follows: $\{\kappa, \alpha\} = \{1, 0.3\}$, $\theta_w = 1$, $\log \theta_s \sim N(1,1)$, $\log g \sim N(0,1)$, $\log A \sim N(0,10)$. The first column of the table reports the results without financial friction, and the second column of the table reports the results with $\lambda = 1$.

Table 8: Estimates for log Worker Productivity and log Solo Productivity

Parameters	Variables	Estimates	Standard Errors
γ_1	log(Education)	0.3986	(0.0078)
γ_2	log(Experience)	0.0965	(0.0045)
β_0	Constant	0.3054	(0.0236)
β_1	log(Net worth)	0.0025	(0.0002)
β_2	log(Education)	0.3247	(0.0042)
β_3	log(Experience)	0.0370	(0.0035)
σ_η	Std. of η	0.1096	(0.0015)

NOTE: This table presents the estimates for the equation: $\log\theta_w = \gamma_1 \log x_1 + \gamma_2 \log x_2$ and $\log\theta = \beta_0 + \beta_1 \log A + \beta_2 \log x_1 + \beta_3 \log x_2 + \eta$, where $\eta \sim N(0, \sigma_\eta^2)$. A is net worth (10,000 USD in 2011). x_1 is the years of education. x_2 is the years of experience. Asymptotic standard errors are in parentheses.

Table 9: Estimates for log Collaborative Skill

Parameters	Variables	Estimates	Standard Errors
g_0	Constant	-1.3726	(0.0354)
g_1	log(Education)	0.2446	(0.0154)
g_2	log(Experience)	0.0192	(0.0029)
σ_u	Std. of u	0.3715	(0.0051)

NOTE: This table presents the estimates for the equation: $\log g = g_0 + g_1 \log x_1 + g_2 \log x_2 + u$, $u \sim N(0, \sigma_u^2)$. x_1 is the years of education. x_2 is the years of experience. Asymptotic standard errors are in parentheses.

Table 10: Estimates for Other Parameters

Parameters	Variables	Estimates	Standard Errors
λ	Collateral constraint	2.1541	(1.0669)
α	Technology	0.1964	(0.0112)
κ	Preference	1.7195	(0.0213)
σ_w	Std. of $\log \epsilon_w$	0.7678	(0.0065)
σ_s	Std. of $\log \tilde{\epsilon}_s$	1.6887	(0.0794)
P_s	–	0.0374	(0.0020)
σ_p	Std. of $\log \tilde{\epsilon}_p$	1.0268	(0.0261)
P_p	–	0.1451	(0.0016)

NOTE: This table presents the estimates for $\{\lambda, \alpha, \kappa\}$ and the outcome shocks. λ captures the extent of collateral constraint. α governs the marginal productivity of capital. κ captures the marginal rate of substitution between consumption and effort. The outcome shock to workers (ϵ_w) is modelled as $\log \epsilon_w \sim N(\mu_w, \sigma_w^2)$, $\mathbb{E}[\epsilon_w] = 1$. The outcome shock to single owners (ϵ_s) is modelled as $\epsilon_s = \tilde{\epsilon}_s - P_s$, $\log \tilde{\epsilon}_s \sim N(\mu_s, \sigma_s^2)$, $\mathbb{E}[\epsilon_s] = 1$. The outcome shock to partners (ϵ_p) is modelled as $\epsilon_p = \tilde{\epsilon}_p - P_p$, $\log \tilde{\epsilon}_p \sim N(\mu_p, \sigma_p^2)$, $\mathbb{E}[\epsilon_p] = 1$. P_s and P_p are some positive constants. Asymptotic standard errors are in parentheses.

Table 11: Financial Friction and Number of Business Owners

	Economy w.o Financial Friction	Benchmark
Single owners	84.17	73.69
Partners	15.83	15.88
# of business owners	100	89.57

NOTE: This table compares the number of single owners and partners from the estimated (benchmark) economy with those from the estimated economy but removing financial friction. The number of business owners from the economy without financial friction is normalized as 100.

Table 12: Decomposing Welfare Losses and Gains Due to Financial Friction by Each Transition Group (the numbers are normalized by the aggregate welfare losses due to financial friction)

	After Financial Friction					
	(A) Welfare Loss			(B) Welfare Gain		
	Workers	Single Owners	Partners	Workers	Single Owners	Partners
Workers	0	0	0	0	0	0.23
Single owners	85.40	11.44	0.49	0	0	0.02
Partners	0.31	0.01	2.35	0	0	1.89

NOTE: Column A of this table presents welfare losses with respect to each transition group after financial friction is introduced. Column B of this table presents welfare gains for each transition group due to financial friction. The aggregate welfare losses from financial friction are normalized as 100: $\sum_{i=1}^{N}(V_i - V_i^f)\mathbb{I}_{\text{Loss}} = 100$. V_i^f and V_i represent the value of agent i with and without financial friction, respectively. $\mathbb{I}_{\text{Loss}}$ represents the indicator function for $V_i - V_i^f$ being positive.

Table 13: Welfare Losses and Gains Due to Mismatch by Low-Wealth Individuals (the numbers are normalized by the aggregate welfare losses due to financial friction)

	Welfare Loss	Welfare Gain
All agents (a)	3.16	2.14
Agents < 20th (b)	2.36	0.05
(b/a)×100	(74.61%)	(2.55%)

NOTE: This table presents losses and gains due to mismatch by low-wealth individuals. Agents < 20th indicate individuals whose net worth is less than the 20th percentile of the wealth distribution. The aggregate welfare losses due to financial friction are normalized as 100: $\sum_{i=1}^{N}(V_i - V_i^f)\mathbb{I}_{\text{Loss}} = 100$. V_i^f and V_i represent the value of agent i with and without financial friction, respectively. $\mathbb{I}_{\text{Loss}}$ represents the indicator function for $V_i - V_i^f$ being positive.

Table 14: Decomposing Welfare Gains for Policy 1 & Policy 2 by Each Transition Group (the numbers are normalized by the aggregate welfare losses due to financial friction)

	After Policy 1			After Policy 2		
	Workers	Single Owners	Partners	Workers	Single Owners	Partners
Workers	0	85.40	0.31	0	0	0.28
Single owners	0	11.44	0.01	0	0	0.01
Partners (G+L)	-0.23	0.47	0.26	-0.18	-0.02	0.27
Group (L)	-0.23	-0.02	-1.45	-0.18	-0.02	-1.33
Group (G)	0	0.49	1.71	0	0	1.61

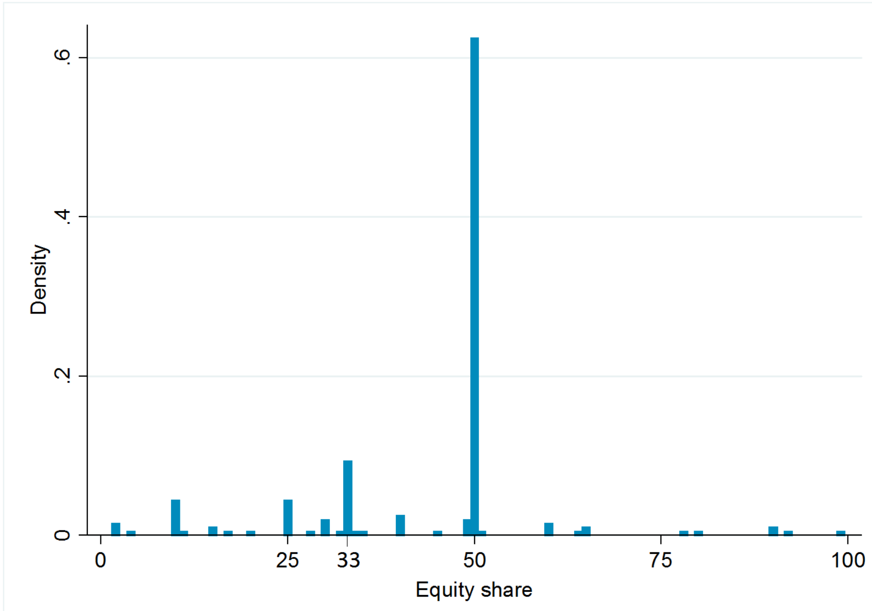
NOTE: The table presents welfare gains generated by Policy 1 and Policy 2, respectively. Policy 1 is a loan program for all businesses with the market interest rate and the maximum lending amount of $25,000. Policy 2 is a loan program for partnership firms with the market interest rate and the maximum lending amount of $25,000. Group (L) indicates ex-partners who incur a loss due to each policy. Group (G) indicates ex-partners who benefit from each policy. A minus figure indicates the welfare *losses* from each policy. To highlight the extent of welfare improvement by policies, I normalize the gains in both policies with respect to the aggregate welfare losses due to financial friction, which is normalized as 100: $\sum_{i=1}^{N}(V_i - V_i^f)\mathbb{I}_{\text{Loss}} = 100$. V_i^f and V_i represent the value of agent i with and without financial friction, respectively. $\mathbb{I}_{\text{Loss}}$ represents the indicator function for $V_i - V_i^f$ being positive.

Table 15: Number of Business Owners after Policy 1 & Policy 2

	Single Owners (a)	Partners (b)	Business Owners (a+b)
Benchmark	82.27	17.73	100
Policy 1	93.93	17.68	111.64
Policy 2	82.28	17.74	100.02

NOTE: This table compares the number of business owners after Policy 1 and Policy 2. Policy 1 is a loan program for all businesses with the market interest rate and the maximum lending amount of $25,000. Policy 2 is a loan program for partnership firms with the market interest rate and the maximum lending amount of $25,000. The benchmark economy is the estimated economy. The number of business owners in the benchmark economy is normalized as 100.

Figure 1: Equity Share for Startup Owners



NOTE: This figure shows the histogram of equity shares for those whose equity share is greater than 1% and less than 100%.

Figure 2: Kernel Density of Log Income

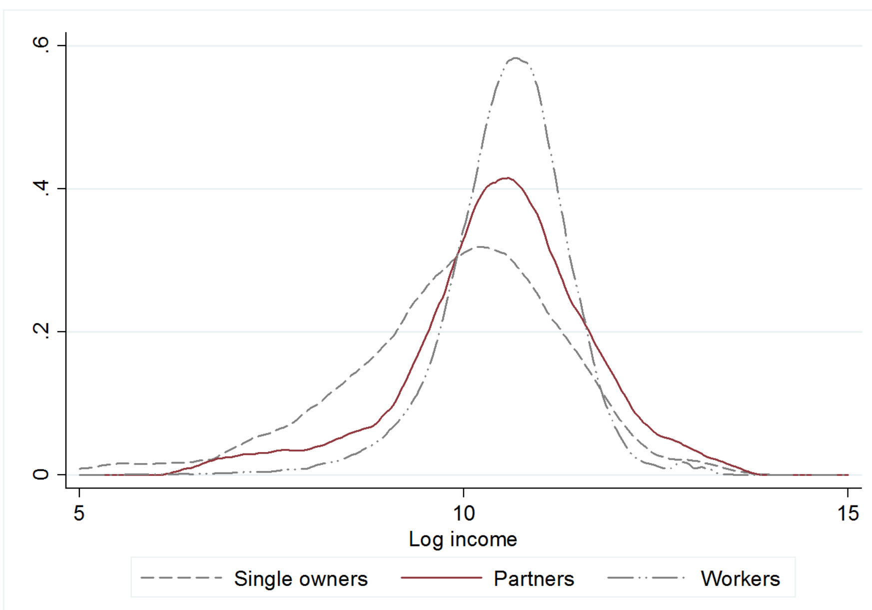


Figure 3: Kernel Density of Net Worth

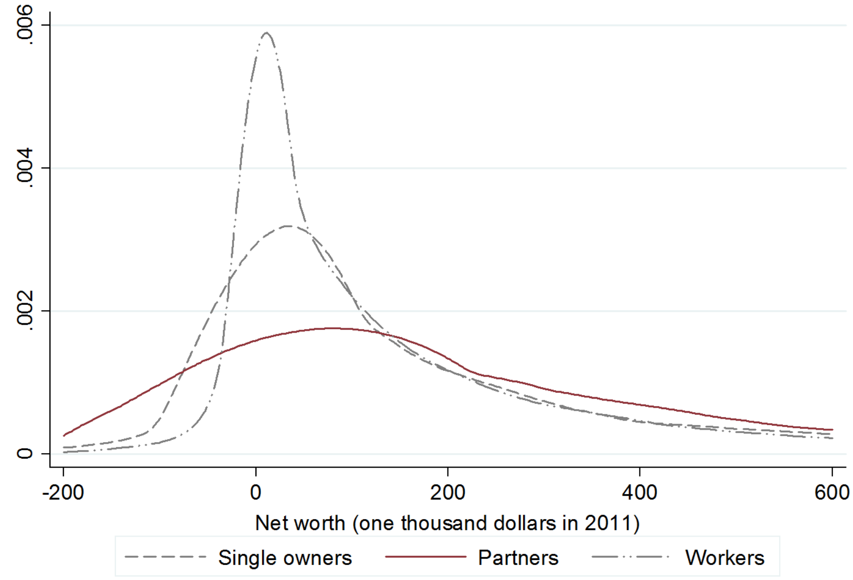
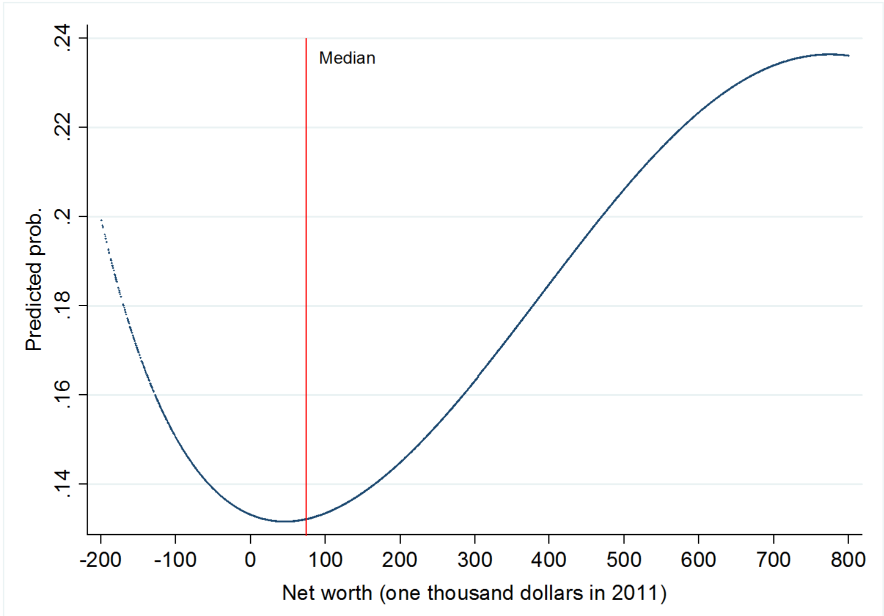
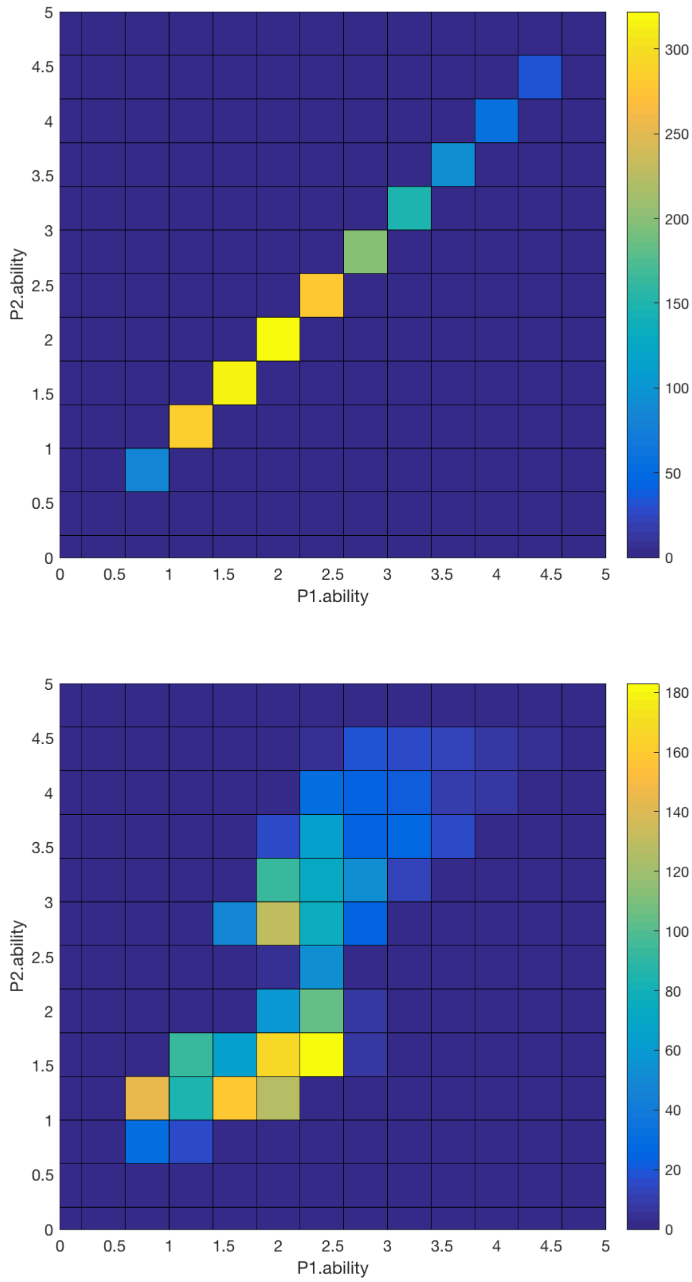


Figure 4: Net Worth and the Predicted Prob. of Becoming a Partner



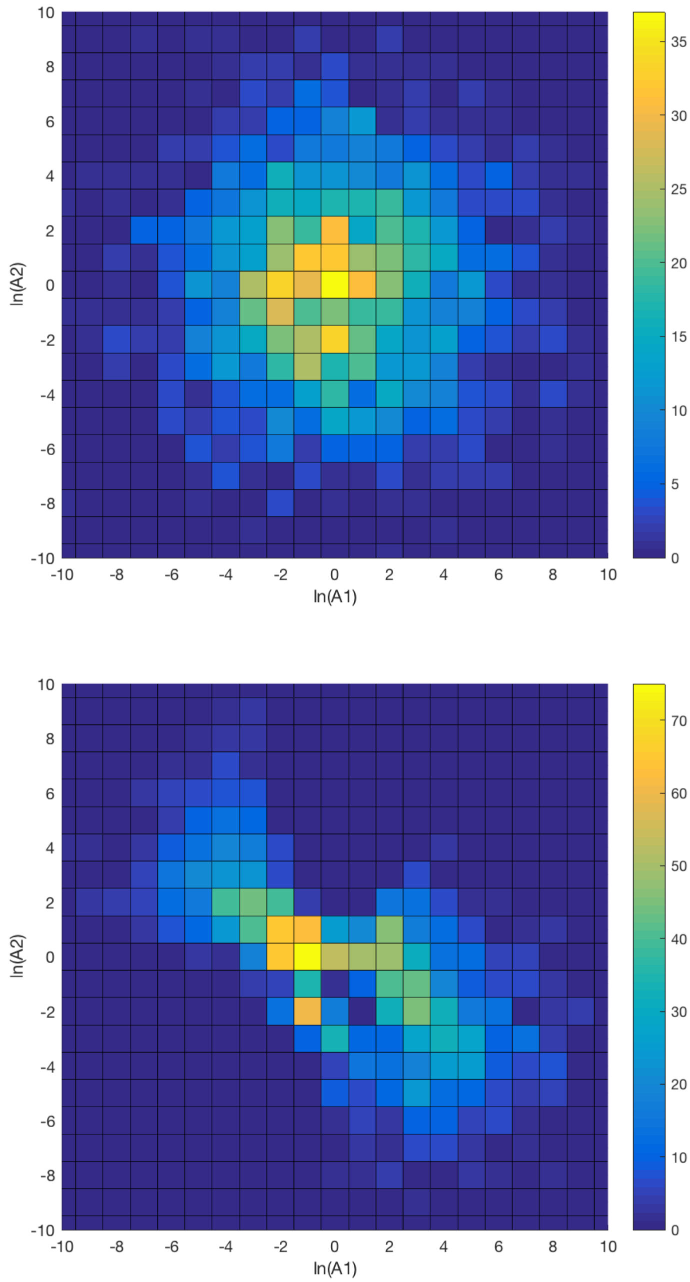
NOTE: This figure depicts the predicted probability of becoming a partner with respect to net worth based on the estimates from the regression in Table 5. The median net worth is 76,480 USD.

Figure 5: Financial Friction and Sorting: Ability



NOTE: The above two figures show the sorting patterns with respect to ability as a partner ($\log(g \cdot \theta_s)$). The upper figure shows the sorting pattern without financial friction. The lower figure shows the sorting pattern when $\lambda = 1$. The correlation in the upper figure is 1 and the correlation in the lower figure is 0.76.

Figure 6: Financial Friction and Sorting: Wealth

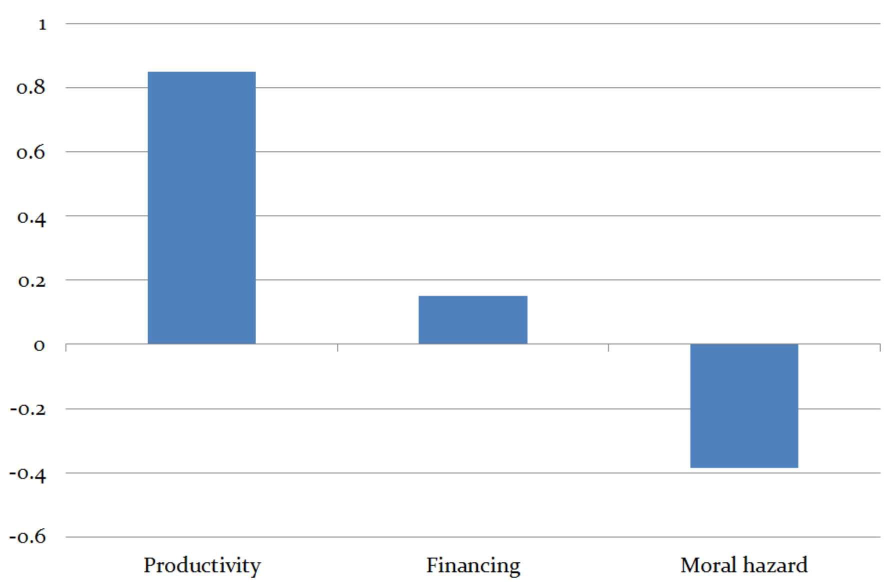


NOTE: The above two figures show the sorting patterns with respect to the level of wealth ($\log(A)$). The upper figure shows the sorting pattern without financial friction. The lower figure shows the sorting pattern when $\lambda = 1$. The correlation in the upper figure is 0 and the correlation in the lower figure is -0.67.

Figure 7: Kernel Density of Collaborative Skill

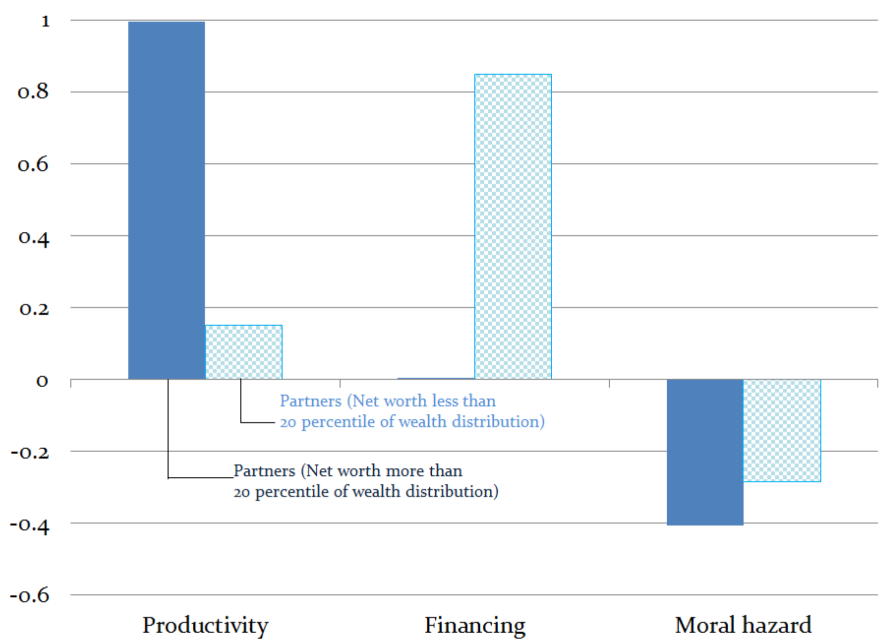
NOTE: This figure shows Kernel density of a simulated value for g given covariates and estimates. g greater than 1 means the productivity as a partner is greater than the solo productivity, and g less than one means the productivity as a partner is less than the solo productivity.

Figure 8: Decomposing Benefits and Costs of Partnerships 1



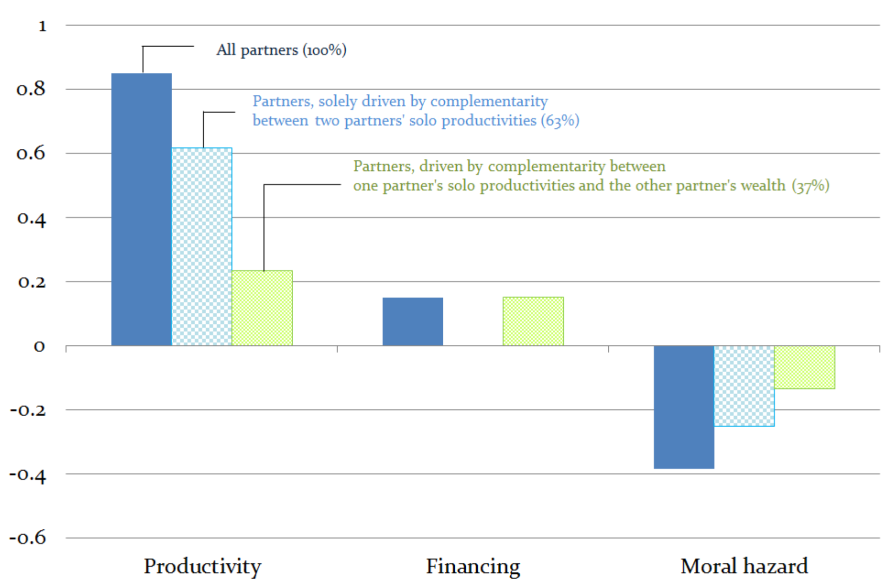
NOTE: This figure depicts the decomposition of benefits and costs from partnerships for all partners. The aggregate gains for all partners are normalized as 1.

Figure 9: Decomposing Benefits and Costs of Partnerships 2



NOTE: This figure depicts the decomposition of benefits and costs from partnerships below and above the 20th percentile of the wealth distribution (blue: partners below the 20th percentile of the wealth distribution; sky-blue: partners above the 20th percentile of the wealth distribution). The aggregate gains for each group are normalized as 1.

Figure 10: Decomposing Benefits and Costs of Partnerships 3



NOTE: This figure depicts the decomposition of benefits and costs from partnerships with respect to complementarities (blue: all partners; sky-blue: partnerships solely driven by complementarity between two partners' solo productivities; green: partnerships driven by complementarity between one partner's solo productivities and the other partner's wealth). The aggregate gains for all partners are normalized as 1.

Appendix

A Sample Construction

In this section, I describe the sample construction in more detail. The SIPP was redesigned in 1996. As a result, the variable names, as well as the data-editing and -imputing procedures, are not consistent between panels before and after 1996. For this reason, I use panels after 1996 including 1996, 2001, 2004, and 2008. The samples between panels are not overlapping.

In SIPP, the respondents were interviewed every four months with questions about, for example, income level and working hours for each month (these questions are labeled as "core modules"). In addition, broader questions ranging from household net worth to child support were asked annually (these questions are labeled as "topical modules"). In particular, for every third wave of interviewing, SIPP provides the household-level net worth and the share of business equity for business owners. Because the household net worth is one of the most important variables for this study and is recorded annually, I construct a panel in which the time unit is a year.

Type of Business Owners A respondent is defined as a business owner if he answered yes to the question "Did you own a business?" *and* his working hours for the business are greater than his wage working hours[30] during at least one of three previous waves (representing one year) when the household net worth is recorded.[31] I define a partner as a business owner whose share of business equity is greater than or equal to 25% and less than or equal to 75%.[32] Business owners whose equity share is greater than 75% are called single owners.

Income SIPP explicitly asks how much each respondent earned for each month in every wave. In principle, one wave covers four months. I use the monthly income only for the survey month because little variation exists in monthly incomes within the same wave. Thus, I use the term "wave" and "month" interchangeably. For example, suppose a respondent reported earned income for only two months and the total amount of earned income for the two months

[30] This definition is to differentiate an active business owner from a casual business owner.

[31] Some respondents in the third wave of 2004 panel were wrongly recorded as business owners (APDJBTHN=5). I drop these respondents. For more information, see SIPP user note for Business Feed-Back Problem.

[32] According to this definition, an incorporated firm with multiple owners is considered a business partnership.

was \$5,000. Then his annual earned income is calculated as $\$5,000 \times \frac{12}{2}$.

One issue regarding business income is that negative income is reported only for the panel after 2004 and not for the panel before 2004. This difference is due to a change in interview questions for business earnings starting in 2004. For example, some portion of earned income from a business is recorded in TPRFTB after 2004 but not before 2004.[33] To make variables consistent across survey years, I first replace negative income with zero. Then, for startup owners with zero income, I impute business incomes to the one reported one year after the subsequent year if it is available.

Other Characteristics Other questions regarding characteristics such as age, sex, race, marital status, and education were asked in the wave after the household net worth is recorded. I use this information as the annual characteristics of each respondent.[34] The core modules present industry information both for workers and for business owners. The core modules also report typical hours worked per week. The potential experience is calculated as max{age - years of education - $6, 1$}.

The Final Sample The final sample is constructed in a similar way to the literature (e.g, Evans and Jovanovic (1989); Hamilton (2000); Hurst and Lusardi (2004)). It is a two-year panel for males ages 18 to 65. This sample is chosen to limit the influence of labor market participation. I call the first year the base year and the second year the subsequent year. I first drop business owners in the base year. Some respondents started their business from the last wave in the base year, and I re-categorized these respondents as new business owners in the subsequent year.[35] I also drop unemployed respondents in the base and the subsequent year.[36] I also dropped those owners who did not report household wealth. In addition, I dropped 15 outliers whose net worth is greater than \$10 billion. Among startup owners in the subsequent year, I drop respondents who answered yes to the question "Was this business owned entirely by members of this household?" I dropped these individuals for two reasons.

[33] For more detailed information, see SIPP user note for Business Income and Profit/Loss.

[34] I impute the years of education for those who did not respond with 13, the average years of education for the whole population conditional on reporting.

[35] A handful of respondents reported business owners only in the last wave in the base year and not in the subsequent year. I dropped these respondents.

[36] The unemployed are defined as non-business owners who reported "no job" (RMESR $\in \{6, 7, 8\}$) at least in two waves during a given year. To limit measurement error, I also drop respondents who were employed but did not report wage earnings in the subsequent year.

First, the motivation to form a family business may be different from the motivation to start a business with non-household members. Second, forming a partnership among household members does not increase the total value of household net worth, an important mechanism this paper investigates. I also dropped business owners who reported equity share less than 25%. The sample consists of 49,996 individuals. Of that number, 1,127 became business owners in the subsequent year, among which 181 are categorized as partners. The number of observations at each stage of sample construction is summarized in Table 18.

B SIPP Oversampling

For SIPP sample design, the Census Bureau assigned the universe of addresses into two strata, one with a higher proportion of poverty than the other. The Census Bureau selects more samples in the high-poverty stratum. Most of the high-poverty regions coincide with areas populated by more African-American, Hispanic, and female-headed family. As a result, most over-sampled low-income individuals or families are African-American, Hispanic, or female-headed families (Huggins and King, 1997). To assess whether the final sample contains relatively more of these low-income individuals, I compare the racial composition of the final sample with that of the Consumer Expenditure Survey (CEX) in 2011.

Table 19 compares the proportion of African-Americans with respect to income both for the final sample and for CEX. The proportion of low-income African-Americans in the final sample is smaller than that of CEX. This observation suggests most of the over-sampled low-income individuals are more likely to be dropped in the process of sample construction.

C Proofs

C.1 Proof of Proposition 1

The planner solves the following problem:

$$\max_{\{z_i, z_j, k\}} F(z_i, z_j, k) = \mathbb{E}\Big[\theta_p k^\alpha (z_i + z_j)^{1-\alpha} - rk\Big]\epsilon_p - \frac{\kappa}{2}\big(z_i^2 + z_j^2\big)$$

$$= \underbrace{\theta_p k^\alpha (z_i + z_j)^{1-\alpha}}_{\text{Aggregate production}} - \underbrace{\Big(rk + \frac{\kappa}{2}\big(z_i^2 + z_j^2\big)\Big)}_{\text{Aggregate cost}}$$

$$\text{subject to} \quad (z_i, z_j, k) > 0, \quad \alpha \in (0,1), \quad \kappa > 0, \quad A_p \geq 0, \quad k \leq \lambda A_p$$

(Case 1) $\lambda A_p \geq 2\hat{a}\theta_p^{\frac{2}{1-\alpha}}$

I first consider the case in which $k \leq \lambda A_p$ is not binding. I show $F(z_i, z_j, k)$ is a concave function on $U = \{x \in \mathbb{R}^3 | (z_i, z_j, k) > 0\}$. Because $F : U \to \mathbb{R}^1$ is a C^2 function and U is a convex open subset of $\mathbb{R}^3$, F is a concave function on U if and only if $D^2F(x)$ is negative semidefinite for all $x \in U$. By deriving leading principal minors, one can easily show $D^2F(x)$ is negative definite for all $x \in U$ and hence negative semidefinite for all $x \in U$. Given that $F(z_i, z_j, k)$ is a concave function on U, it is sufficient to show the unique $x^* \in U$ exists satisfying $DF(x^*) = 0$ to guarantee x^* is the unique global max of F on U.

The first-order conditions are:

$$(1-\alpha)\theta_p\Big(\frac{k}{z_i + z_j}\Big)^\alpha = \kappa z_i \tag{7}$$

$$(1-\alpha)\theta_p\Big(\frac{k}{z_i + z_j}\Big)^\alpha = \kappa z_j \tag{8}$$

$$\alpha\theta_p\Big(\frac{k}{z_i + z_j}\Big)^{\alpha-1} = r \tag{9}$$

(7) and (8) imply $z^* = z_i = z_j$ for any given k. The first-order conditions reduce

$$(1-\alpha)\theta_p\Big(\frac{k}{2z^*}\Big)^\alpha = \kappa z^* \tag{10}$$

$$\alpha\theta_p\Big(\frac{k}{2z^*}\Big)^{\alpha-1} = r \tag{11}$$

By putting (11) into (10), I get

$$z^* = \Big(\frac{1-\alpha}{\kappa}\Big)\theta_p^{\frac{1}{1-\alpha}}\Big(\frac{\alpha}{r}\Big)^{\frac{\alpha}{1-\alpha}} \quad \text{and hence} \quad k^* = 2\Big(\frac{1-\alpha}{\kappa}\Big)\Big(\frac{\alpha}{r}\Big)^{\frac{1+\alpha}{1-\alpha}}\theta_p^{\frac{2}{1-\alpha}} = 2\hat{a}\theta_p^{\frac{2}{1-\alpha}}$$

Therefore, I derived the unique $x^* = (z^*, z^*, k^*)$ such that $DF(x^*) = 0$.

Given that the aggregate production is distributed equally, the value function per parter is given by

$$V_p^E(\theta_p, A_p) = \frac{1}{2}\Big[\theta_p k^{*\alpha}(2z^*)^{1-\alpha} - rk^*\Big] - \frac{\kappa}{2}z^{*2} = a_1\theta_p^{\frac{2}{1-\alpha}}$$

(Case 2) $\lambda A_p < 2\hat{a}\theta_p^{\frac{2}{1-\alpha}}$

In this case, $k \leq \lambda A_p$ is binding and $k^* = \lambda A_p$. The problem reduces

$$\max_{\{z_i, z_j\}} F(z_i, z_j) = \Big[\underbrace{\theta_p k^\alpha (z_i + z_j)^{1-\alpha}}_{\text{Aggregate production}} - \underbrace{\Big(rk + \frac{\kappa}{2}\big(z_i^2 + z_j^2\big)\Big)}_{\text{Aggregate cost}}\Big]$$

$$\text{subject to} \quad (z_i, z_j) > 0, \quad \alpha \in (0,1), \quad \kappa > 0, \quad A_p \geq 0, \quad k = \lambda A_p$$

Following the same argument as in (Case 1), there exists the unique maximum and

$$z_i = z_j = z^* = \Big(\frac{1-\alpha}{\kappa}\Big)^{\frac{1}{1+\alpha}}\Big(\frac{\lambda A_p}{2}\Big)^{\frac{\alpha}{1+\alpha}}\theta_p^{\frac{1}{1+\alpha}}$$

Therefore,

$$V_p^E(\theta_p, A_p) = \frac{1}{2}\Big[\theta_p k^{*\alpha}(2z^*)^{1-\alpha} - rk^*\Big] - \frac{\kappa}{2}z^{*2} = a_2\Big(\frac{\lambda A_p}{2}\Big)^{\frac{2\alpha}{1+\alpha}}\theta_p^{\frac{2}{1+\alpha}} - \frac{r\lambda A_p}{2} \quad \blacksquare$$

D Non-transferable Utility vs. Transferable Utility

Although the observed equity share is mostly 50% to 50%, potential partners may use an ex-ante transfer to attract a better partner during the matching stage. In this section, I allow an ex-ante transfer in the matching stage and compare the matching outcome with the benchmark outcome in which an ex-ante transfer is not allowed.

Once we allow an ex-ante transfer, the matching problem becomes the so-called roommate problem with transferable utility. Before explaining the computational algorithm under transferable utility, I first discuss how I handle a fundamental problem arising when assuming transferable utility for the roommate problem: a stable matching may not exist. To guarantee the existence of a stable matching, I "clone" the entire population. Then I define the original population as Side 1 and the cloned population as Side 2, and find a stable matching by assuming an agent from Side 1 can form a partnership only with an agent from Side 2, and vice versa. Agent x on Side 1 cannot form a partnership with Agent y on Side 1, but the Agent x can always find an identical Agent y in Side 2. Although restrictive, this procedure always guarantees a stable matching. Moreover, the sorting pattern from this procedure without financial friction is identical to the one with non-transferable utility, so that I can clearly compare the impact of financial friction on the sorting pattern under different transferability assumptions.

The problem in the production stage is the same as before. In the matching stage, agents decide with whom they want to match and how much they want to split the outcome produced in the production stage. We can think this procedure as allowing an ex-ante transfer in the matching stage. Suppose Agent i and j are matched in the stable matching, and the division of the outcome for Agent i and j are 40% and 60%, respectively. This situation corresponds to the one in which the equity share in the production stage is 50% to 50%, and Agent i transfers 10% of the outcome in cash to Agent j in the matching stage.

To find the stable matching with transferable utility, I use the algorithm developed by Crawford and Knoer (1981).[37] They provide a transfer-adjustment process and show the process generates a stable matching and it terminates with a finite times. The process starts with agents on one side, say, Side 1, making an offer to an agent on Side 2 as follows:

`STEP1`

- `For Agent` i `in Side 1, calculate the initial transfers` $t_{ij}(0) = o_j$`, where` o_j `is the outside option value for Agent` j `on Side 2.`

`STEP2`

[37] Andersson et al. (2014) provide an algorithm to find a stable matching, or exclusively disproves the existence of any equilibrium under a one-sided setup. Without guaranteeing the existence of a stable matching, however, the procedure may not generate a matching outcome. Moreover, implementing the algorithm is computationally very costly. For these reasons, I use the current cloning methodology.

- Calculate $\max_j \{V_{ij} - t_{ij}(0)\}$. If the maximized value is less than the outside option of Agent i, do not make an offer. If the maximized value is greater than the outside option, make an offer $t_{ij^*}(0)$ to Agent j^* on Side 2.

STEP3

- An agents on Side 2 who receives one or more offers rejects all but his or her favorite, which he or she tentatively accepts.

STEP4

- Offers not rejected in previous periods remain in force. If Agent j on Side 2 rejects an offer from Agent i on Side 1 in period $t-1$, update the transfer as $t_{ij}(t) = t_{ij}(t-1) + d$, where d is a constant. If not, $t_{ij}(t) = t_{ij}(t-1)$. Rejected Agents on Side 1 continue to make offers to their favorite Agents on Side 2, taking into account their current permitted transfers.

STEP5

- The process stops when no rejection occurs.

I parameterize an economy to be same as the one in section 3.4, and simulate 50 individuals:

$$\{\kappa, \alpha\} = \{1, 0.3\}, \quad \log \theta_w = 0, \quad \log \theta_s \sim N(1,1), \quad \log g \sim N(0,1), \quad \log A \sim N(0,10)$$

Then I clone 50 simulated individuals so that the total number of agents in a matching market is 100. With the same individuals, I compute stable matching, one under non-transferable utility (NTU) and the other under transferable utility (TU).

The results are reported in the first column of Table 20 and Figure 11. I first report the results without financial friction. The selection pattern, the number of individuals for each choice, and the sorting pattern among patterns are identical both for NTU and TU. For NTU, a positive assortative matching with respect to ability as a partner arises as in section 3.4, so the best partner is matched with his cloned agent in the market, the second-best partner is matched with his cloned agent in the market, and so on. As a result, the correlation between partners' ability and the correlation between partners' log wealth are both 1. This selection and sorting pattern is the one generating the highest aggregate utility, and hence they are also equilibrium selection and sorting pattern for TU. Indeed, the computational algorithms for TU and NTU are very different, but they generate identical equilibrium outcomes.

Now I introduce financial constraints by setting $\lambda = 1$. The results are reported in the second column of Table 20 and Figure 12. First, the selection pattern, the number of individuals for each choice, is identical both for NTU and TU. Second, as shown in section 3.4, the positive assortative sorting with respect to ability is less pronounced once the financial constraints are introduced. For example, with TU, the ability correlation between two partners is 0.46 with λ being equal to 1, as opposed to 1 without financial friction. On the other hand, the sorting pattern with respect to log wealth exhibits a negative assortative sorting once the financial constraints are introduced. For example, with TU, the log wealth correlation between two partners is -0.67, with λ being equal to 1, as opposed to 1 without financial friction. Third, the sorting pattern, both for ability and log wealth, are very similar across NTU and TU. For example, the ability correlation between two partners is 0.46 and 0.40 for NTU and TU, respectively, and the log wealth correlation between two partners is -0.67 and -0.67 for NTU and TU, respectively.

Figure 13 shows the histogram for the division of the outcome for partners on Side 1 under TU. When no financial friction is present, the share is concentrated near 0.5, but the agents on Side 1, who offer the transfer in the transfer-adjustment process, always have more shares than their partners. When λ is equal to 1, the share among agents on Side 1 is much more dispersed compared to the one without financial friction, and the share for agents on Side 1 is often less than 0.5.

As a robustness check, I simulate two other economies. First, with other parameters being equal as before, I change the distribution of g as $\log g \sim N(-0.3, 1)$ so that the number of partners decreases at the stable matching. Second, with other parameters being equal as before, I change the distribution of g as $\log g \sim N(0.3, 1)$ so that the number of partners increases at the stable matching. The results are reported from Table 21 to Table 22, and from Figure 14 to Figure 17. First of all, the selection and the sorting pattern without financial friction are identical across NTU and TU for all cases. Even in the case of λ being equal to 1, the selection and the sorting pattern are very similar across NTU and TU for all cases.

Computational Difficulty with Non-transferable Utility Although the equilibrium outcome is very similar between NTU and TU, the computational time increases much faster for TU than for NTU as the number of agents increases. Moreover, the equilibrium outcome often depends on the discrete offer d in STEP 4 for TU. For example, as d becomes larger, the positive assortativeness with respect to ability becomes less pronounced.

E Random Matching

As a robustness check, I introduce a search friction into the model. I estimated the parameters under the assumption that the matching market is frictionless. The frictionless assumption has an implication for the estimates of the collaborative skill. Without a search friction, the collaborative skill may be estimated as low to match the small proportion of business partners in the data.

A search friction can be implemented as follows. The frictionless matching market allows an agent to be matched with any other agent in the market. We can limit this possibility by dividing the market into, for example, two groups and not allowing an agent in one group to be matched with any agent in the other group. As an extreme, two agents in the market are randomly matched to each other and not allowed to form a partnership with any other agent except for the randomly matched agent. I re-estimate the model under this random-matching assumption. For estimation, I assign each individual in the final sample a matched agent who is drawn from the uniform distribution over the final sample with replacement.

The parameter estimates under the random matching are similar to those under the frictionless matching. Notably, g_0, the constant term for log collaborative skill, is still estimated to be negative; it was estimated as -1.3726 under the frictionless matching, and is estimated as -1.3283 under the random matching. I also simulate the collaborative skill with the new estimates and compare it with Figure 7. The result is shown in Figure 18. The distribution of g is shifted toward the right. Hence, the proportion of agents whose productivity as a partner is greater than their solo productivity increases from 3.5% to 4.5%. Even so, most individuals are still estimated to have less productivity as a partner than alone.

F Further Characterization of Matching Outcome

Allowing correlation between θ_s and wealth

To see how the correlation between one's ability as a single owner θ_s and wealth affects the matching outcome under financial friction, I simulate the identical economy as in section 3.4:

$$\{\kappa, \alpha, \lambda\} = \{1, 0.3, 1\}, \quad \log \theta_w = 0, \quad \log \theta_s \sim N(1, 1), \quad \log g \sim N(0, 1), \quad \log A \sim N(0, 10)$$

The outcome from the benchmark economy where the correlation is zero is reported in the first column in Table 23. I also simulate three identical economies except for the correlation between $\log \theta_s$ and $\log A$. The matching outcome with correlations of 0.1, 0.3, and 0.5 are reported in the second, third, and fourth columns in Table 23, respectively.

First, both the average log earnings for single owners and the average log earnings for partners increase as the correlation increases. Those who have a high θ_s will become business owners. If the correlation between θ_s and wealth is positive, those with a high θ_s are more likely to have high wealth, and hence are less likely to be financially constrained compared to the case where the correlation is zero.

Second, when the correlation between θ_s and wealth is positive, those with a high θ_s are more likely to have high wealth, and thus have less incentive to find a partner for financing. As a result, the number of single owners increase slightly, and the number of partners decreases slightly. On the other hand, the number of workers varies little as the correlation changes.

Third, regarding the sorting pattern among partners, positive sorting with respect to ability increases and negative sorting with respect to wealth decreases as the correlation between θ_s and wealth increases. Those who have high ability as a partner are more likely to have high wealth if the correlation is positive, and hence are less likely to sacrifice the productivity gain in exchange for the financing gain.

Overall, the correlation between θ_s and wealth may change business owners' average log earnings and their sorting pattern, but the selection pattern and average log earnings for workers change only slightly.

Allowing correlation between g and worker ability

In this section, I introduce an unobserved worker ability, and let it correlate with the collaborative skill g. More specifically, I simulate the same economy as in section 3.4 except for making the worker ability θ_w follow a log normal distribution with $\mathbb{E}[\theta_w] = 1$, and allowing it to be correlated with g:

$$\{\kappa, \alpha, \lambda\} = \{1, 0.3, 1\}, \quad \log\theta_w \sim N(-0.5, 1), \quad \log\theta_s \sim N(1, 1), \quad \log g \sim N(0, 1), \quad \log A \sim N(0, 10)$$

The outcome from the benchmark economy where the correlation is zero is reported in the first column in Table 24. I also simulate three identical economies except for the correlation between $\log\theta_w$ and $\log g$. The matching outcome with correlations of 0.1, 0.3, and 0.5 are reported in the second, third, and fourth columns in Table 24, respectively.

First, the average log earnings for workers decrease and the average log earnings for partners increase as the correlation between worker ability and collaborative skill increases. Those who become partners have higher collaborative skill, and are more likely to have higher worker productivity if the correlation is positive. Thus, those who do not become partners have lower worker productivity on average, and hence the average log earnings for workers will be lower. At the same time, some individuals who could have become partners without a positive correlation receive a high outside option value and become workers. The positive assortative matching occurs without those individuals, and some individuals who were at the margin to be a partner cannot find a partner and are forced to become either a worker or a single owner. As a result, the number of partners slightly decreases and the average log earnings for partners increase.

Second, because those who do not become partners have lower worker productivity on average, individuals who have low ability as a single owner are more likely to become single owners. As a result, the number of single owners increases, and the average log earnings for single owners decrease.

Overall, although the correlation between worker ability and the collaborative skill may change the average log earnings for each occupation, the selection pattern and the sorting pattern change only slightly.

Implication to main results Because a positive correlation between worker ability and collaborative skill may change the average log earnings for each occupation, the estimates for the earning equations may be biased if we assume the correlation to be zero while the true correlation is positive. For example, the estimates for the wage equation could be biased below under a positive correlation between worker ability and collaborative skill.

Nevertheless, the main results would not change much, because the selection and the sorting pattern change only marginally with the correlation. Note the results in section 5.2, 6, and 7 quantify the relative importance between the productivity and the financing gains. Because those results mainly depend on the selection and the sorting pattern, the results would not change much even under a positive correlation between worker ability and collaborative skill given that the selection and the sorting pattern change only marginally with the correlation.

G Additional Tables and Figures

Table 16: Moments for Ownership Choice

K_i	Z_i	Observed $\frac{1}{n}\sum_{i=1}^{n} K_i Z_i$	Simulated $\frac{1}{n}\sum_{i=1}^{n} \tilde{K}_i(\psi) Z_i$
$\mathbb{I}_{si}$	1	0.0206	0.0204
	A_i	0.5697	0.5632
	x_{1i}	0.2862	0.2953
	x_{2i}	0.4570	0.3476
	$A_i x_{1i}$	8.5304	8.5514
	$A_i x_{2i}$	14.3210	10.9464
$\mathbb{I}_{pi}$	1	0.0044	0.0046
	A_i	0.1693	0.1050
	x_{1i}	0.0628	0.0680
	x_{2i}	0.0911	0.0955
	$A_i x_{1i}$	2.4609	1.6459
	$A_i x_{2i}$	4.1321	2.5353

NOTE: This table compares the actual and the simulated moments for ownership choice. $\mathbb{I}_{si}$ is the indicator function for single owners. $\mathbb{I}_{pi}$ is the indicator functions for partners. A is net worth (10,000 USD in 2011). x_1 is the years of education. x_2 is the years of experience.

Table 17: Moments for log Conditional Incomes

K_i	Z_i	Observed $\frac{1}{n}\sum_{i=1}^{n} K_i Z_i$	Simulated $\frac{1}{n}\sum_{i=1}^{n} \tilde{K}_i(\psi) Z_i$
$\pi_{wi}\ \mathbb{I}_{wi}$	1	1.3409	1.3557
	x_{1i}	19.3565	19.0884
	x_{2i}	30.7715	30.6790
$\left(\pi_{wi} - \frac{1}{\sum \mathbb{I}_{wi}} \sum \pi_{wi}\mathbb{I}_{wi}\right)^2 \mathbb{I}_{wi}$	1	0.6141	0.6117
$\pi_{si}\ \mathbb{I}_{si}^s$	1	0.0096	0.0112
	A_i	0.4691	0.3750
	x_{1i}	0.1480	0.1680
	x_{2i}	0.2349	0.2146
	$A_i x_{1i}$	7.4289	5.9648
	$A_i x_{2i}$	12.1086	7.8525
$\left(\pi_{si} - \frac{1}{\sum \mathbb{I}_{si}^s} \sum \pi_{si}\mathbb{I}_{si}^s\right)^2 \mathbb{I}_{si}^s$	1	0.0409	0.0539
$\mathbb{I}_{si}^f$	1	0.0024	0.0025
$\pi_{pi}\ \mathbb{I}_{pi}^s$	1	0.0049	0.0051
	A_i	0.2097	0.1239
	x_{1i}	0.0729	0.0769
	x_{2i}	0.0985	0.1123
	$A_i x_{1i}$	3.0885	1.9712
	$A_i x_{2i}$	5.0356	3.2836
$\left(\pi_{pi} - \frac{1}{\sum \mathbb{I}_{pi}^s} \sum \pi_{pi}\mathbb{I}_{pi}^s\right)^2 \mathbb{I}_{pi}^s$	1	0.0056	0.0075
$\mathbb{I}_{pi}^f$	1	0.0003	0.0003

NOTE: This table compares the actual and the simulated moments for log conditional incomes. π_{wi} is log income conditional on i being a worker. π_{si} is log income conditional on i being a single owner, and i reports a positive income. $\mathbb{I}_{si}^s$ is the indicator function for single owners who report a positive income. $\mathbb{I}_{si}^f$ is the indicator function for single owners who report a negative or zero income. π_{pi} is log income conditional on i being a partner, and i reports a positive income. $\mathbb{I}_{pi}^s$ is the indicator function for partners who report a positive income. $\mathbb{I}_{pi}^f$ is the indicator function for partners who report a negative or zero income. A is net worth (10,000 USD in 2011). x_1 is the years of education. x_2 is the years of experience.

Table 18: Number of Observations at Each Stage of Sample Construction

Drop if	Workers	Single Owners	Partners
	250,609	13,686	3,174
Business owners in the base year	247,860	3,301	508
Female	114,985	1,772	300
Age < 18 or > 65	66,200	1,584	284
Unemployed in either one of periods	49,911	1,270	250
No info. on net worth	49,186	1,251	247
Net worth $>$ \$10 billion	49,171	1,251	247
Family business	48,869	1,200	181
Equity share $< 25\%$	48,869	946	181

NOTE: Business owners whose equity share is less than 25% were categorized as single owners before being deleted.

Table 19: Proportion of African-Americans with Respect to Income before Tax

	$\sim$ \$18,559	\$18,559 $\sim$ \$35,645	\$35,645 $\sim$ \$58,272	\$58,272 $\sim$ \$93,837	\$93,837 $\sim$
CEX 2011 (%)	20	14	11	11	6
Final sample (%)	12	12	9	7	4

NOTE: Dollar in 2011. This table compares the proportion of African-Americans in terms of income levels both for the final sample and for CEX 2011. For the final sample, incomes in the base year is used.

Table 20: Sorting Pattern ($\log g \sim N(0,1)$): NTU vs. TU

	Economy with $\lambda = \infty$		Economy with $\lambda = 1$	
	NTU	TU	NTU	TU
# of workers	20	20	22	22
# of single owners	36	36	26	26
# of partners	44	44	52	52
Corr(P1.ability, P1.ability)	1	1	0.46	0.40
Corr($\log A1$, $\log A2$)	1	1	-0.67	-0.67

NOTE: This table reports the selection and the sorting pattern from two simulated economies. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha\} = \{1, 0.3\}$, $\theta_w = 1$, $\log \theta_s \sim N(1,1)$, $\log g \sim N(0,1)$, $\log A \sim N(0,10)$. The first two columns of the table report the results without financial friction, and the last two columns of the table report the results with $\lambda = 1$. NTU refers to the matching market not allowing ex-ante transfer. TU refers to the matching allowing ex-ante transfer.

Table 21: Sorting Pattern ($\log g \sim N(-0.3, 1)$): NTU vs. TU

	Economy with $\lambda = \infty$		Economy with $\lambda = 1$	
	NTU	TU	NTU	TU
# of workers	28	28	30	30
# of single owners	50	50	38	36
# of partners	22	22	32	34
Corr(P1.ability, P1.ability)	1	1	0.36	0.48
Corr(log $A1$, log $A2$)	1	1	-0.89	-0.75

NOTE: This table reports the selection and the sorting pattern from two simulated economies. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha\} = \{1, 0.3\}$, $\theta_w = 1$, $\log \theta_s \sim N(1, 1)$, $\log g \sim N(-0.3, 1)$, $\log A \sim N(0, 10)$. The first two columns of the table report the results without financial friction, and the last two columns of the table report the results with $\lambda = 1$. NTU refers to the matching market not allowing ex-ante transfer. TU refers to the matching allowing ex-ante transfer.

Table 22: Sorting Pattern ($\log g \sim N(0.3, 1)$): NTU vs. TU

	Economy with $\lambda = \infty$		Economy with $\lambda = 1$	
	NTU	TU	NTU	TU
# of workers	18	18	18	20
# of single owners	26	26	16	16
# of partners	56	56	66	64
Corr(P1.ability, P1.ability)	1	1	0.35	0.40
Corr(log $A1$, log $A2$)	1	1	-0.67	-0.71

NOTE: This table reports the selection and the sorting pattern from two simulated economies. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha\} = \{1, 0.3\}$, $\theta_w = 1$, $\log \theta_s \sim N(1, 1)$, $\log g \sim N(0.3, 1)$, $\log A \sim N(0, 10)$. The first two columns of the table report the results without financial friction, and the last two columns of the table report the results with $\lambda = 1$. NTU refers to the matching market not allowing ex-ante transfer. TU refers to the matching allowing ex-ante transfer.

Table 23: Matching Outcome under Correlation between θ and Wealth

	correlation between θ and wealth			
	Benchmark	corr = 0.1	corr = 0.3	corr = 0.5
# of workers	2,983	2,992	2,977	2,983
# of single owners	2,533	2,544	2,589	2,617
# of partners	4,484	4,464	4,434	4,400
Corr(P1.ability, P1.ability)	0.68	0.69	0.72	0.74
Corr(log $A1$, log $A2$)	-0.67	-0.65	-0.63	-0.60
Ave. log earnings for workers	-0.68	-0.68	-0.68	-0.68
Ave. log earnings for single owners	1.48	1.49	1.53	1.57
Ave. log earnings for partners	2.51	2.54	2.57	2.60

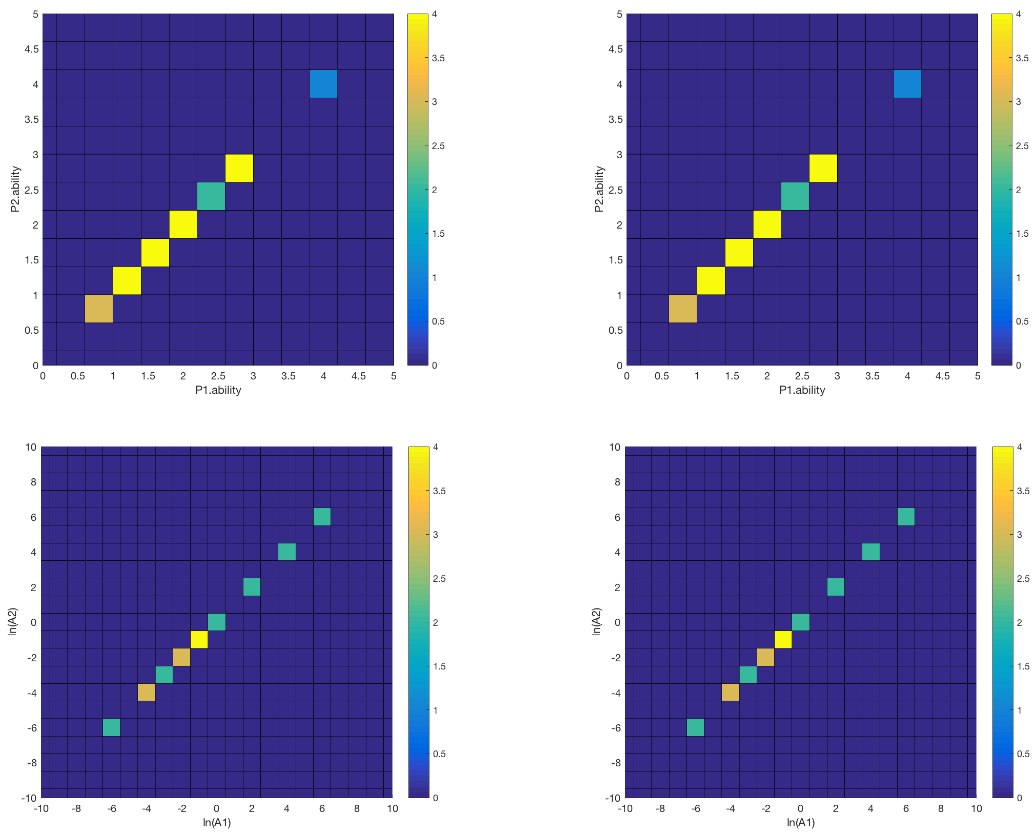
NOTE: This table reports the selection and the sorting pattern as well as the average log earnings for each occupation from four simulated economies. I simulate 10,000 individuals from the economy characterized as follows: $\{\kappa, \alpha, \lambda\} = \{1, 0.3, 1\}$, $\log \theta_w = 0$, $\log \theta_s \sim N(1, 1)$, $\log g \sim N(0, 1)$, $\log A \sim N(0, 10)$. Benchmark refers to the economy without correlation between $\log \theta_s$ and $\log A$. "corr" refers to the correlation between $\log \theta_s$ and $\log A$.

Table 24: Matching Outcome under Correlation between g and Worker Ability

	correlation between g and worker ability			
	corr = 0	corr = 0.1	corr = 0.3	corr = 0.5
# of workers	2,585	2,559	2,492	2,413
# of single owners	2,863	2,909	3,010	3,121
# of partners	4,552	4,532	4,498	4,466
Corr(P1.ability, P1.ability)	0.85	0.85	0.85	0.86
Corr(log $A1$, log $A2$)	-0.62	-0.63	-0.62	-0.60
Ave. log earnings for workers	-0.77	-0.80	-0.87	-0.96
Ave. log earnings for single owners	1.15	1.12	1.05	0.98
Ave. log earnings for partners	2.45	2.46	2.48	2.51

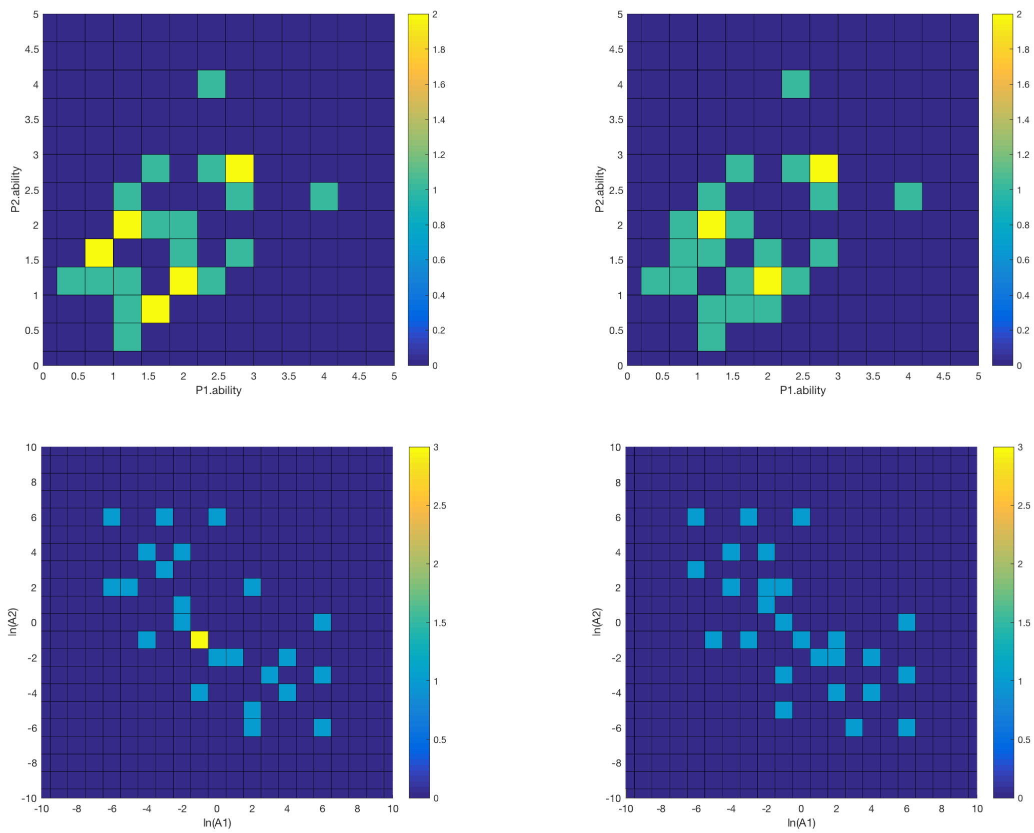
NOTE: This table reports the selection and the sorting pattern as well as the average log earnings for each occupation from four simulated economies. I simulate 10,000 individuals from the economy characterized as follows: $\{\kappa, \alpha, \lambda\} = \{1, 0.3, 1\}$, $\log \theta_w \sim N(-0.5, 1)$, $\log \theta_s \sim N(1, 1)$, $\log g \sim N(0, 1)$, $\log A \sim N(0, 10)$. Benchmark refers to the economy without correlation between $\log \theta_w$ and $\log g$. "corr" refers to the correlation between $\log \theta_w$ and $\log g$.

Figure 11: Sorting Pattern without Financial Friction: NTU (Left Column) vs. TU (Right Column)



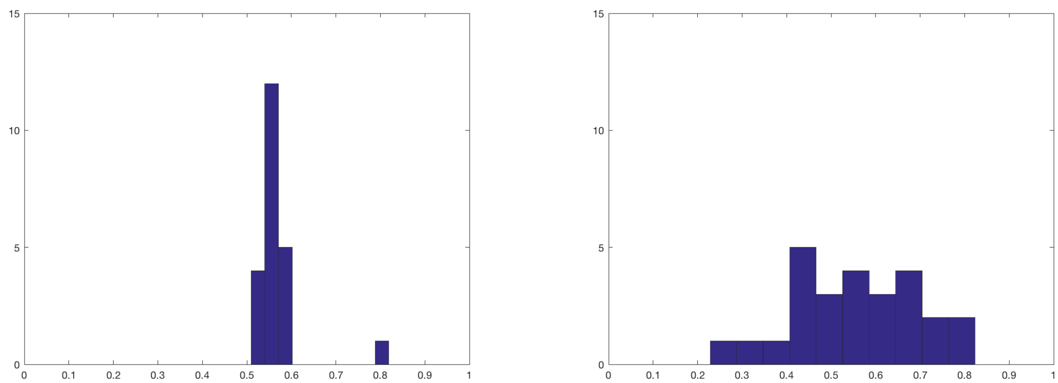
NOTE: The left column is the sorting pattern under non-transferable utility (NTU). The right column is the sorting pattern under transferable utility (TU). The top two figures show the sorting patterns with respect to ability. The bottom two figures show the sorting patterns with respect to log wealth. P1.ability and P2.ability refer to Partner 1's ability and Partner 2's ability, respectively. ln(A1) and ln(A2) refer to Partner 1's log wealth and Partner 2's log wealth, respectively. Different colors represent a different number of observations. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha\} = \{1, 0.3\}$, $\log \theta_w = 0$, $\log \theta_s \sim N(1, 1)$, $\log g \sim (0, 1)$, $\log A \sim (0, 10)$.

Figure 12: Sorting Pattern with $\lambda = 1$ ($\log g \sim N(0,1)$): NTU (Left Column) vs. TU (Right Column)



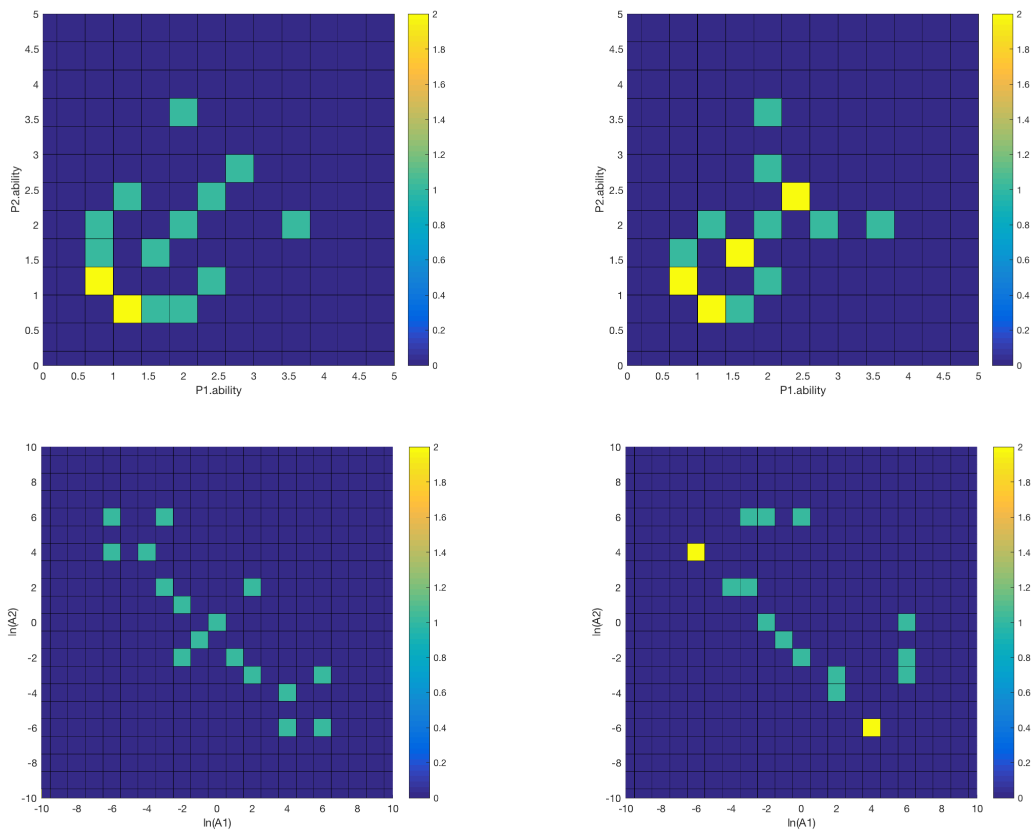
NOTE: The left column is the sorting pattern under non-transferable utility (NTU). The right column is the sorting pattern under transferable utility (TU). The top two figures show the sorting patterns with respect to ability. The bottom two figures show the sorting patterns with respect to log wealth. P1.ability and P2.ability refer to Partner 1's ability and Partner 2's ability, respectively. ln(A1) and ln(A2) refer to Partner 1's log wealth and Partner 2's log wealth, respectively. Different colors represent a different number of observations. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha, \lambda\} = \{1, 0.3, 1\}$, $\log \theta_w = 0$, $\log \theta_s \sim N(1, 1)$, $\log g \sim (0, 1)$, $\log A \sim (0, 10)$.

Figure 13: The Division of the Outcome for Agents on Side 1 ($\log g \sim N(0,1)$): No Financial Friction (Left) vs. $\lambda = 1$ (right)



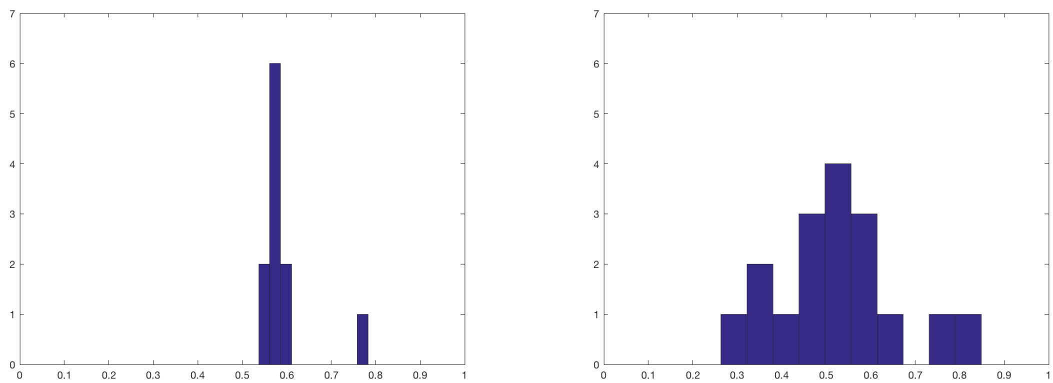
NOTE: The left figure shows the histogram for the division of the outcome for agents on Side 1 when no financial friction is present. The right figure shows the histogram for the division of the outcome for agents on Side 1 when $\lambda = 1$. The number is normalized by the total value from the partnership. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha\} = \{1, 0.3\}$, $\log \theta_w = 0$, $\log \theta_s \sim N(1,1)$, $\log g \sim (0,1)$, $\log A \sim (0,10)$

Figure 14: Sorting Pattern with $\lambda = 1$ ($\log g \sim N(-0.3, 1)$): NTU (Left Column) vs. TU (Right Column)



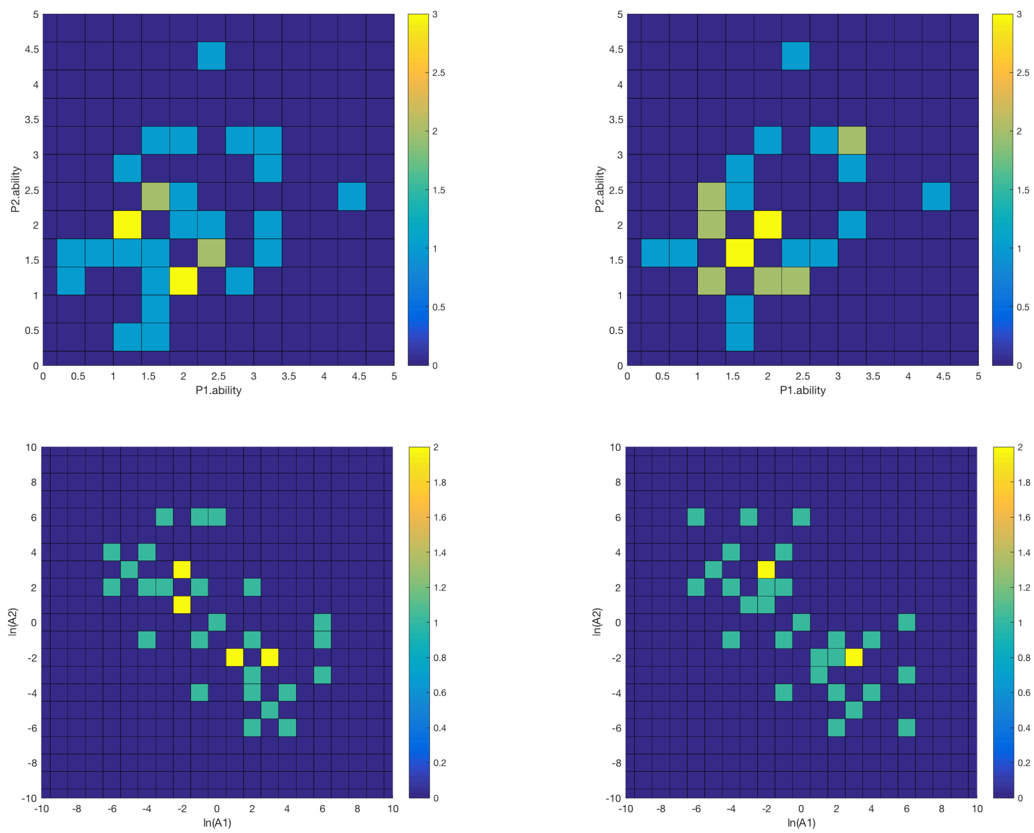
NOTE: The left column is the sorting pattern under non-transferable utility (NTU). The right column is the sorting pattern under transferable utility (TU). The top two figures show the sorting patterns with respect to ability. The bottom two figures show the sorting patterns with respect to log wealth. P1.ability and P2.ability refer to Partner 1's ability and Partner 2's ability, respectively. ln(A1) and ln(A2) refer to Partner 1's log wealth and Partner 2's log wealth, respectively. Different colors represent a different number of observations. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha, \lambda\} = \{1, 0.3, 1\}$, $\log \theta_w = 0$, $\log \theta_s \sim N(1, 1)$, $\log g \sim (-0.3, 1)$, $\log A \sim (0, 10)$.

Figure 15: The Division of the Outcome for Agents on Side 1 ($\log g \sim N(-0.3, 1)$): No Financial Friction (Left) vs. $\lambda = 1$ (right)



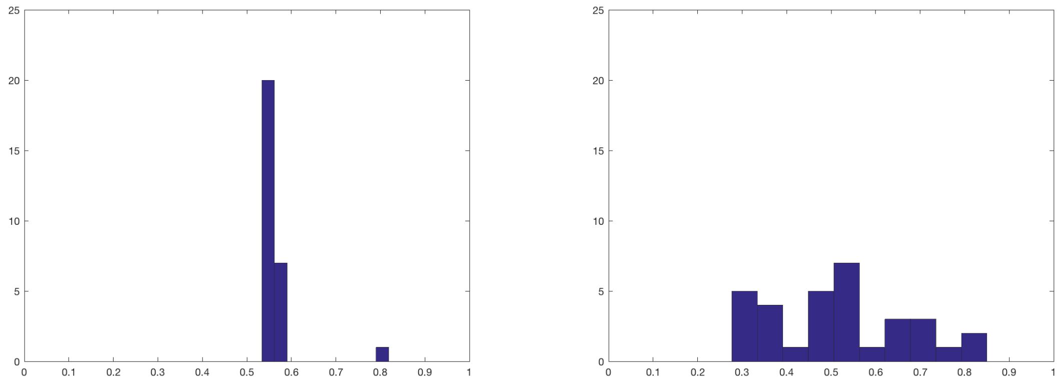
NOTE: The left figure shows the histogram for the division of the outcome for agents on Side 1 when no financial friction is present. The right figure shows the histogram for the division of the outcome for agents on Side 1 when $\lambda = 1$. The number is normalized by the total value from the partnership. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha\} = \{1, 0.3\}$, $\log \theta_w = 0$, $\log \theta_s \sim N(1, 1)$, $\log g \sim (-0.3, 1)$, $\log A \sim (0, 10)$.

Figure 16: Sorting Pattern with $\lambda = 1$ ($\log g \sim N(0.3, 1)$): NTU (Left Column) vs. TU (Right Column)



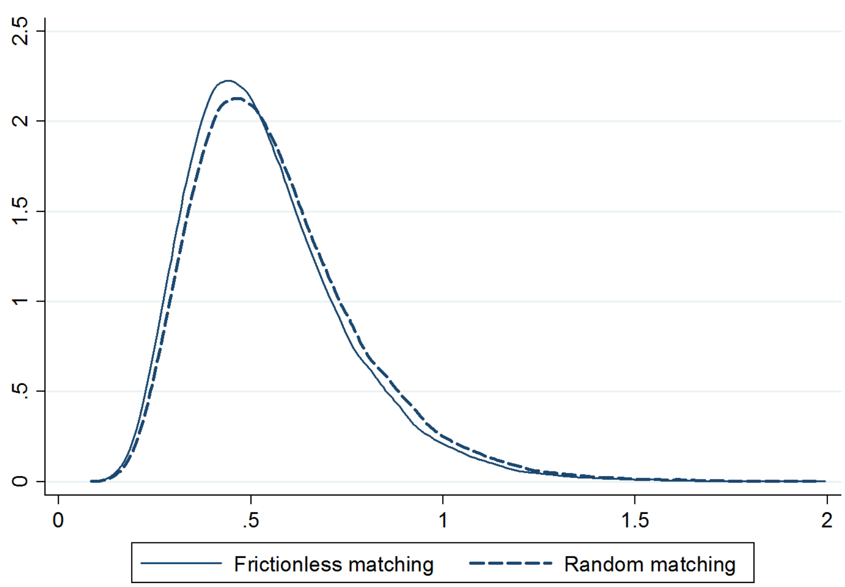
NOTE: The left column is the sorting pattern under non-transferable utility (NTU). The right column is the sorting pattern under transferable utility (TU). The top two figures show the sorting patterns with respect to ability. The bottom two figures show the sorting patterns with respect to log wealth. P1.ability and P2.ability refer to Partner 1's ability and Partner 2's ability, respectively. ln(A1) and ln(A2) refer to Partner 1's log wealth and Partner 2's log wealth, respectively. Different colors represent a different number of observations. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha, \lambda\} = \{1, 0.3, 1\}$, $\log \theta_w = 0$, $\log \theta_s \sim N(1, 1)$, $\log g \sim (0.3, 1)$, $\log A \sim (0, 10)$.

Figure 17: The Division of the Outcome for Agents on Side 1 ($\log g \sim N(0.3, 1)$): No Financial Friction (Left) vs. $\lambda = 1$ (right)



NOTE: The left figure shows the histogram for the division of the outcome for agents on Side 1 when no financial friction is present. The right figure shows the histogram for the division of the outcome for agents on Side 1 when $\lambda = 1$. The number is normalized by the total value from the partnership. I simulate 100 individuals, as explained in Appendix D, from the economy characterized as follows: $\{\kappa, \alpha\} = \{1, 0.3\}$, $\log \theta_w = 0$, $\log \theta_s \sim N(1, 1)$, $\log g \sim (0.3, 1)$, $\log A \sim (0, 10)$.

Figure 18: Kernel Density of Collaborative Skill: Frictionless Matching vs. Random Matching



NOTE: This figure shows Kernel density of a simulated value for g given covariates and estimates under different matching markets. g greater than 1 means productivity as a partner is greater than the solo productivity. g less than 1 means productivity as a partner is less than the solo productivity.