Sorting into Entrepreneurial Teams*

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July 2025

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Abstract

This paper studies how entrepreneurs sort into teams and how team entrepreneurship affects the equilibrium distribution of firms. Leveraging employer-employee administrative records matched with private companies' balance sheet data for Portugal, we show that firms of entrepreneurial teams have higher sales, productivity and survival rates than those of single entrepreneurs. We then exploit information on agents' careers before opening a firm to establish that there is a strong degree of sorting in entrepreneurial teams along observed and unobserved heterogeneity. A novel theory of career choices and team formation rationalizes why similarity in entrepreneurs' overall talent and dissimilarity in their skill specialization lead to better firm outcomes, providing insights into the micro-foundations of firm growth.

*We thank Gadi Barlevy, Alessandro Ferrari, Lukas Freund, Francois Gourio, Sasha Indarte, Christopher Moser, Emi Nakamura, Francisco Queiró, Morten Ravn, Tom Schmitz, Jon Steinsson, Vincent Sterk, Gianluca Violante, and participants at UCL, Queen Mary University London, CREI, Goethe University, the Inter-American Development Bank, Banco de Portugal, Universitat Autonoma de Barcelona, LMU, Northwestern University, Bank of England, the Chicago FED seminars, the LSE Junior Macro Conference, the SED, T2M, Esade, the NYU Abu Dhabi Conference on New Frontiers, and the NBER Summer Institute for Policy Evaluation for helpful feedback. Elena Casanovas provided excellent research assistance. Acabbi gratefully acknowledges the financial support from the Comunidad de Madrid (Programa Excelencia para el Profesorado Universitario, convenio con Universidad Carlos III de Madrid, V Plan Regional de Investigación Científica e Innovación Tecnológica), the Spanish Ministry of Science and Innovation (project PID2022-137707NB-I00), and the Fundación Ramón Areces (projects CISP20S12348 and CISP22S15759). The views expressed reflect only the view of the authors and not those of the Bank of England or its policy committees.
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1 Introduction

Firm productivity stands as a fundamental driver of economic growth and forms the cornerstone of macroeconomic models of firm dynamics. What's more, research has established that firms' heterogeneity, especially at birth, is highly indicative of their life-cycle trajectories (Sterk, Sedláček and Pugsley 2021) – including differences in firm selection at entry (Bhandari et al. 2022), their initial pool of workers (Choi et al. 2023) and their early investments into physical capital (De Haas, Sterk and Van Horen 2022). This paper takes a different angle, and focuses on how the sorting of entrepreneurs into teams affects firm productivity and, consequently, the equilibrium distribution of firms.

While between 30 and 40% of privately held firms in advanced economies is multi-owned,[1] limited attention has been devoted to the sorting patterns of entrepreneurial teams, although the literature suggests that entrepreneurs in teams have work experience in similar industries (Feliz, Karmakar and Sedlácek 2021). Our aim is to investigate more broadly how entrepreneurs select co-founders and whether they have similar (or dissimilar) talent and skills, and then offer an explanation as to why these sorting patterns influence firm outcomes. Combining a novel theoretical framework and empirical evidence, we show that entrepreneurial sorting in talent and skills is key for capturing the determinants of heterogeneity in productivity, especially at firm inception.

We first build a model that encompasses the core dynamics of team sorting within a framework of entrepreneurship and career choice. In our model economy, individuals are endowed with a combination of skills across multiple dimensions. Equilibrium wages in each occupation provide a price for each single skill. If choosing to become entrepreneurs, individuals use a combination of their entire skills set, and then demand labor depending on relative wages. Crucially, entrepreneurial teams' productivity emerges as a combination of each skill at the individual level. We assume that, before career and entrepreneurial choices are made, each individual has a chance to meet another one, randomly sampled from the same joint skills distribution. Teams are formed when both individuals in the match prefer starting a firm in a team rather than alone, or supplying labor as a worker.

The model yields four main predictions: (i) conditional on their overall productivity, individuals whose skill endowment is more dispersed are more likely to become members of entrepreneurial teams; (ii) in presence of search frictions, the productivity of members of entrepreneurial teams is on average higher than that of single entrepreneurs; (iii) firms with heterogeneity in the skill composition of team members are larger and more productive; (iv) firms with high and similar overall productivity of team members are larger and more productive.

[1] In our dataset, for example, entrepreneurial teams constitute approximately 30% of all privately-held firms, employ more than 40% of their workforce, and account for more than 40% of their total gross sales.

We analyze empirically the formation and performance of entrepreneurial teams, leveraging comprehensive administrative data covering the universe of employer-employee matches in Portugal from 1991 to 2019, which can also be linked to the balance sheets of privately-held firms. This dataset is unique in two important dimensions: first, on top of several demographic variables, it records the entire occupational trajectory of millions of individuals, including their transitions in and out of self-employment. Second, it makes it possible to investigate the performance of firms started by the entrepreneurs in our sample, including those firms founded by a team.

To test the predictions of our theoretical framework, we need measures of individuals' talent and skills, which we recover by tracing the career paths of workers and entrepreneurs alike in our sample. First, we exploit information on the occupations agents held before starting a firm, together with official EU-wide crosswalks between occupations and essential competences, to provide an individual-level measure of skills. Second, we use yearly wages to estimate agents' unobserved heterogeneity – a measure of their (latent) talent – following methods in Abowd, Kramarz and Margolis (1999) and Bonhomme, Lamadon and Manresa (2019). Crucially, for individuals who become entrepreneurs, we focus on their working careers before the first entrepreneurial spell.

By analyzing entrepreneurs' employment histories, we find evidence in support of the prevalent view in entrepreneurship, dating back to Lucas (1978) and expanded in Levine and Rubinstein (2017), suggesting entrepreneurs are positively selected with respect to workers on talent (or, said differently, unobserved productivity). We also establish a novel empirical fact, consistent with the second prediction of our theory: entrepreneurs in teams are more selected on talent with respect to single entrepreneurs. In our model, for someone to prefer team entrepreneurship over all other outside options, they must have relatively high levels of at least one skill and to have met a potential business partner with relatively high levels of at least one complementary skill. Along this line – and consistent with the first prediction of our model –, we show empirically that talented individuals with unbalanced skills in our sample are more likely to be part of entrepreneurial teams.

The key novelty of our empirical strategy is to disentangle different sorting dimensions within entrepreneurial teams, distinguishing between similarity in talent (ability across all skills possessed) and complementarity in competences (e.g., technical vs business expertise). In turn, the analysis of entrepreneurs' employment histories before teaming up – linked to firm-level outcomes – lends further empirical support for the third and fourth predictions of the model. Specifically, our findings indicate that positive sorting along talent correlates with higher firm sales and total factor productivity. Yet, teams exhibiting greater skill diversity achieve better firm outcomes, suggesting that complementarity in competences enhances firm success.

We also find evidence consistent with substantial search frictions. When analyzing team formation, we see that couples of workers with different talent and work history have a significantly lower probability of forming a team. Replicating this exercise with simulated data from the model informs our calibration of the matching process, which we find to be substantially biased towards generating meetings among very similar workers.

In our calibrated model, entrepreneurial teams represent a third of the top 10% largest firms (43% in the data) and make up for 38% of total sales (40% in the data), despite being only a fourth of all firms. The unexpected departure of a founder causes a significant decline of sales in the data, as shown by Choi et al. (2021); our model predicts that teams with a highly heterogeneous skill composition will suffer a larger decline in sales. This intuition is confirmed in the model and in the data, with the difference in sales decline between most and least diverse teams amounting to 10% of pre-shock sales. These results align with empirical estimates from Portugal, and highlight how entrepreneurial teams shape the firm distribution and hence contribute to macroeconomic outcomes.

Overall, by integrating empirical evidence with a model of career choice and team formation, we make three contributions to existing works on the aggregate consequences of entrepreneurial dynamics. First, we add to the research on entrepreneurial selection by highlighting the importance of co-founder choice in determining firm-level trajectories. Second, we provide novel insights into knowledge spillovers within teams, analyzing entrepreneurial sorting patterns along observed and unobserved traits. Finally, we build on studies examining the drivers of firm success by linking entrepreneurial team composition to long-run firm outcomes, both in the data and in a model. The tension between positive sorting and skill heterogeneity provides novel insights into the micro-foundations of firm growth. We also find limited evidence that financial or cyclical factors primarily drive team formation, reinforcing the argument that, unlike workers sorting early into startups (Bias and Ljungqvist 2023), entrepreneurial sorting is linked to intrinsic attributes rather than external constraints.

Related Literature. Our work relates to four strands of research. First, we contribute to the existing body of evidence on the labor market determinants of entrepreneurship. Our empirical analysis is related to Gendron-Carrier (2024), Humphries (2022), and Queiró (2022), who explore the human capital accumulation and career patterns leading to entrepreneurship. Since we focus on the heterogeneous components of individual skills, we also relate to Argan, Indraccolo and Piosk (2024), who use Danish data to show that workers with very specialized skills are less likely to become entrepreneurs.

Second, we contribute to the literature that studies skill complementarities and how they lead to the sorting of individuals in labor markets. In this sense, our focus on two-people teams that are core to their organization is close to Freund (2022), although we analyze teams of entrepreneurs, not workers. Moreover, our theory of mutual learning between entrepreneurs is an extension of Acabbi, Alati and Mazzone (2024), and is also related to Jarosch, Oberfield and Rossi-Hansberg (2021) and Herkenhoff et al. (2024).

Third, we contribute to an emerging literature on entrepreneurial teams. Notably, Choi et al. (2021) shows that the death of a member of a firm's founding team negatively affects its performance, while D'Acunto, Tate and Yang (2024) discuss the role of skill complementarities between employees hired at firm start with similar previous industry experiences. We build and expand on these results by explicitly investigating the determinants of entrepreneurial team formation along both the vertical and horizontal differentiation of individual skills and talent, and studying – empirically and theoretically – the role of team sorting for the life-cycle performance of firms.

Finally, our model of career choice builds on the classic *span of control* framework proposed by Lucas (1978) by adding multiple individual skills and entrepreneurial team formation.[2] Importantly, our focus on the direction of sorting across dimensions of individuals' characteristics follows intuitions discussed in Eeckhout and Kircher (2011). A different approach to complementarities in production is presented in Boerma, Tsyvinski and Zimin (2025) focusing on teams of size three – two workers and a project. In related work, Boerma et al. (2023) explore the coexistence of positive and negative assortative matching when matches are characterized by concave mismatch costs, while Mukoyama and Sahin (2005) discuss the emergence of negative sorting between skills for pairs of workers. Our paper illustrates how, when looking at teams of entrepreneurs, the notions of positive and negative sorting can coexist, depending on whether one looks at skills separately or if all of them are taken into account into a measure of overall talent.

The remainder of this paper is structured as follows. Section 2 develops a general equilibrium model of career decisions and team entrepreneurship, whose key predictions will be then tested empirically. Section 3 outlines the data sources and provides descriptive statistics for our sample. Section 4 presents the empirical strategy and discusses our results, including robustness checks and alternative explanations to team formation. Section 5 provides a quantification of the model and its main predictions. Finally, Section 6 concludes with policy implications and directions for future research.

2 Model

In what follows, we propose a static general equilibrium model of career decisions, characterized by heterogeneous (workers') occupations, entrepreneurship, and entrepreneurial team formation. The economy we analyze is populated by a continuum of risk-neutral agents, each endowed with one unit of time and a heterogeneous combination of skills among N existing ones, which we think of as their human capital.

[2] Other notable extensions of the entrepreneurial model by Lucas (1978) that already consider multiple dimension of individual ability or skills include Cagetti and De Nardi (2006) and Poschke (2013).

Agents in this economy have access to three career choices: (i) working as an employee, (ii) founding a single-owned firm, or (iii) forming a multi-owner entrepreneurial team. Individuals that choose the first option can supply labor in any of N different occupations, which uses intensively one of the N skills, and earn a wage that clears the corresponding labor market. Entrepreneurs derive profits from firm operations, while the formation of entrepreneurial teams follows instead a matching process, where agents search for and pair with potential co-founders if the expected joint profits exceed individual alternatives.

Wages across occupations and entrepreneurial profits are determined in general equilibrium, and so are career choices, which depend on the (endogenous) returns to starting a firm – solo or in a team – relative to working as an employee. Therefore, the structure of the economy, including the wage-setting mechanism and the matching process of entrepreneurial teams, leads to equilibrium outcomes in which agents select into different careers based on their comparative advantage and expected earnings.

The output of firms depends on the human capital of their founders, labor inputs from the external market, and the technology that governs production. Firms demand labor from each occupation depending on their own specialization and on prevailing wages.

2.1 Environment

Agent Heterogeneity. Each agent is characterized by the N-dimensional skill vector:

$$\mathbf{\Theta} = [\theta_1, \theta_2, \ldots, \theta_N]$$

Given the combination of their skill levels, individuals will be both *vertically* and *horizontally* differentiated - the former depending on the average level of all their skills, the latter on how balanced their skills are across all dimensions. To use a terminology close to Freund (2022), vertical differentiation can be interpreted more generally as individuals' talent, while horizontal differentiation speaks to their specialization. Note that the joint distribution $G(\mathbf{\Theta})$ captures the heterogeneity in individuals' skill endowments as a multivariate probability distribution over $\mathbb{R}^N$. Formally, we can write:

$$\mathbf{\Theta} = [\theta_1, \theta_2, \ldots, \theta_N] \sim G(\theta_1, \theta_2, \ldots, \theta_N)$$

Occupational Choices. Agents can choose to work in paid employment. When they supply labor to firms, agents' productivity as workers is occupation-specific and is given by the increasing and concave function $h(\mathbf{\Theta}|\, j) : \mathbb{R}_+ \to \mathbb{R}_+$. Importantly, we assume that skills are fully unbundled across occupations, so that $h(\mathbf{\Theta}|\, j) = h(\theta_j)$.[3] An individual i with skills given by the vector $\mathbf{\Theta}_i$ and who is employed in occupation j will be paid

[3]See Edmond and Mongey (2021) on the assumption that skills can be priced separately.

according to the occupation-specific wage w_j. The value of choosing paid employment for agent i can then be summarized as $R_i(\mathbf{\Theta}_i) = \max_j \{w_j\, h(\theta_{i,j})\}$ with $j = 1, \ldots, N$.

Alternatively, individuals can become entrepreneurs. If they do, their productivity as entrepreneurs is given by function $\zeta(\mathbf{\Theta}) : \mathbb{R}^N_+ \to \mathbb{R}_+$, assumed to be increasing in each coordinate and super-modular.[4] Since we abstract from the use of capital in production, the profit maximization problem of a single-owned firm run by individual i is given by:

$$\pi_i\left(\mathbf{\Theta}_{\boldsymbol{i}}, \boldsymbol{L}, \boldsymbol{w}\right) = \zeta\left(\mathbf{\Theta}_i\right) \cdot f(\boldsymbol{L})^{\nu} - \sum_{j=1}^{N} w_j L_j \tag{1}$$

where $f(\cdot)$ is increasing and concave. We assume decreasing returns to scale, hence we assume the output elasticity to the composite labor input $f(\mathbf{L})$ to be $\nu < 1$. Productivity $\zeta(\mathbf{\Theta}_i)$ of individual i thus enters the firm problem as in the general class of models of entrepreneurial *span of control* (Lucas 1978).[5] In addition to starting firms alone, we allow for agents to team up in pairs and run firms jointly. When they do, they face a maximization problem analogous to **Equation 1**. In entrepreneurial teams, however, overall firm productivity is a function of the skill vectors of each of the two members of the team. Specifically, each skill is aggregated across members via the horizontal skills aggregator $\psi(\cdot,\cdot) : \mathbb{R}^2_+ \to \mathbb{R}_+$, and then:

$$\mathbf{\Theta}^T_{i,i'} = [\psi(\theta_{1,i}, \theta_{1,i'}), \psi(\theta_{2,i}, \theta_{2,i'}), \ldots, \psi(\theta_{N,i}, \theta_{N,i'})] \tag{2}$$

for every team where agent i is teaming up with another agent of generic type i'.

Payoffs. Each firm chooses labor inputs to maximize profits – $\boldsymbol{L}^*_i$ is firm i's labor demand, and the payoff from starting a single-owned firm is $\pi_i\left(\mathbf{\Theta}_{\boldsymbol{i}}, \boldsymbol{L}^*(\mathbf{\Theta}_i), \boldsymbol{w}\right)$. To ease notation, we indicate the payoff for opening a single-owned firm as $\pi^*_{I,i}\left(\mathbf{\Theta}_i\right)$. Similarly, the payoff of becoming part of an entrepreneurial team for agent i is $\pi^*_{T,i}\left(\mathbf{\Theta}^T_{i,i'}\right)$ - and it will depend on the characteristics of the other team member, whose skill vector is $\mathbf{\Theta}_{i'}$. As discussed above, the payoff of paid employment is $R_i(\mathbf{\Theta}_i) = \max_j \{w_j\, h(\theta_{i,j})\}$, with $j = 1, \ldots, N$.

Matching. Before making career choices, each agent randomly meets another, drawn from the same distribution $G(\mathbf{\Theta})$, according to the matching function $m(\mathbf{\Theta}_{i'}|\mathbf{\Theta}_i)$. This implies that there is a non-zero measure of entrepreneurial teams for some sections of the skills space $\mathbf{\Theta}$ where suitable matches can be formed, and a measure zero of teams when $\mathbf{\Theta}_{\boldsymbol{i}}$ is such that no entrepreneurial team can be formed, whatever type i' is i meeting.

[4] An important assumption we make is that worker skills can be transferred from individuals as workers to entrepreneurship – Gyetvai and Tan (2023) provide evidence consistent with our model choice.

[5] Notice that, for an appropriate specification of $h(\cdot)$ that collapses worker heterogeneity into a single type, and for $N = 1$, our framework boils down to the original span of control model by Lucas 1978.

2.2 Equilibrium Characterization

Choice Sets. The set of any two individuals i and i' that choose to be workers and supply labor in occupation j is a subset of the product space $\mathbf{\Theta}_i \times \mathbf{\Theta}_{i'}$, and is given by:

$$\mathcal{W}_j \; = \; \Big\{ \{\mathbf{\Theta}_i, \mathbf{\Theta}_{i'}\} \; \Big| \; w_j \, h(\theta_{i,j}) \;\; \geq \;\; \max \left\{ w_k \, h(\theta_{i,k}), \pi^*_{I,i} \left(\mathbf{\Theta}_i\right), \pi^*_{T,i} \left(\mathbf{\Theta}^T_{i,i'}\right) \right\} \quad \forall k \neq j \Big\}$$

for any individual i matched with an individual i'. Clearly, this choice set is defined for *pairs* of skill vectors, reflecting the complementarities arising from different potential meetings. We can similarly define the set of individual and team entrepreneurs, given by:

$$\mathcal{E}_I = \Big\{ \{\mathbf{\Theta}_i, \mathbf{\Theta}_{i'}\} \; \Big| \; \pi^*_{I,i} \left(\mathbf{\Theta}_i\right) \geq \max \left\{ w_j \, h(\theta_{i,j}), \, \pi^*_{T,i} \left(\mathbf{\Theta}_{i,i'}\right) \right\} ; \, \forall j \in 1, \ldots, N \Big\}$$
$$\mathcal{E}_T = \Big\{ \{\mathbf{\Theta}_\iota, \mathbf{\Theta}_{\iota'}\} \; \Big| \; \pi^*_{T,\iota} \left(\mathbf{\Theta}_{\iota,\iota'}\right) \geq \max \left\{ w_j \, h(\theta_{\iota,j}), \pi^*_{I,\iota} \left(\mathbf{\Theta}_\iota\right) \right\} ; \, \forall j \in 1, \ldots, N; \, \iota, \iota' \in \{i, i'\} \Big\}$$

and $\iota \neq \iota'$. Notice that the set of team entrepreneurs requires a *double coincidence* or, differently said, *bilateral agreement*, as it includes only those pairs where both individuals prefer forming an entrepreneurial team to all other outside career options. With the choice sets at hand, we can thus define the aggregate labor demand for each occupation j as:

$$\text{LD}_j \; = \; \int \int_{\mathcal{E}_I} L^*_j \left(\mathbf{\Theta}_i\right) dG \left(\mathbf{\Theta}_i\right) dG \left(\mathbf{\Theta}_{i'}\right) + \int_{\mathcal{E}_T} \int_{\mathcal{E}_T} L^*_j \left(\mathbf{\Theta}_i, \mathbf{\Theta}_{i'}\right) dG \left(\mathbf{\Theta}_i\right) dG \left(\mathbf{\Theta}_{i'}\right)$$

Integrating across agents choosing to work, the labor supply for occupation j becomes:

$$\text{LS}_j \; = \; \int \int_{\mathcal{W}_j} h_j(\theta_{i,j}) \, dG \left(\mathbf{\Theta}_i\right) \; dG \left(\mathbf{\Theta}_{i'}\right)$$

Finally, equilibrium wages are given by the vector $\boldsymbol{w} = [w_1, \ldots, w_N]$ and, together with occupation and entrepreneurial choices, they clear the N labor markets.

Timing and Information. While the model is static in nature, agents' key decisions are taken sequentially. Specifically, before any other choice is made, every agent randomly meets another one whose type is drawn from the same joint distribution of skills. As match are formed, all decisions are taken simultaneously: individuals decide whether to open firms together or alone, each firm demands its optimal amount of labor from each occupation, and workers choose occupations based on their skills and prevailing wages.

2.3 The Two-Skills Model in Partial Equilibrium

We first analyze the partial equilibrium allocation in a model with $N = 2$ skills. With two skills, there are also two occupations, and we can represent individual choices graphically. Results of this section are illustrative and depend on two assumptions on the environment: (i) that skills are independently distributed across the population, and (ii) that the matching process boils down to each individual meeting their perfect complement with probability q, along with a number of standard assumptions on functional forms.[6]. We will relax these assumptions in the quantitative exercise in **Section 5**

The objective of our model of occupation choices and entrepreneurial sorting is to understand the properties of firm creation and career decisions in a setting with multi-dimensional skills. The first property is analogous to the main intuition of Lazear (2004): in the presence of multiple skills, entrepreneurs are more likely to be generalists.

Property 2.1 (Solo Entrepreneurs as Generalists). *If the distribution of skills is more dispersed:*

i) the share of solo entrepreneurs declines

ii) the marginal solo entrepreneur is more productive

ii) the average entrepreneurial team is more productive

This property comes from observing that there is a unique individual average talent cutoff between solo entrepreneurs and paid employees for every level of skills dispersion. We thus formalize **Model Prediction I**: *Individuals with unbalanced skills are more likely to become part of entrepreneurial teams, conditional on their oveall talent.* There is also, conditional on a suitable match, a unique individual average skill dispersion cutoff between solo entrepreneurs and team entrepreneurs for every level of average talent. Since the first threshold is increasing in the dispersion of skills, the marginal solo entrepreneur will therefore run a more productive firm.

The intuition for this result is as follows: as skills become more dispersed, there is a larger share of specialists (i.e. individuals with unbalanced skills), who can earn more from supplying labour in one of the occupations. If they are productive enough, however, they would prefer to form an entrepreneurial team. The motive for team formation is consistent with D'Acunto, Tate and Yang (2024), who highlight the role of skill complementarities as drivers of entrepreneurial partnerships. Another property of the model tells us that gains from skill heterogeneity are not unbounded: positive talent sorting is also important.

Property 2.2 (Positive Sorting in Teams' Talent). *Distance in average talent between team members, net of its effect on skills heterogeneity, decreases team productivity.*

We thus have two predictions on team performance: when considered jointly, we should observe a positive effect of horizontal differentiation and a negative effect of

[6]We assume that $\zeta(\cdot)$ is homogeneous of degree one, monotonic, concave, and supermodular, while $\psi(\cdot)$ is homogeneous of degree one, monotonic, and Schur-convex. Assumptions and analytical results are discussed in detail in **Appendix A.1**

vertical differentiation. We can, however, also say something about the observed average performance of teams when compared to solo-run firms. The property below illustrates a key prediction of the model, and introduces the role of search frictions.

Property 2.3 (Teams Overperform Solo Entrepreneurs)**.** *With search frictions, firms of entrepreneurial teams are on average more productive than solo entrepreneurs' ones.*

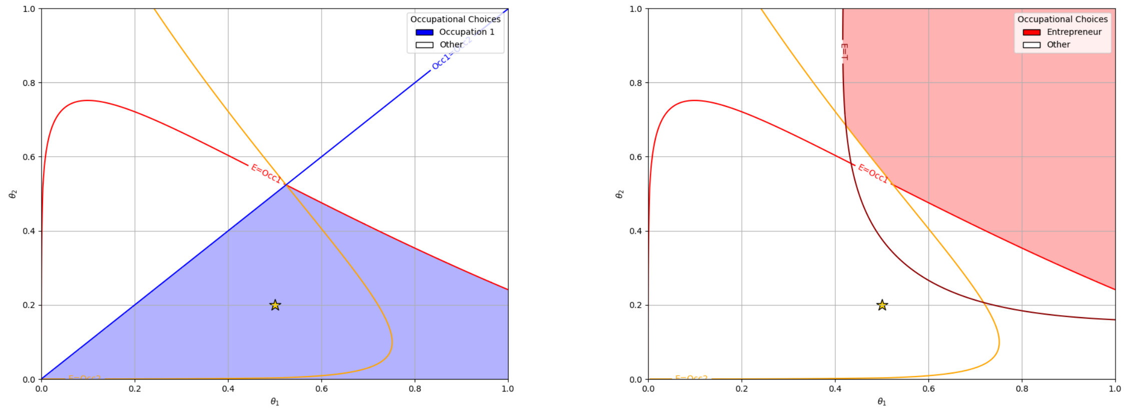
To understand this property, observe that the two thresholds mentioned above imply the existence of three groups of individuals who run firms. The first two consist of individuals that, conditional on meeting a suitable partner, prefer being part of a team. In presence of search frictions, a fraction (group B) will not meet a suitable match, and open a solo firm. Group A, instead, is composed of successfully matched team entrepreneurs. Finally, group C consists of generalists who prefer starting a solo firm regardless. Results from **Property 2.1** imply that average productivity of group B is below the one of the other two groups. Depending on the curvature of $\zeta(\cdot)$ and $\psi(\cdot)$, any ranking between group A and C is possible. Hence, the relative performance of solo entrepreneurs vs teams depends on how many specialists fail to meet a partner, and end up starting suboptimal solo firms. As search frictions grow, so does the number of inefficient solo firms. In the Appendix we also show that, if there are strong enough complementarities in $\zeta(\cdot)$, the relative over-performance of teams grows with average skills dispersion in the population, which makes existing teams more productive and solo ones less productive.

The properties discussed here can be summarized by three additional predictions, which will be tested empirically in the next section. First, conditional on the presence of search frictions, we get: **Model Prediction II**: *The productivity of entrepreneurial teams is on average higher than that of single entrepreneurs.* Two more predictions can be then taken from the analytical properties of the model, and involve the performance of teams with different compositions. **Model Prediction III**: *Firms run by individuals with different skills are larger and more productive.* High skill complementarity leads to *negative* sorting in single skills. The other property gives **Model Prediction IV**: *Firms run by individuals with similar levels of talent are larger and more productive.* While individual skills are negatively sorted, positive sorting in overall talent increases firm performance. These predictions contrast the patterns of career choice for workers, who simply sort on their strongest skill. Because labor demand is clearly stronger for more productive firms, we expect size and productivity to move in the same direction.

As a remark, one implication of the model properties is that the distribution of both dissimilarities will be skewed, as most teams still involve relatively unspecialized individuals, but with a long tail. In addition, because skill dissimilarity predicts (successful) team formation, while talent dissimilarity does the opposite, the equilibrium distribution of skill dissimilarities will have a fatter tail. Both implications are evident

Figure 1: Individual choices given match with [0.5,0.2]

(a) Share of Occupation 1 **(b)** Share of Solo Entrepreneurs



from the plot of the equilibrium distribution of dissimilarities, presented in **Figure 12**.

Individual Choices. Some features of this economy can be illustrated more effectively by describing the choices of a particular individual. As an example, we simulate a version of the model with calibration choices consistent with the hypotheses underlying the properties described above. We then consider the choice set of an agent i, who – at the beginning of the model period – draws a potential match with another agent i' , characterized by the skill bundle $\{\theta_1 = 0.5; \theta_2 = 0.2\}$ - the skill bundle of i' is represented with a star symbol. Clearly, matched agent i' is a "specialist" in skill 1, but for which values does agent i consider themselves a specialist in skill 1? The area in the $\{\theta_1, \theta_2\}$ space for which individual i chooses occupation 1 is portrayed in **Figure 1a**.

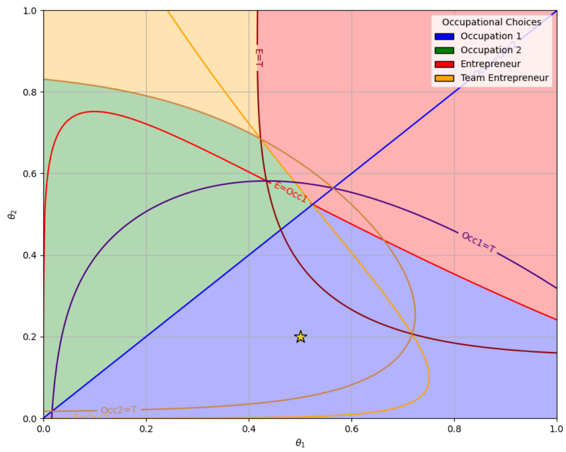
The dark blue line represents the locus of points (i.e. combinations of skills in individuals' bundles) for which agent i is indifferent between occupations 1 and 2. Given symmetry assumptions, the line has a 45° slope. For individuals with very high levels of (combined) θ_1 and θ_2, another relevant boundary is given by the red line, which is the indifference locus between occupation 1 and becoming a single entrepreneur.

The area of single entrepreneurs is only partially determined by the indifference (red) line between entrepreneurship and occupation 1. Indeed, the maroon line shows the locus of points where individuals have a skill mix that potentially makes them indifferent between becoming entrepreneurs alone or in a team; the yellow line, finally, applies to high-θ_2 types whose θ_1 levels are not high enough to start a firm alone. The red shadowed area, therefore, covers the values of the skill bundle $\boldsymbol{\Theta}_i$ for which single entrepreneurship is preferred to supplying labor in either occupation and to joining an entrepreneurial team, encapsulating the intuition of Lazear (2004) that many entrepreneurs have "*balanced*" skills, or in other words, they are talented *generalists*.

Putting these elements together, we see for which values agent i will pick occupation 2, or will want to team up with individual i' in **Figure 2**. However, one additional feature is highlighted by the figure, a novel feature of our model: *vertical differentiation*. Individuals in the green area end up going towards occupation 2, because, like those who form teams, their skills are specialized towards θ_2. However, those who become team entrepreneurs have higher overall talent. We therefore see the role of vertical and horizontal differentiation in shaping agents' sorting into different career choices.

The boundaries of the choice regions are heavily dependent on the skill endowment of the potential team partner drawn by any given individual. Indeed, **Figure A.2** displays the same choice sets but for a different case, in which the potential match has both higher talent and lower specialization. In that scenario, individuals who are specialized in both skill 1 and skill 2 end up forming a team. However, the set of individuals with a specialization in skill 2 who joins a team shrinks, because the matched individual would rather start a firm alone than with an individual that is too close in skills composition, or too distant in talent. These intuitions shape model predictions also in the general case.

Figure 2: All Choices, given match with $[0.5, 0.2]$

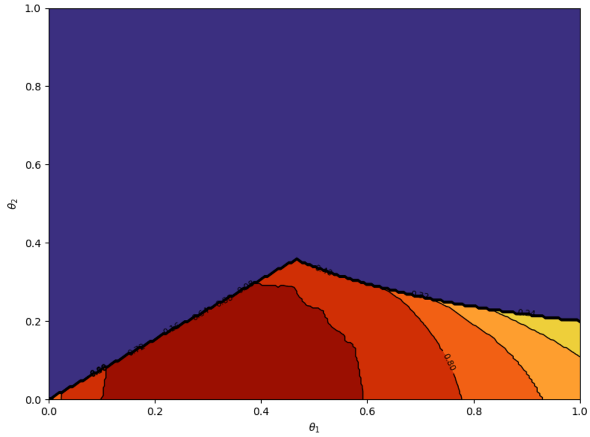


Aggregating Individual Choices. We now consider the case in which all individuals get to meet another one, drawn from the same ex-ante skill distribution $G(\boldsymbol{\Theta})$. Numerically, $G(\boldsymbol{\Theta})$ is the same as in the previous example, but we here analyze equilibrium outcomes.

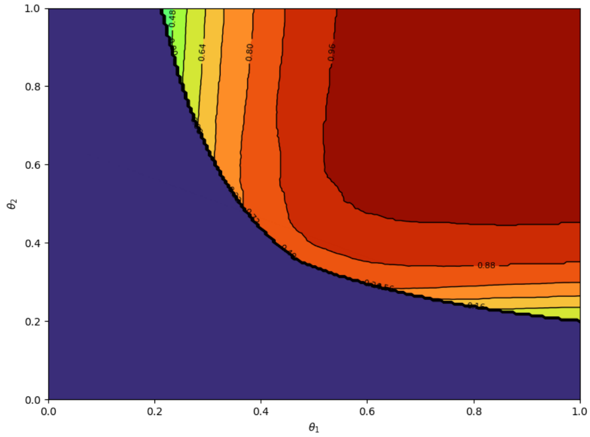
Figure 3 displays individual choices over the θ_1, θ_2 space: the color is dark purple when no agent in that point of the skills space takes that given career choice. Warmer colors correspond to higher probability of the choice being taken, with deep red indicating a given choice (e.g., being a single entrepreneur in panel **Figure 3b**) having probability 1. While single entrepreneurs are high-talented generalists, **Figure 3b** shows that both high talent and high specialization increase the likelihood of forming a team. However, because of the high complementarities involved in the choice of opening a firm within a team, no

Figure 3: Team Formation and Equilibrium: Shares by Type

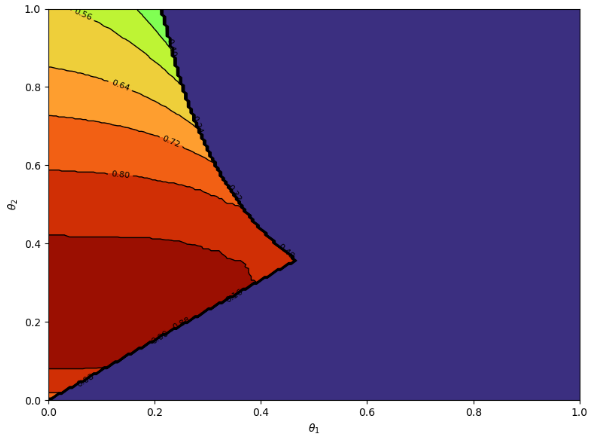
(a) Occupation 1



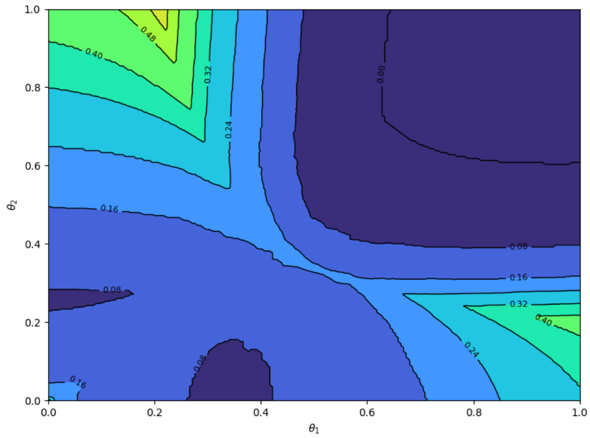
(b) Single Entrepreneur



(c) Occupation 2



(d) Team Entrepreneur



type has certainty of becoming a team member: some high-talented specialists will choose to supply labor in other firms, while others will prefer to start a firm alone. Clearly this depends on the skills of the other potential team member the agent has drawn. As such, it can easily be shown that there is an indifference threshold over the $\{\theta_1, \theta_2\}$ space above which the matched agent becomes desirable as a team partner. Conversely, a team is formed only if the individual is in the acceptance region of the matched agent as well.

These dynamics give no a priori indication regarding the average productivity of team entrepreneurs vis à vis single ones - as individual talent grows, their own acceptance region regarding potential team members shrinks, but the likelihood of entering the acceptance region of their matches increases. As highlighted by **Property 2.3**, this outcome depends on assumptions regarding match probabilities, as well as underlying distributions.

The next sections explore whether these predictions hold in the data, discuss the role of alternative channels behind team formation, and calibrate a general version of the model to quantify the aggregate contribution of team sorting to productivity and output.

3 Data

Our theory of career choices, featuring different occupations, entrepreneurship and entrepreneurial team formation, has four key predictions regarding the matching patterns of individuals in teams, and on how the (dis)similarity in entrepreneurs' skills and talent relate to firm performance. Verifying these predictions empirically requires a dataset that encompasses workers and entrepreneurs, records the performance of single-owned and team-owned firms, and in which it is possible to infer or observe individuals' talent and competences. The following section explains how we put together such dataset for Portugal, and outlines few initial descriptives on entrepreneurial teams.

3.1 Sample Construction

Our main source of data is the Portuguese administrative employer-employee sample from *Quadros de Pessoal* (hereafter: QP), which contains roughly 4 millions of individual-firm matches per year, from 1991 to 2019. QP exploits an administrative mandatory survey filled in during the October of every year with information on the workforce composition of each firm for the reference month. In terms of individual characteristics, QP reports agents' age, gender, nationality, education, occupation codes[7], earnings and hours (both contractual and extra), contract characteristics (part-time vs full-time, permanent vs temporary or seasonal contracts) and hierarchical qualification within the firm. On the firm side, it includes information on their industry sector, geographical location, legal status[8], total employment, sales and founding year. Although Portugal is a relatively small country, its firm distribution compares to that of several other OECD countries.[9]

The advantage of using the QP is twofold: first, individuals are characterized as either "employees", "employers" or "self-employed", which makes it possible to identify entrepreneurs within privately held firms.[10] Second, by recording yearly labor market information for all individuals in the labor force (each with a unique id), its longitudinal dimension allows us to observe transitions between working and entrepreneurial spells. This is key for the scope of our analysis, because it enables us to characterize agents' careers before starting a firm and/or before teaming up with another entrepreneur(s).

To provide a measure of individual skills, we merge QP with the European Skills,

[7]Over the years, the occupational classification in Portugal has changed three times. In this paper, we exploit an harmonized classification, based on ISCO-08, at the 3-digit occupational level.

[8]We have very detailed information on whether the firm is incorporated or not, and its specific kind of legal entity. This allows us to to identify precisely which firms, by their own nature, are privately owned.

[9]The distribution of firms in Portugal resembles closely the one of Italy and Spain, for example. Also, note that the employment share of Portuguese firms with 10+ employees is only between 7 and 9 percentage points (p.p.) lower than that of French or German firms in the same size category.

[10]We identify as "self-employed" professionals with at most one employee assisting them throughout all years observed in the data. All other employers have multiple employees at some point in time.

Competences, Qualifications and Occupations (ESCO) database, which provides EU-wide links between occupations and essential skills or competences required to workers.[11] Specifically, ESCO reports a zero to one index on the intensity that each skill or competence is used in each 3-digit occupation. Different aggregation levels are available, raging from 296 granular groups to 74 or 8 very coarse categories of skills.[12]

Table 1: Descriptive Statistics from *Quadros de Pessoal* – Entrepreneurs

Variable	Mean	SD	Median	P25	P75	N
Age	44.52	10.29	44	37	52	4,027,361
Age at Founding	41.75	10.00	41	34	49	3,518,134
College %	16.28	36.92	0	0	0	3,886,812
Firm Age	12.56	12.58	9	4	17	4,027,361
# Employees	2.19	0.97	2	1	3	3,849,674
Firms Owned	1.06	0.39	1	1	1	4,027,361
# Founders	1.49	1.15	1	1	2	4,027,361
# Owners	1.64	1.01	1	1	2	4,027,361
Log Sales	13.89	1.31	12.21	11.30	13.27	3,801,998

Note: The table reports descriptive statistics for entrepreneurs in the matched employer-employee sample from *Quadros de Pessoal*, covering all years from 1985 to 2018. Sales are deflated by using the 2010 CPI.

Finally, for a subsample of firms active or started between the years 2004 and 2018, we can also retrieve balance-sheet variables from the *Sistema de Contas Integradas das Empresas* (hereafter: SCIE) – for instance regarding firms' capital and debt structure, as well as their intermediate inputs. However, given the limited time frame of SCIE, we use it for robustness checks and additional analyses, and keep QP as our baseline dataset.[13]

Table 1 reports summary statistics for privately-held firms in QP of which we are able to identify the set of entrepreneurs. Note that these firms make up for 65% of all businesses contained in QP, covering 66% of aggregate sales and 76% of overall employment.[14]

3.2 Descriptives of Entrepreneurial Teams

To start, we provide few definitions for entrepreneurs and firm-ownership in our sample. We consider *owners* all those individuals who are employers within a firm at a given point of its life-cycle. We instead identify as *founders* all individuals listed as owners within the first 3 years of the stated foundation year. Clearly, these two definitions tend to overlap, especially in the first 10 years of a firm's life-cycle; however, given the scope of

[11]We use the latest mapping between skills and occupations in ESCO v1.2 published in May 2024.

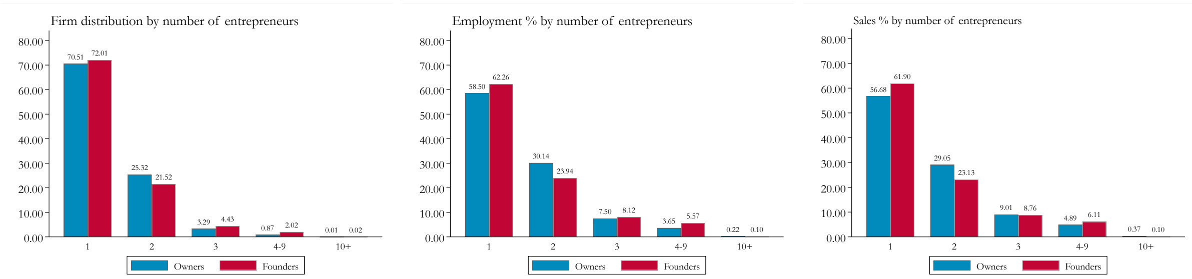
[12]Examples of coarse skill categories are *Management* or *Communication, Cooperation and Creativity*, while very granular skills required by occupations can be *Hammering, nailing and riveting*, *Tending and breeding aquatic animals*, *Analyzing business operations* or *Managing budgets or finances*.

[13]In terms of overlap, the merge between SCIE and QP covers 97% of total employment and 88% of sales. Note that SCIE does not contain firms within the finance and insurance sectors and public services.

[14]See **Appendix B.1** and **Table C.1** for details on the QP and worker-level descriptive statistics.

our research question, our baseline is to focus on founding entrepreneurs.[15] In addition, note that we consider a firm to be single-owned or single-founded if it is associated to only one owner or one founder respectively, and multi-owned or multi-founded otherwise.

Figure 4: Distributions of Firms, Employment and Sales by Number of Entrepreneurs



The figure shows the distribution of privately-held firms (left), employment by these firms (center), and sales of these firms (right), by number of owners (in blue) and number of founders (in red). Data is from the matched employer-employee sample of *Quadros de Pessoal*, covering all years from 1985 to 2018.

Figure 4 above illustrates that entrepreneurial teams are a relevant macroeconomic phenomenon in Portugal, as firms with more than one entrepreneur make up for roughly 40% of overall employment and sales in our sample,[16] albeit they represent roughly 28% of all privately held firms. In addition, entrepreneurial teams are a cross-industry and cross-years phenomenon, which means that our results do not hinge on a specific time-frame and/or sector only (**Figure C.1**). Also, more than 3/4 of entrepreneurial teams in our sample are formed by two individuals, and **Figure C.2** shows that there is no relationship between team size and number of firms owned (i.e. most entrepreneurs own one firm only, regardless of their team size), which facilitates the mapping to our theoretical framework.

Importantly, our analysis focuses primarily on founders, as the model disregards ownership changes at the firm-level. In this spirit, **Table 2** reports some descriptive statistics regarding the characteristics of "single" founders with respect to team founders. Overall, no very stark difference stands out in terms of demographics for the two groups. Team founders tend to be slightly older, but are less likely to be sequential entrepreneurs (i.e. having had previous entrepreneurial spells). In terms of experience and previous earnings (as workers), team founders are actually *less* likely to have got a university degree or have been managers, and have lower cumulative previous earnings.

[15] In terms of demographics and previous careers, founders tend to be on average slightly younger and less educated than owners. Relatedly, founders' average earnings before entrepreneurship are slightly lower, and the average length of their entrepreneurial spells slightly longer compared to owners.

[16] Note that we exclude entrepreneurs from the labor headcount when computing employment shares.

Table 2: Characteristics of Single and Team Founders

	Mean	SD	Median	P25	P75	N
Single founders						
Age at foundation	40.6	10.4	33	40	48	434,642
Sex	.302	.459	0	0	1	435,005
Share high educated	.159	.366	0	0	0	410,978
Share previously manager	.145	.352	0	0	0	192,555
Last wage	12,039	11,268	5,710	8,373	14,062	205,368
Previous 5y avg. earnings	11,444	10,234	5,640	8,124	13,412	205,472
Cumulative earnings	62,182	87,856	12,400	31,867	75,072	205,522
Previous employee jobs	5.03	4.2	2	4	7	205,522
Share w/ previous entrep. exp.	.174	.379	0	0	0	435,005
Team founder						
Age at foundation	44.8	10.3	37	44	52	325,738
Sex	.289	.453	0	0	1	325,738
Share high educated	.128	.334	0	0	0	308,110
Share previously manager	.128	.334	0	0	0	131,117
Last wage	11,633	10,558	5,717	8,304	13,487	139,899
Previous 5y avg. earnings	11,058	9,532	5,688	8,075	12,911	139,945
Cumulative earnings	57,287	78,607	12,306	30,713	69,935	139,971
Previous employee jobs	4.91	4.1	2	4	7	139,971
Share w/ previous entrep. exp.	.139	.346	0	0	0	325,738

Note: The table reports descriptive statistics regarding entrepreneurs being solo founders of their firm, or members of founding teams. Data is from the matched employer-employee sample of *Quadros de Pessoal*, covering all years from 1985 to 2018. The characteristics are measured at the time of foundation, and all nominal values are deflated by the 2010 CPI. The share of individuals with previous entrepreneurial experience identifies entrepreneurs who, during their lives, have opened more than one firm.

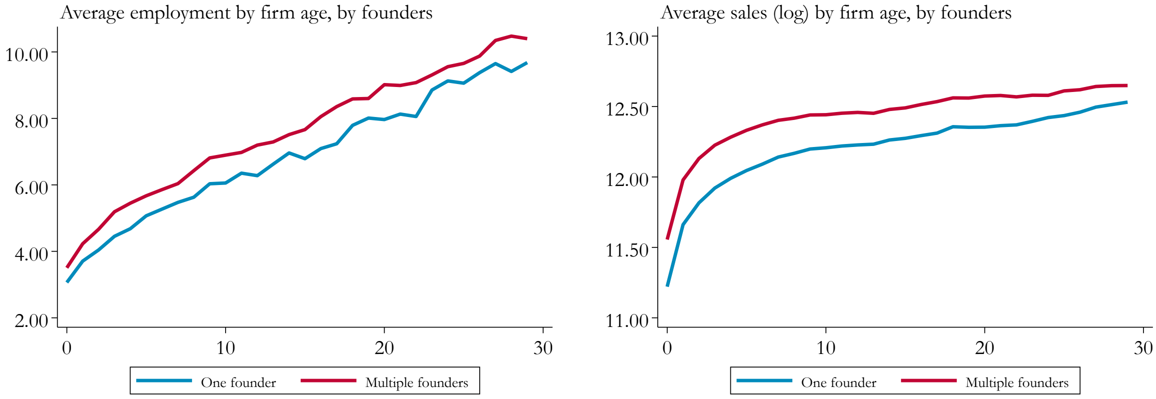
3.3 Firm Performance of Entrepreneurial Teams

In what follows, we outline few distinctive characteristics – in terms of performance – of firms founded by either a single or a team of entrepreneurs. The left panel in **Figure 5** shows that firms with multiple founders have higher average employment than single-founded ones, and consistently so over the life-cycle. A similar conclusion holds when comparing average (log) sales of firms with one or multiple founders (in the right panel of **Figure 5**).[17] **Figures C.3** confirms this finding for a balanced panel of firms, ensuring that results are not mainly driven by selection in and out of the sample of surviving firms.

Firms with more than one founder register higher growth in the first 10 years of operations, as reported in **Figure C.5**. Moreover, **Figures C.6** and **C.7** show that multi-founded firms have higher labor productivity – computed as yearly sales over employment (or, alternatively, wage-bill) – and significantly lower exit rates over the

[17] When using the definitions of single and multi-owned firms (instead of single and multi-founded), we observe larger differences in their average employment and sales, as reported in **Figure C.4**. This could be due to the fact that successful single-founded firms may attract more or better owners as they grow.

Figure 5: Average Life-Cycle Employment and Sales by Number of Entrepreneurs



Note: The figure shows firms' average number of workers (left) and average log sales (right) by firm age. Employment headcount excludes entrepreneurs. Red lines represent firms founded by more than one entrepreneur while blue lines represent firms founded by one entrepreneur only. Data is from the matched employer-employee sample of *Quadros de Pessoal*, covering all years from 1991 to 2019.

life-cycle compared to single-founded firms. It is key to stress again that our results are not driven by time- or industry-specific patterns, and highlight that entrepreneurial teams tend to have better firm-level performances within given industries and years.

We can then exploit the subsample of firms for which we have balance sheet data and estimate yearly firm-level TFP, following common production function estimation strategies in the literature (Gandhi, Navarro and Rivers (2020)). In particular, assuming sector-level input elasticities, gross output Y in sector s for firm j at time t is defined as:

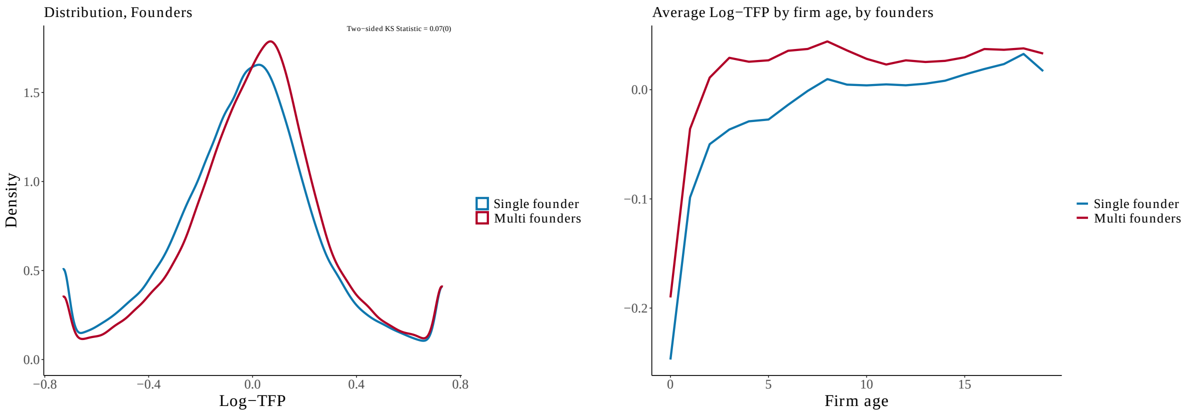
$$Y_{j,t} = e^{TFP_{j,t}} F_{s(j)}(K_{j,t}, L_{j,t}, M_{j,t})$$

where K is computed via perpetual inventory methods (PIM) with sectoral depreciation rates (*OECD-STAN)* and deflators (*EU-KLEMS*), L is total employment (headcount) and M are intermediate inputs (services and materials). Since TFP has a strong sectoral component, we further residualize our estimates using sector $\times$ year fixed-effects (FE). **Figure 6** highlights that TFP is higher in firms founded by a team of entrepreneurs, with the distribution on the left panel showing a higher mean and a fatter right tail.

Summarizing the evidence presented so far, our initial exploratory analysis seems to provide support to **Model Prediction II**: *The productivity of entrepreneurial teams is on average higher than that of single entrepreneurs.* It is important to stress that, through the lens of the theoretical framework presented in Section 2, the higher average productivity of multi-founded relative to single-founded firms is due to two key mechanisms: (i) a stronger selection process of individuals into team entrepreneurship compared to single entrepreneurship, and the (ii) sorting (in talent and skills) between individuals in teams.

In particular, our theory predicts that individuals with balanced skills are more likely

Figure 6: Residualized Firm-level log-TFP by Number of Entrepreneurs



Note: The figure reports the distribution of average firm-level log-TFP (left) and the average firm-level TFP by firm-age (right) in the matched SCIE-Quadros de Pessoal sample for firms with single and multiple founders, covering all years from 2004 to 2018. Firm-level TFP is estimated using Gandhi, Navarro and Rivers (2020) separately for each sector (one-digit) and then residualized by sector and year effects. KS tests on the distributions allow to reject the null that the two distribution are similar.

than others to become entrepreneurs, whereas those with unbalanced skills tend to take specialist roles outside of entrepreneurship. Therefore, in order for a given agent to prefer team entrepreneurship over all their other outside options, they must have relatively high levels of at least one skill and, equally important, to have met a potential business partner with relatively high levels of at least one complementary skill. Indeed, it is not two talented entrepreneurs, but rather two *skill-complementary* and similarly *high-talent* entrepreneurs that contribute to a better firm performance. The next section explores in detail these two mechanisms, by specifically taking Model Predictions I-IV to the data.

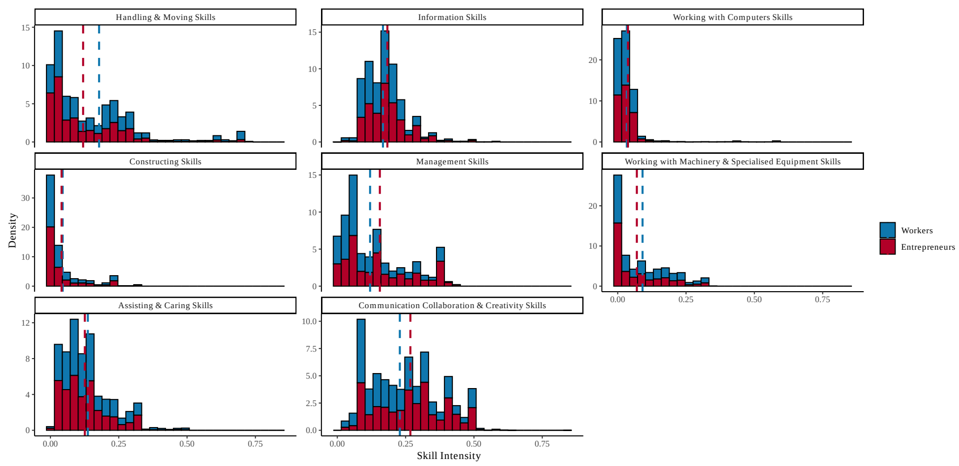
4 Sorting Patterns of Entrepreneurial Teams

4.1 Measuring Skills and Talent

In order to explore the sorting patterns of individuals within entrepreneurial teams and link them to the predictions of our theory, we first need to define and measure three key variables: Agents' (i) skills, (ii) talent, (iii) and the similarity of (i) and (ii) among individuals in entrepreneurial teams. We explain how we construct these variables below.

Skills. Using the ESCO mapping between 3-digit occupations and the essential skills required to workers, we construct time-varying measures of (cumulative) individual skills, exploiting information on agents' occupational history until any point in time t, and weighting ESCO's skill indexes by the years agents spent in each occupation. Recall that different aggregation levels are available within the ESCO database, so we construct two measures of individual skills, one using 8 coarse skill categories (mostly for graphical purposes) and one based on 74 finer ones. Importantly, for workers that eventually become entrepreneurs, we consider employment histories before their first entrepreneurial spell.

Figure 7: Skill Distribution for Workers and Entrepreneurs



Note: The figure presents the distribution of the broader 8 ESCO skill-categories for workers and for the subset that eventually become entrepreneurs. Dashed lines report the averages for each distribution.

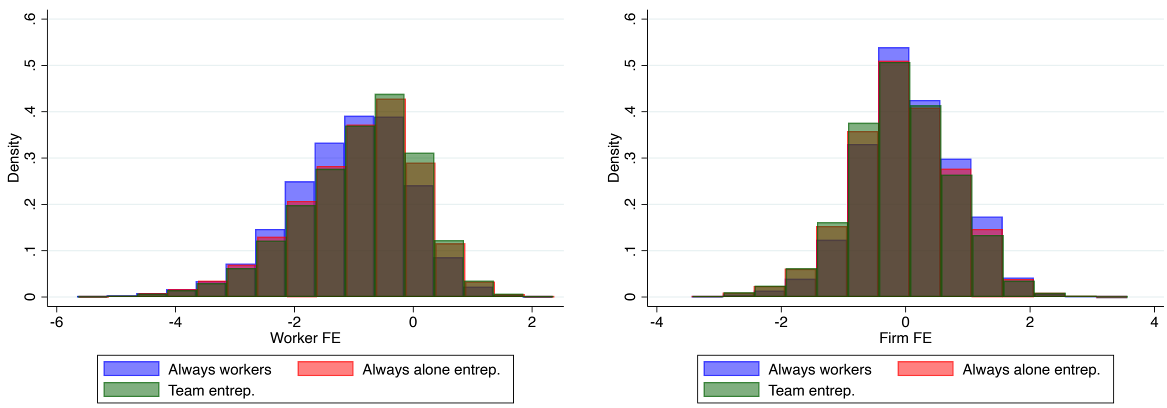
Overall, **Figure 7** shows that, relative to agents that stay workers their entire careers, those who become entrepreneurs at some point of their life-cycle – whether alone or in a team – have on average higher levels of managerial competences, as well as higher levels of communication, collaboration and creativity skills. Yet, while we can use individuals' occupational history jointly with the ESCO database for a measure of their competences, this is only one of the two elements defining agents' human capital for the scope of our analysis. Specifically, through the lens of the theory presented in Section 2, individuals' career choices are informed not only by the relative composition of their skill bundles, but also by how talented agents are, i.e. their productivity. For workers, it is their productivity and relative combination of skills that define occupational choices and wages. For single and team entrepreneurs, it is their own productivity and relative combination of skills that define the productivity of their firms. So, how can we measure individual talent? We exploit again agents' working histories, but this time focusing on earnings.

Talent. In the QP sample, we observe yearly wages for all individuals employed in any given t and for all the years in which they are working. This is true also for those who eventually become entrepreneurs: in particular, as the average age of an entrepreneur is 45 years old, we have on average 20 years of wage histories pre-entrepreneurship. Borrowing the strategy from Abowd, Kramarz and Margolis (1999) (hereafter: AKM), we hence estimate unobserved worker and workplace heterogeneity via the following regression:

$$\log(w_{i,t}) = X'_{i,t}\beta + \alpha_i + \psi_{j(i)} + \epsilon_{i,t} \tag{3}$$

where $X_{i,t}$ include age^2 and year FE, α_i measures latent worker quality, and $\psi_{j(i)}$ measures latent workplace quality. For individuals that become entrepreneurs at least once in their career, worker quality (or FE) reflects their type as workers before their first entrepreneurial spell, while firm quality (or FE) is intended as their past workplace type *before* they opened their own firm.[18] **Figure 8** then plots the distribution of the estimated worker and workplace FEs, distinguishing between individuals that remain workers their entire career, those that become entrepreneurs at least once but always alone, and those that become entrepreneurs at least once and at least once in a team.

Figure 8: Distribution of Worker and Firms' FEs, by Entrepreneurial Type



Note: The figures present the distributions of workers' and firms' fixed effects, as estimated by the AKM specification in Equation 3. The figure pools all years, with fixed effects coming for every year from AKM specifications estimated on a 5 years backward looking rolling window. For entrepreneurs, the relevant fixed effects come from the last year before the first entrepreneurial spell. Individuals are identified as "always workers" if they never undertook any entrepreneurial activity, "always alone entrepreneur" if they were at any point entrepreneurs, but never participated to a team, or "team entrepreneurs".

Two observations can be made looking at **Figure 8**. First, there is positive selection into entrepreneurship based on worker qualities, and a small negative selection based on workplace (for entrepreneurs: past workplace) qualities. This result supports the prevalent view in entrepreneurship, dating back to Lucas (1978), suggesting entrepreneurs are positively selected on productivity compared to workers.[19] Second, and a key contribution of our empirical analysis, entrepreneurs who open a firm with a team at least once tend to be more positively selected on their worker type (i.e. their talent) compared to single entrepreneurs and individuals who will always be workers. This finding connects to **Model Prediction II**, and helps explain why firms by teams are more productive than those by single entrepreneurs, as we will further clarify later.

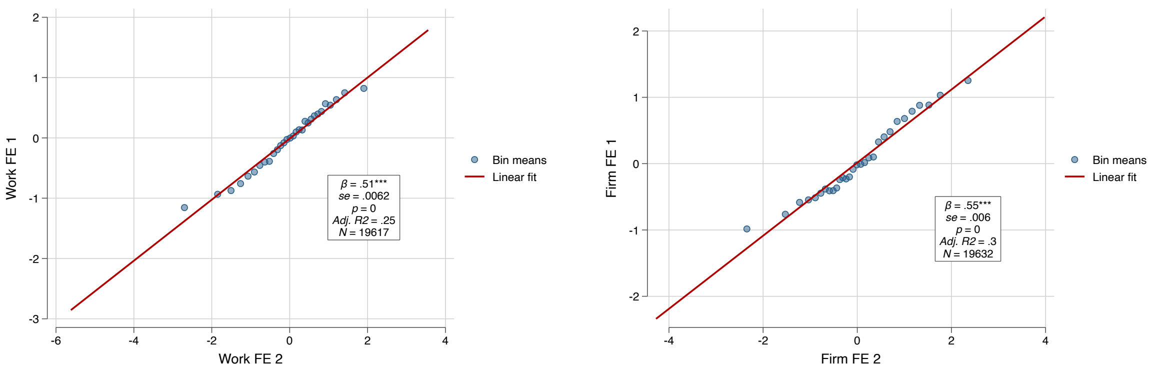
[18] We refer the reader to **Appendix B.4** for details regarding the AKM estimation.

[19] **Figure B.1** clarifies that the worker-type FEs estimated through AKM regressions for those who eventually become entrepreneurs are strongly associated with the TFP of the firms they found, suggesting indeed that unobserved workers' quality can be a proxy of agents' (unobserved) quality as entrepreneurs.

4.2 Measuring Team Similarity

In what follows, we show that entrepreneurs in teams are positively sorted with respect to their (latent) worker types – or talent, and negatively sorted with respect to their skills, and then summarize this evidence into measures of vertical and horizontal similarity.

Figure 9: Correlation of Worker and Past Workplace Types for Entrepreneurial Teams



Note: The figures present binned scatterplots of individuals' (left) and workplaces (right) AKM fixed effects (FEs) for entrepreneurs in two-member teams. FEsare estimated for every year on a 5 years backward looking rolling window. The FEs come from the last year before the first entrepreneurial spell.

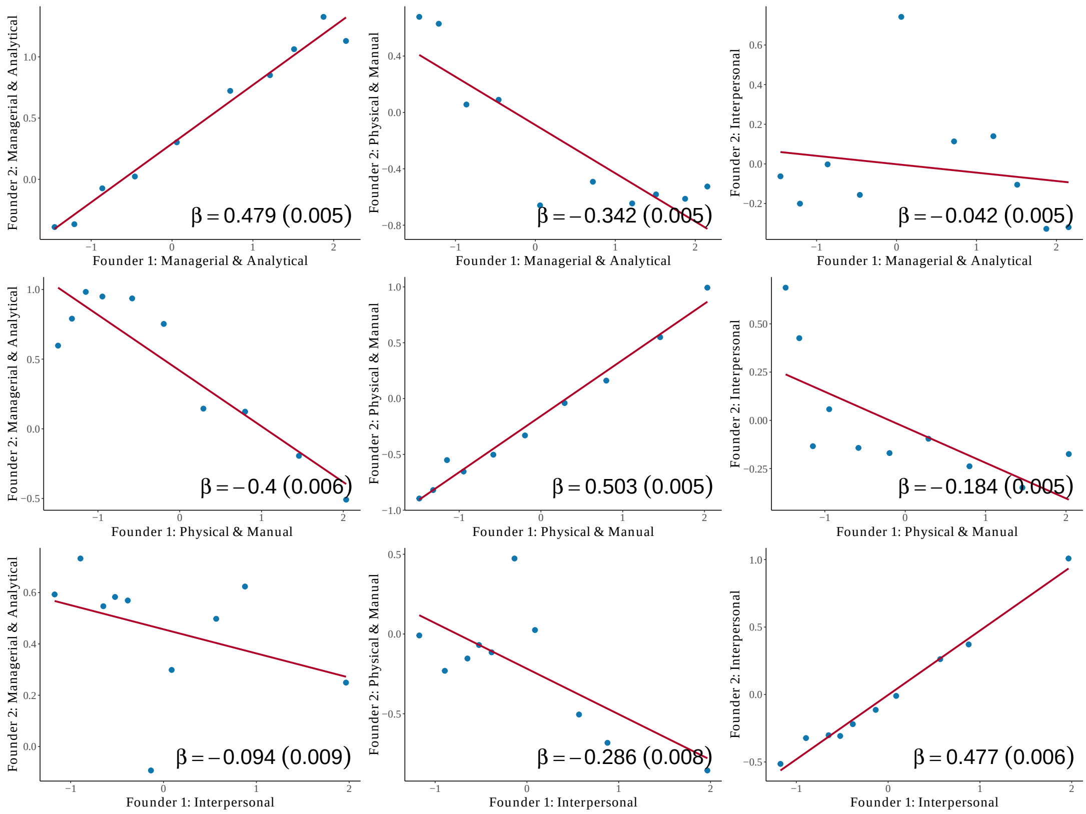
To start, **Figure 9** plots the correlation coefficient between the worker (on the left) and past workplace types (on the right) of entrepreneurs within 2-member teams. Clearly, there is a strong positive correlation in talent between entrepreneurs within teams. This suggests that – empirically – entrepreneurial teams tend to be characterized by a *vertical similarity* in latent types, further reconciling the mechanisms at work in our model with the evidence from the data. Moreover, note that this result holds true when residualizing the correlations in **Figure 9** by a host of individuals' covariates, and when following an alternative strategy by Bonhomme, Lamadon and Manresa (2019) to estimate worker and workplace types (we report these robustness checks in **Figures C.11** and **C.10**).[20]

As a second step, **Figure 10** plots the binscatters and correlations between the first 3 principal components (PCs) of the ESCO skill categories in teams with two founders (here, we exploit PC analysis for graphical purposes given the high dimensionality of skill vectors in teams).[21] On the rows, we report the PCs of Founder 1's skills, and on the columns the PCs of their companion founder. What emerges from the analysis is that there is a high degree of heterogeneity in observable skills for teams with two founders, and, interestingly, entrepreneurial teams are likely to be formed by agents specialized in relatively similar skills. We will exploit this sorting patterns across skills in founding

[20]We refer the reader to **Appendix B.4** for details on the clustering procedure.

[21]To be able to label the principal components more clearly, we exploit the broad 8 ESCO skill groups to compute the PCs subject to non-negative loadings. The first three PCs account for $\sim 60\%$ of the variance. **Figure C.14** reports all sixty-four pairwise raw skill distributions of two-founders teams.

Figure 10: Distribution of Skills in Two-Members Founding Teams



Note: Each panel shows a binscatter of Founder 2's against Founder 1's score on one of the first three non-negative, principal components (PCs) extracted from the eight ESCO skill categories ("Managerial & Analytical" "Physical & Manual", and "Interpersonal") across two-founder teams. The solid line is the linear regression of Founder 2's PC score on Founder 1's; we report the slope coefficient and its robust standard error (in parentheses). For raw distributions of all eight ESCO categories, see Figure C.14.

teams to discipline the matching frictions among founders in the quantitative section.

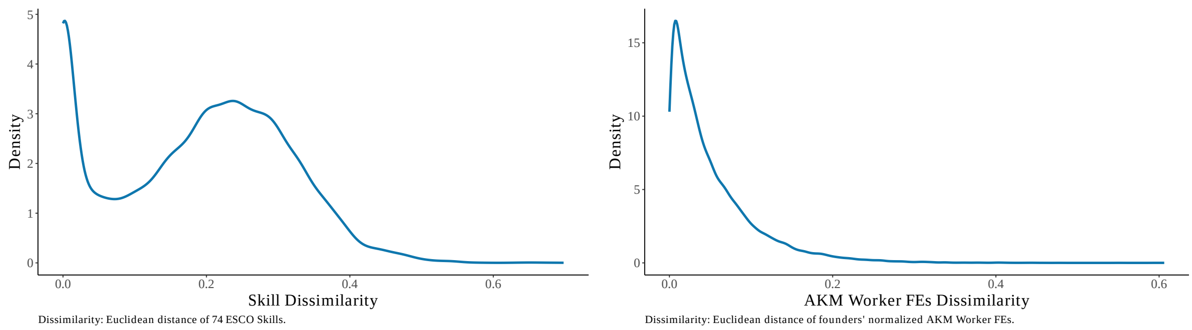
Similarity. As both our talent and skills measures are highly dimensional and difficult to compare across teams, we reduce their dimensionality by computing the average of pairwise Euclidean distances in each entrepreneurial team (we report similar measures computed with Gower indexes in **Figure C.13**). Formally, let f be a founding team of size N_f, and $\mathbf{x}_i$ be a K–dimensional vector of characteristics for a generic team member $i \in f$. For each pair (i, i') of founders in f, we can compute $d(\mathbf{x}_{ii'}) = \|\mathbf{x}_i - \mathbf{x}_{i'}\|$ as the Euclidean distance between characteristics of members i and i'. We then measure within-team similarity (or dissimilarity) by the average pairwise distance, given by:

$$\Delta_f(\mathbf{x}) = \frac{2}{N_f(N_f - 1)} \sum_{(i,i') \in f} d(\mathbf{x}_{ii'}).$$

From now onwards, we refer to *horizontal dissimilarity* as the Euclidean distance of team members' skills, and to *vertical dissimilarity* as the Euclidean distance of team members' talent. **Figure 11** plots the distributions of these similarity indexes for the teams of founders in our sample. The figures higlights that there is substantial variation in founding teams similarities along both measures. In addition, **Figure C.12** shows that individuals in entrepreneurial teams are more similar in talent and skills than two randomly selected entrepreneurs or two randomly selected individuals in the workforce.

Figure 11: Skill and Type Similarity in Founding Teams

(a) ESCO Skills **(b)** AKM Worker Fixed Effects



Note: The figure reports the distributions for the average pairwise Euclidean distances between 74 ESCO skills (a) and the estimated AKM worker fixed effects normalized in [0,1] in (b) for each founding team in our sample.

4.3 Predictors of Team Formation

Individual level analysis. With these measures of individual talent and skills, and within-teams dissimilarities in both, we validate **Model Prediction I** regarding which characteristics are good predictors of joining a team of founders as opposed to start a firm solo, by running the following linear probability model at the founder level:

$$\mathbb{I}\{|\text{Co-founders}|_{f(i)} > 0\} = \beta_0 \text{Log-Earnings}_i + \beta_1 \hat{\alpha}_i + \beta_3 \sigma(\boldsymbol{\theta}_i) + \boldsymbol{\beta}' \mathbf{X}_i + \Phi + \epsilon_i, \tag{4}$$

where $\mathbb{I}\{|\text{Co-founders}|_{f(i)} > 0\}$ is a dummy variable that takes a value equal to one if entrepreneur i has at least one co-founder in the founding team of firm f. On the right-hand side, we include the log of (cumulative) previous labor market earnings, the estimated AKM fixed effects as workers, $\hat{\alpha}_i$, and the standard deviation of entrepreneurs' ESCO skills $\sigma(\boldsymbol{\theta}_i)$ as a measure of their specialization.[22] We include a set of fixed effects and additional controls to account for individual characteristics or sector-time variation at the time of the team formation. We report the results of this estimation in **Table 3**.

Two main findings emerge. First, high previous labor market earnings reduce the likelihood of joining a founding team with a fellow entrepreneur. This result may be consistent with *some* entrepreneurial teams emerging as a response to the presence of liquidity constraints, as discussed in Evans and Jovanovic (1989). Second, conditional on

[22] A high standard deviation in the measures of individual skills implies a more specialized entrepreneur, as it signals they had occupations characterized by high values of the ESCO indexes only on few skills.

Table 3: Predictors of Team formation

Dependent Variable:	$\mathbb{I}\{\lvert\text{Co-Founders}\rvert > 0\}$	
Model:	(1)	(2)
Variables		
Prev. Log-Earnings	-0.006***	-0.006***
	(0.002)	(0.001)
Work FE	-0.003	-0.001
	(0.002)	(0.002)
S.D. in Skills	0.481**	0.987***
	(0.220)	(0.298)
Fixed-effects		
Serial Entrep.	Yes	Yes
College	Yes	Yes
Sex	Yes	Yes
Age at found.	Yes	Yes
Sector	Yes	Yes
Founding year	Yes	Yes
Prev. Occupation		Yes
Additional Controls		
Skill Levels	Yes	
Fit statistics		
Observations	185,815	180,254
R^2	0.075	0.079
Within R^2	0.003	0.0003

Clustered (Sector × Founding Date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table reports the correlations between the probability of having at least one co-founder and entrepreneurs' characteristics. *S.D. in Skills* is the standard deviations across ESCO skills for each entrepreneur, *Prev. Log-Earnings* are the cumulative earnings in the 10 years before becoming an entrepreneur, *Work FE* are the AKM fixed effect of each entrepreneur as worker.

talent – proxied by the AKM FE as a worker – the degree of skill specialization (measured by the standard deviation of skills within each founder) increases the likelihood of forming a founding team both when controlling for the overall level of individual skills (Column 1) or when including a FE for the last occupation held as a worker (Column 2).[23] These empirical correlations are in line with **Model Prediction I**: *Individuals with unbalanced skills are more likely to become part of entrepreneurial teams, conditional on their talent.*

Dyadic analysis. To assess how the characteristics of founders' pairing influence the probability of forming a team we would like to estimate a linear probability model, akin to the one in **Equation 5**, on *all* possible pairings between founders in our sample:[24]

$$\mathbb{I}\{\text{Team}_{i,i'}\} = \beta_0 \bar{\hat{\alpha}}_{i,i'} + \beta_1 d(\boldsymbol{\theta}_{i,i'}) + \beta_2 d(\hat{\boldsymbol{\alpha}}_{i,i'}) + \beta_3 \Delta(\text{Log-Earnings})_{i,i'} + \Psi_{i,i'} + \Phi_{i,i'} + \varepsilon_{i,i'}, \quad (5)$$

[23]Approximately 90% of entrepreneurs is employed in 2 or fewer occupations (with more than 50% reporting only one), therefore the last occupation as a worker is a good proxy of their overall skill level.

[24]For a similar econometric strategy applied to the analysis on how political affiliation of workers and employers influences the probability of a match see Colonnelli, Neto and Teso (2024).

Table 4: Dyadic regressions: Average coefficients (percentage points)

Dependent Variable:	$\mathbb{I}\{\text{Team}_{i,i'}\}$	
Model:	(1)	(2)
Variables		
Log-Earnings	-0.031^{***}	-0.007^{***}
	(0.001)	(0.001)
Average Work FE	-0.022***	-0.006***
	(0.002)	(0.001)
Skill Dissimilarity (HD)	-0.707***	-0.199***
	(0.012)	(0.008)
Worker FE Dissimilarity (VD)	-0.042***	-0.010***
	(0.001)	(0.001)
Bias Controls	No	Yes

Clustered (dyad members, two-way) standard errors in parentheses.
Signif. Codes, *** : 0.01,** : 0.05,* 0.1.

Note: The table reports the average – in percentage points – for the main coefficient of interest from the linear probability model in **Equation** 5. The sample is based on entrepreneurial teams with only two members and conditional on surviving for at least 3 years, augmented with a random 1/4 of all possible non-team combinations between entrepreneurs. **Figure C.15** reports the full time series of estimated coefficients for both specifications. Bias controls include dummies that are equal to one when dyad members have: the same past employer, the same past occupation, same sex, same educational attainment and same age.

where the dependent variable, $\mathbb{I}\{\text{Team}_{i,i'}\}$, is equal to 1 if the dyad (i, i') is a founding team and 0 otherwise, $\overline{\hat{\alpha}}_{i,i'}$ is the average across the entrepreneurs' talent in the dyad, $d(\hat{\boldsymbol{\alpha}}_{i,i'})$ and $d(\boldsymbol{\theta}_{i,i'})$ are entrepreneurs' similarities across their talent and skills – measuring horizontal and vertical similarity respectively – and $\Psi_{i,i'}$ represents a set of dummy variables that are meant to control for possible biased matches. They take value one when the two members of the dyad have the same sex or age, shared their last employer and occupation or had the same educational level prior to becoming entrepreneurs, $\Phi_{i,i'}$ is a set of entrepreneur-level FEs controlling for their main demographic characteristics, and $\Delta(\text{Log-Earnings})_{i,i'}$ is the difference between their past cumulated labor earnings.

For computational feasibility, however, we run the specification in **Equation 5** year by year and on sample constructed as follows: first, for each year from 1995 to 2015 we take the set of founders that founded a firm that survived for at least 3 years and for which we are able to observe their past labor market history; then, we calculate all possible pairings between these founders and, finally, we augment our list of two-founders team in that year with a random 1/4 of non-entrepreneurial teams pairings. We report the estimates of the main coefficient of interest averaged across all year in **Table 4**.

Three main points are worth emphasizing. First, the coefficient on vertical dissimilarity between entrepreneurs is significantly negative, albeit small, indicating that strong dissimilarities in talent decrease the likelihood of founding a firm. Second, the negative and insignificant coefficient on the difference in labor earnings between potential founders indicates that is unlikely that founding teams are formed by capital-rich entrepreneurs simply providing funding to talented ones. Third, the coefficient on skill dissimilarity – our proxy for horizontal dissimilarity in teams – is negative. Since the major determinant of the likelihood of forming a team is also whether or not the two potential founders were colleagues in their previous job,[25] we take both as evidence of frictions in the matching process between entrepreneurs. In particular, this speaks to our model assumption on the potential bias governing the matching function of agents in entrepreneurial teams, whereby the sign of the bias is indicative of which types are more or less likely to meet – a.k.a. the strength of random matching.[26] We will go back to and exploit this estimation in our quantitative exercise.

4.4 Team Composition and Firm Performance

Having established that teams are characterized by horizontal dissimilarity in entrepreneurs' skills and vertical similarity in their talent, we finally quantify the effect of these sorting patterns on firm performance. To this end, we estimate the following:

$$\log(y)_{f,t} = \beta_0 \overline{\hat{\alpha}}_f + \beta_2 \Delta_f(\hat{\boldsymbol{\alpha}}) + \beta_3 \Delta_f(\boldsymbol{\theta}) + \Phi_{f,t} + \epsilon_{f,t}, \tag{6}$$

where $\log(y)_{f,t}$ denotes log sales in year t, $\overline{\hat{\alpha}}_f$ is the average latent type – their AKM FEs as workers – for firm f's founders, $\Delta_f(\hat{\boldsymbol{\alpha}})$ is the average dissimilarity of founders' types within the team, and $\Delta_f(\boldsymbol{\theta})$ is the average dissimilarity of founders' skills within the team. Moreover, Φ is a set of FEs that control for sector and time variation, the firm incorporation type and, indirectly, for the resources available to the founding team as the quintiles of founders cumulative labor earnings and the quintiles of total assets the firm reports at incorporation. Importantly, we use firm-level sales to maximize the number of data points. Unfortunately, other metrics such as TFP are available only for the reduced SCIE sample, and the estimation of the AKM FEs and skill dissimilarities are already demanding on the data, as they require information on past careers for all team members.

Table 5 shows the main coefficients of interest from the estimation of **Equation 6**. Column (1) reports our baseline model: first, firms founded by entrepreneurs with high average latent types (as workers) perform better. In addition, higher *vertical dissimilarity* in founders' latent types is associated with worse firm performance, but

[25]This is consistent with evidence on the QP by Rocha, Carneiro and Varum (2018), see **Table C.2**.

[26]Indeed, removing controls for the bias in matching, such as individuals being the same age or sex, being colleagues, having worked in the same occupation or having the same educational level, makes the coefficient on their skill (horizontal) dissimilarity even more negative, as shown in **Figure C.15**.

Table 5: Founding Team Characteristics and Firm Performance

Dependent Variable:	Log Sales				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Avg. Work FE	0.200***	0.141***	0.136***	0.099***	0.096***
	(0.006)	(0.005)	(0.005)	(0.008)	(0.008)
Worker FE dissimilarity	-0.019***	-0.016***	-0.015***	-0.016***	-0.015***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)
Skill dissimilarity	0.192***	0.223***	0.211***	0.165***	0.154**
	(0.051)	(0.044)	(0.043)	(0.061)	(0.061)
Fixed-effects					
Incorporation type	Yes	Yes	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes	Yes
Initial size, Employment quintiles		Yes	Yes	Yes	Yes
Size, Employment quintiles			Yes		Yes
Log Total Earnings, quintiles				Yes	Yes
Log Initial Fixed Assets, quintiles				Yes	Yes
Fit statistics					
Observations	83,916	83,916	83,916	26,141	26,141
R^2	0.273	0.526	0.541	0.534	0.555
Within R^2	0.021	0.016	0.016	0.010	0.010
No Firms	25,401	25,401	25,401	8,072	8,072

Clustered (Sector × Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table reports the relationship between founding team characteristics and firm performances based on **Equation 6**. *Avg. Work FE* is the average AKM worker FEs of founders, *Worker FE dissimilarity* is the average of pairwise Gower indexes of founders' AKM worker FEs, and *Skill dissimilarity* is the average of founders' pairwise Euclidean distances across 74 ESCO skill categories. The estimation sample is based on firms surviving up to 5 years. We report robustness on the sample selection, dissimilarity measures and additional controls in **Appendix C**.

the effect is reversed when we account for the *horizontal dissimilarity* across founders. In fact, the positive and significant β_2 coefficient indicates that founding teams that are more horizontally-diversified tend to over-perform relative to less heterogeneous ones. These findings are consistent with **Model Predictions III-IV** on team performance.

Our baseline effects are robust to the inclusion of several FEs and size controls (Column (2)). **Table 5** also reports estimates of the coefficients of interest including financial controls. Specifically, Column (3) shows that our main result survives the inclusion of FEs for the quintiles of total assets in the year of incorporation of the firm. Alternatively, controlling for the funds available to the founding team, proxied by the

FE on the sum of founders' past total labor earnings, does not invalidate our main result, as shown in Column (4). Column (5) reveals that our main findings are robust to controlling for both channels. We report additional robustness checks in **Appendix C**.

4.5 Robustness Analysis

As a concluding remark, we briefly discuss few robustness exercises, which lend support to the importance of the sorting of entrepreneurs into teams based on their talent and skills, in addition to other relevant motives for which team entrepreneurship may occur.

4.5.1 The role of initial employees

One might think that our results are actually confounded by non controlling directly for the skill composition of another fundamental group of individuals determining early firm performance: the set of initial employees (Choi et al., 2023). As we posit that what matters in our analysis is the skill composition of the founders' team, we would expect that controlling for measures of skill dispersion of employees should not affect our results. For this reason, in **Table**we control explicitly in the analysis for the dissimilarity in workers' fixed effects and ESCO skills. In no cases our results are substantially affected, both quantitatively and qualitatively.

4.5.2 Financial Frictions and the Business Cycle

A valid concern is that our results on the patterns of entrepreneurial sorting and their relevance for firm performance could be driven just by the existence of financial frictions, or that teams were simply a response to negative (or positive) movements of the business cycle. On the former point, we are able to exploit information on firms' financial variables from the merge of QP with SCIE balance sheets. **Table 5** shows that entrepreneurs' talent, skills, and the similarity of these within teams are relevant for life-cycle sales beyond the effect of firms' initial capital. On the latter concern, **Figure C.8** clarifies that the stock and the flow of entrepreneurial teams have no main cyclical component.

We also extend the financial variables used as controls in **Equation 6**. In particular, we include the Whited and Wu index (Whited and Wu, 2006) and the quintiles of tangible assets, as reported in **Table C.5**. Our main results are not affected by these additions.

4.5.3 Changes to Team Composition

To further highlight the relevance of entrepreneurial team founders in terms of firm performance, we follow Choi et al. (2023) and check what happens to firm sales when a founding member leaves the team. Since leaving a team could be endogenous to firm's performance, we condition on those individuals that leave the firm (not close to retirement age) and disappear forever from the QP sample, namely from the Portuguese labor force. This can happen, for instance, in case of death but also migration, which we cannot unfortunately rule out. We run an event study on separation events, matching separated individuals below the age of 60 with plausible controls by nearest neighbor propensity score. The variables on which the matching is run are founder age at separation, gender, education, firm size (sales and employment), sector, number of owners, the average across founders' worker types (AKM FEs), cumulative earnings and skills' PC dissimilarity. We run the following regression separately for firms above or below the median level of horizontal dissimilarity in the year before the separation:

$$\log(\text{Sales}_{f,t}) = \phi_t + \phi_f + \sum_{h=-5}^{5} \beta_h \, T_f \times \mathbb{I}\{t - \tau_f = h\} + \Phi_{f,t} + \varepsilon_{f,t} \tag{7}$$

What emerges from the analysis, reported in **Figure C.9**, is that losing a founder leads to a persistent decrease in sales between 10% and 20%. Notably, the strongest losses are observed in teams with ex ante high dissimilarity, suggesting stronger effects in teams where the loss of a member reduces by more the dissimilarity in skills between founders.

4.5.4 "Sequential" entrepreneurs

Team formation and the relative dissimilarity of founders could be less important in case some special, more experienced and possibly successful individuals were part of the team. We define as "sequential" entrepreneurs those individuals who, throughout their working career, own more than one business at any point in time. For this reason we reproduce the analysis in **Equation 6** only in a sample of firms who feature a sequential founder among their initial team. Results are shown in **Table C.6**. All effects of interest are both qualitatively and quantitatively analogous to the ones detected for the full sample.

5 Bringing the Model to the Data

In what follows, we quantify our theoretical framework and calibrate its main parameters to replicate the aggregate distribution of wages across occupations, the share of individuals in each occupation and in solo vs team entrepreneurship, as well as moments related to the average correlation of skills and talent between team members, and the average dispersion of skills for all entrepreneurs. The calibrated economy is then left to replicate – as untargeted moments – **Model Predictions I-IV**, and to provide estimates for how the sorting of individuals in entrepreneurial teams may contribute to aggregate sales and employment, and hence shape the equilibrium distribution of firms.

5.1 Calibration Strategy

We calibrate the model to match moments generated using a two-dimensional representation of the skills distribution, following the PCs decomposition described in **Section 4.2** and focusing on the first two principal components – **M** for the Managerial and Analytical PC, and **P** for Physical and Manual one. In the model, we are assuming that each occupation employs only one skill - to follow this interpretation of skills as closely as possible in the data, for each worker we compute the maximum skill level between **M** and **P** and use the maximum between the two skills as our empirical counterpart.[27] Skills - and then occupations, are thus labeled as $j = \{M, P\}$. Occupational shares for each period correspond to the percentage of full-time equivalent workers labeled as working in each occupation j during year t across all workforce.[28]

In its 2-skills dimensional representation, the model features 14 parameters in total. **Table 6** collects 3 externally calibrated parameters. The remaining 11 parameters are all chosen to match selected moments in the data: **Table 7** reports all the targeted moments and the associated parameters, and **Table 8** shows the quantitative fit of the model.

Table 6: Externally Calibrated Parameters

Parameter	Description	Value	Note
ν	Returns to Scale in Production	0.7	Standard
σ_L	Elasticity in Production CES	0.6	Following Autor, Katz and Kearney (2008) (see text)
a	Logsum Parameter	10.0	Acabbi, Alati and Mazzone (2024)

Technology. We assume the production function to be $F(\mathbf{\Theta}, \boldsymbol{L}) \equiv \zeta(\mathbf{\Theta}) f(\mathbf{\Theta})^{\nu}$. Labor inputs at the firm level are aggregated using a CES form, with share parameter δ_L and substitution parameter σ_L. We further assume decreasing returns to scale in production – that is, $\nu < 1$ – to allow for the existence of a non-degenerate distribution of firms in equilibrium. Both ν and σ_L are externally fixed to standard values in the literature (see **Table 6**), while we internally calibrate δ_L to match wage ratios across occupations.[29] In particular, computing relative wages in the model implies obtaining relative skill prices across occupations $j = \{M, P\}$. To perform instead this exercise in the data, we use a

[27]As in **Section 4.1**, skill levels of worker i are computed by looking at their entire work experience. For entrepreneurs, we instead only consider the work experience prior to the first entrepreneurial spell.

[28]We could alternatively classify each narrowly-defined occupation in the data according to the largest component j, obtaining 3 groups of occupations, then compute the shares over the 3 groups.

[29]To calculate σ_L, we compute the co-movement of occupation wage gaps and relative supplies over time in our QP sample, exploiting all years from 1991 to 2019 and according to our classification of occupations within the set $\{M, P\}$. The estimated coefficient relates to σ_L as explained in Autor, Katz and Kearney (2008).

wage regression that explicitly models wages as a function of skill measures for each worker i in occupation j at time t, $\mathbf{x}_{i,j,t}$, controlling for other relevant worker-level observables:

$$\log(w_{i,t}) = \alpha_i + \alpha_{S(i,t)} + \sum_{j=1}^{3} \beta_j \cdot \mathbf{x}_{i,j,t} + \mathbf{Z}'_{i,t}\theta + \varepsilon_{i,t} \tag{8}$$

We include worker FEs α_i and sector-year FEs $\alpha_{S(i,t)}$, and the matrix Z contains age, gender, and contract type (temporary vs open-ended, full-time vs part-time) FEs. The estimated coefficients β_j, with $j = \{M, P\}$ are interpreted as empirical approximations of the market valuation of each skill dimension. An alternative specification is instead:

$$\log(w_{i,t}) = \alpha_i + \alpha_{S(i,t)} + \sum_{j=1}^{3} \beta_j \cdot \mathbf{x}_{i,j,t} \cdot \mathbb{I}\{j(i,t) \in j\} + \sum_{j=1}^{3} \gamma_j \cdot \mathbf{x}_{i,j,t} \cdot \mathbb{I}\{j(i,t) \notin j\} + \mathbf{Z}'_{i,t}\theta + \varepsilon_{i,t}, \tag{9}$$

where $\mathbb{I}\{j(i,t) \in j\}$ indicates that occupation of worker i in t, i.e. $j(i,t)$, corresponds to its assigned dominant skill j. The objective of this specification is to identify the price of skills where they are primary constituents of the given occupation separately from their contribution to wages in occupations where another skill is the major contributor.

Table 7: Internally Calibrated Parameters

Parameter	Description	Value	Interpretation	Empirical Target
	Initial Distribution			
$\alpha_\beta, \beta_\beta^1, \beta_\beta^2$	Shape Parameters	2.25, 4.5, 3.6	2-Dimensional Skill Vector	Occupational Shares
ρ	Copula Parameter	0.30	Skill Correlation	Avg Dispersion of Entrep Skills
η	Meeting Bias	20.0	Likelihood Similar Matches	Skill Dissimilarity Coeff in Dyadic Regression
	Returns to Paid Work			
κ, ψ	Human Capital (scale and slope)	1.10, 0.9	Skill Adjustment for Labor Supply	Workers' Earnings Distribution
	Firm Technology			
δ	Labor Aggregation CES (share)	0.5	Labor (Skill) Specialization	Relative Wages
	Entrepreneurial Skills Aggregation			
δ_E	Entrep Productivity CES (share)	0.5	Skill Composition in Entrep Productivity	Avg Corr of Team Entreps Skills
σ_E	Entrep Productivity Elasticity CES	0.75	Skill Subst in Entrep Productivity	$\frac{\Delta Sales}{\Delta HD}$ Coeff in Entrep Death Regression
ξ	Logsum Penalty	0.6	Convergence of Skills in Teams	Avg Corr of Team Entreps Worker FE

Note: Internal calibration using Simulated Method of Moments.

Workers. The function $h(\cdot)$ that translates skills into labor productivity is given by $h_j(\theta_j) = \kappa \cdot \theta_j^\phi$ and $h_j(\theta_k) = 0$ for all $k \neq j$, with $\phi \in (0,1)$. Notice that, as $\phi \longrightarrow 0$, workers' heterogeneity disappears, as all individuals supply exactly one unit of labor when working as employees, although their entrepreneurial productivity remains heterogeneous. To calibrate κ and ϕ we target two moments related to the distributional properties of wages in the data. Specifically, we target the p90/p10 and the p90/p50 ratios of the earnings distribution (we compute the quantiles by year and then average them out).

Entrepreneurial Productivity. Individual skills contribute to entrepreneurial productivity according to the function $\zeta(\mathbf{\Theta})$, which is CES with share parameters δ^E

and substitution parameter σ^E. In the case of an entrepreneurial team, skills are first aggregated at the team level – before being passed to the function $\zeta(\mathbf{\Theta})$ – according to:

$$\mathbf{\Theta}^T_{i,i'} = [\psi(\theta_{1,i}, \theta_{1,i'}), \psi(\theta_{2,i}, \theta_{2,i'}), \ldots, \psi(\theta_{N,i}, \theta_{N,i'})]$$

To calibrate $\psi(\cdot)$, we adopt a functional form similar in spirit to the "catch-up" technology in Acabbi, Alati and Mazzone (2024). The underlying idea is that each entrepreneur could eventually accumulate the skills in which the other team member is relatively more abundant. However, since our model is static, we need to collapse the skill accumulation dynamics to a single shift. While assuming that the catch-up immediately happens would be akin to assume $\psi(\theta_{j,i}, \theta_{j,i'}) = \max(\theta_{j,i}, \theta_{j,i'})$, with $j = \{M, P\}$, a more flexible form is:

$$\psi(\theta_{j,i}, \theta_{j,i'}) = \frac{\log\left(\xi \exp^{a\cdot\theta_{j,i}} + \xi \exp^{a\cdot\theta_{j,i'}}\right)}{a} \quad \text{for} \quad j = \{M, P\}$$

This is a logsum expression, with a penalty term ξ that shifts the expression downward. As $a \to \infty$, the penalty term becomes irrelevant, and $\psi(\theta_{j,i}, \theta_{j,i'}) \to \max(\theta_{j,i}, \theta_{j,i'})$.

When quantifying the model, we externally set a according to the literature, and instead calibrate internally the logsum penalty and the CES parameters of the entrepreneurial productivity. Regarding the former, we target the correlation in talent between team members, as reported in **Figure 9**, which corresponds to the correlation in team members' $\zeta(\mathbf{\Theta})$ in our model. For the CES share parameter δ^E, we match the average (horizontal) skill dissimilarity across team members, namely the empirical mean of the left hand-side distribution depicted in **Figure 11**. Finally, to calibrate the substitution parameter σ^E, we exploit our simulated model to replicate the effect of the death of one team member. Our model is static, but we construct a counterfactual scenario by taking a random subsample of all formed teams and removing arbitrarily one team member before production would take place. Then, we compare the effect that this "sudden" death would have on firm sales (on impact) across teams that are ex-ante more or less dissimilar, and target the p.p. difference of these regression coefficients, which have empirical counterparts estimated through the analysis of **Section 4.5.3**.

Skill Distributions. We calibrate the joint distribution of skills $G(\mathbf{\Theta})$ by combining $N = 2$ independent marginal Beta distributions with shape parameters $\left\{\alpha^j_\beta, \beta^j_\beta\right\}$, for $j = \{M, P\}$ by means of a Gaussian copula. The copula allows us to model skill correlation separately from their marginal distributions, and to capture it with parameter(s) $\rho_{j,j'}$ for $j \neq j'$. Since they affect the relative scarcity of each skill, the shape parameters are calibrated to match the overall share of entrepreneurs, the share of team entrepreneurs and, consequently, the share of agents in each occupation. The copula parameter is instead set to replicate the average dispersion of skills for all entrepreneurs in our sample, as it influences to which extent all N skills may be possessed by each agent in the economy.

Meeting Technology. Every agent i meets another agent i' at the start of the period, drawn from the same distribution. The matching function has the following form:

$$m(\mathbf{\Theta}_{i'}|\mathbf{\Theta}_i) = \frac{G(\mathbf{\Theta}_{i'}) \cdot K(\mathbf{\Theta}_i, \mathbf{\Theta}_{i'}; \eta)}{\int G(\Xi) \cdot K(\mathbf{\Theta}_i, \mathbf{\Theta}_{i'}; \eta) d\Xi},$$

where $K(\cdot)$ gives different weights to nearby types in the matching function. As previously explained, the parameter η shapes the degree of random matching: if $\eta > 0$, nearby types are more likely to meet, while if $\eta < 0$, nearby types are less likely to meet. Our empirical results in **Section 4.3** show that the likelihood of team formation is positively related to having been co-workers and having relatively similar sets of skills, suggesting a significant deviation from random matching. Hence, exploiting our simulated model, we calibrate $\eta > 0$ to replicate the dyadic regression coefficient β_1 in **Equation 5**, namely the contribution of agents i and i''s skill dissimilarity to the probability of teaming up.

Table 8: Model Fit on Targeted Moments

Moment	**Model**	**Data**
Employment Share in Skill(Occ) 1 (out of all workers)	0.450	0.470
Share of Entrepreneurs (out of all agents)	0.020	0.024
Share of Entrepreneurial Teams (out of all agents)	0.017	0.005
Dyadic Coefficient on Skill Dissimilarity	-0.003	-0.002
Wage-occ1/Wage-occ2	1.080	1.080
Avg Dispersion of Entrepreneurial Skills (within all entreps)	0.101	0.126
Avg Skill Dissimilarity in Entrepreneurial Teams	0.123	0.186
Corr of Talent within Entrep Team Members	0.470	0.478
Elasticity of Sales to Entrep Death: High vs Low Skill-Dissimilar Teams	-0.260	-0.210
Earnings distribution: p90/p10	2.432	1.450
Earnings distribution: p90/p50	1.430	1.250

5.2 Quantitative Predictions

Our last exercise validates the calibrated model against the main predictions from our theory, which have also been verified empirically. First, recall that vertical dissimilarity in entrepreneurial teams measures the distance between team members' talent (i.e. the level of all their skills), and, in an economy with only $N = 2$ skills, is given by:

$$\text{VD} = \sum_{j=1,2} (\zeta(\theta_i) - \zeta(\theta_{i'}))^2$$

Horizontal dissimilarity speaks instead to the difference in the composition of team members' skill sets (i.e. their specialization), and, for given agents i and i', reads as:

$$\text{HD} = \sum_{j=1,2} \left(\theta_{i,j} - \theta_{i',j}\right)^2$$

Figure 12: Skill and Talent Similarities in the Calibrated Model

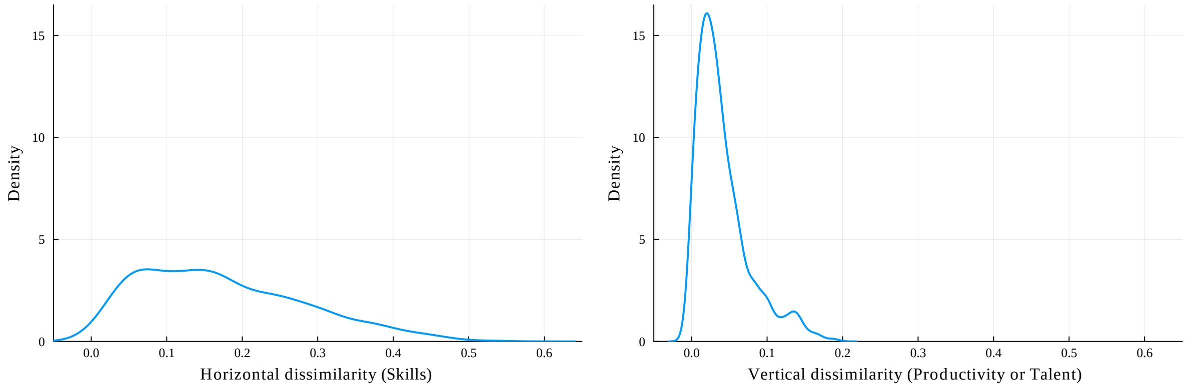
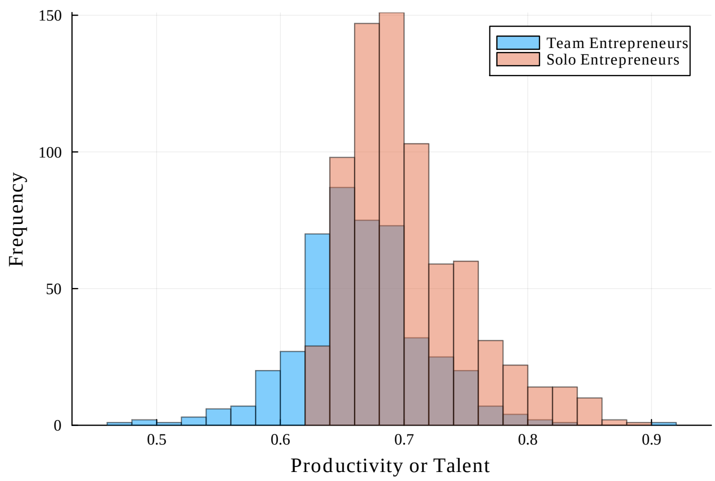


Figure 12 plots the distributions of HD and VD in the calibrated economy. This shows that, in the model as in the data, the distribution of teams HD has a fatter tail compared to the VD one (note that only the mean of HD is explicitly targeted), aligning with **Model Prediction I**: Entrepreneurs in teams have relatively unbalanced skill sets.

Second, we compute firm productivity for both solo and team entrepreneurs in our calibrated economy and overlay them in **Figure 13**. Teams have, on average, higher firm productivity, as per our **Model Prediction II**, due to a stronger selection into the entrepreneurial sample and the complementarities of team members' talent and skills within firm production. Note that this result from the quantitative model aligns as well with the empirical comparison of solo and team-entrepreneurs' TFP shown in **Figure 6**.

Figure 13: Productivity Distribution of Single Entrepreneurs vs Teams



Third, we investigate the relationship between teams' similarity in skills and talent and firm-level outcomes by regressing firm log-productivity (and log-sales) on teams' HD and VD, as computed in the calibrated economy. **Table 9** illustrates that, controlling for the average productivity of the team (akin to the average AKM worker types in the regressions of **Table 5**), teams' HD has a positive relation with firm performance, while the opposite is true for teams' VD. The magnitudes of the coefficients are admittedly far from their empirical counterparts, but the signs of both relationships aligns with the findings in **Table 5** and with **Model Prediction III-IV**. In particular, they show that two similarly talented but skill-complementary entrepreneurs benefit firm-level outcomes.

Table 9: Team Composition and Firm Performance

	Firm Productivity	Firm Sales
Horizontal Dissimilarity (HD)	1.169***	3.896***
	(0.013)	(0.043)
Vertical Dissimilarity (VD)	-0.414***	-1.379***
	(0.039)	(0.130)
Average Team Productivity	✓	✓

Fourth, we estimate the contribution of talent dissimilarity between two potential entrepreneurial partners to the likelihood of team formation, and compare it in the data and in the model. In particular, recall that our calibration exploits the relationship between skill dissimilarity and team formation, as estimated through the set of dyadic regressions in **Equation 5**. In the simulated model, we adopt a similar econometric approach and construct a counterfactual sample of team and non-team pairs of entrepreneurs. Then, we measure the likelihood of two given agents i and i' forming a team, controlling for the pair's average talent (or productivity) $\bar{\alpha}_{i,i'}$ through:

$$\mathbb{I}\{\text{Team}_{i,i'}\} = \beta_0 \bar{\alpha}_{i,i'} + \beta_1 VD_{i,i'} + \beta_2 HD_{i,i'} + \varepsilon_{i,i'}$$

The first row of **Table 10** reports the coefficient of teams' HD on team formation, which

Table 10: Team Composition and Firm Performance

	$\eta = 5$	$\eta = 15$	$\eta = 20$	Data
Horizontal Dissimilarity (HD)	0.165***	0.021**	-0.003	-0.002***
	(0.012)	(0.015)	(0.015)	(0.001)
Vertical Dissimilarity (VD)	-0.272***	-0.176***	-0.145***	-0.001***
	(0.013)	(0.018)	(0.018)	(0.00005)
Average Team Productivity	✓	✓	✓	✓

we target in the calibration exercise by setting $\eta = 20$ (Column (3)) to replicate its empirical counterpart (Column (4)). The second row presents instead the coefficient of teams' VD on team formation, which is an untargeted moment in our exercise, and whose sign aligns qualitatively (not quantitatively though) with its empirical counterpart. The progression of Columns (1)-(3) shows how the bias η in the meeting technology affects the contribution of potential team members' HD and VD to the likelihood of team formation, as it influence the probability with which agent i meets other agents of nearby skill types.

Table 11: Entrepreneurial Teams' Contribution to Aggregate Outcomes

Moment	Model	Data
Entrepreneurial teams' sales share (out of all firms)	0.38	0.40
Entrepreneurial teams' share within top 10% largest firms	0.34	0.43

Finally, we close with a tentative answer to one of our original questions: does the sorting of agents into entrepreneurial teams – based on their talent and competences – affect the equilibrium distribution of firms? And can this sorting matter for aggregate outcomes? To this end, **Table 11** shows the contribution of entrepreneurial teams to aggregate sales and their share among the top 10% largest producers, considering the entire set of privately held firms in our Portuguese sample and comparing empirical moments to model-implied ones. Our calibrated framework reveals that the sorting of entrepreneurs into teams can explain a large fraction of the overall performance of multi-owned firms in the economy and significantly shape the equilibrium distribution of firms.

6 Conclusions

We study the sorting of individuals into entrepreneurial teams according to their talent and skills, and establish it as a critical determinant of firm-level and aggregate outcomes. In particular, the paper proposes a novel theory of career and entrepreneurial choices, where individuals with complementary but unbalanced skills are more inclined to join entrepreneurial teams, resulting in higher productivity for team-based ventures compared to solo entrepreneurship. In our empirical analysis, we then leverage employer-employee administrative data from Portugal: by linking agents' pre-entrepreneurship occupational trajectories to subsequent firm performance, we demonstrate that positive sorting along talent, and negative sorting along skills specialization is associated with larger firms, increased sales, and improved survival rates. Our findings suggest that the micro-level dynamics of team formation are driven primarily by intrinsic attributes rather than by external financial or cyclical constraints, and significantly contribute to aggregate outcomes. Our paper contributes to the joint understanding of the equilibrium interactions between firm entry and exit and labor market dynamics. The framework naturally lends itself to the analysis of policies aimed at improving quantity and quality of firm entry.

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A Model Appendix

A.1 Discussion and Proofs

In this section we discuss the analytical results that yield our main Model Predictions. We present propositions and corresponding proofs that yield the properties discussed in **Section 2.3**, but organized in a way that follows the logic dependence of one from the other.

Since the analysis is conducted over the partial equilibrium behavior of the model, we omit the dependence of wages on any other primitive. We also assume skills are independently distributed across individuals. All assumptions on functional forms will be listed as follows:

A.1 Homogeneity of Degree One: $g(\lambda\boldsymbol{\Theta}_i) = \lambda g(\boldsymbol{\Theta}_i), \quad \lambda \in \mathbb{R}$

A.2 Differentiability: $g \in \mathcal{C}^2$

A.3 Monotonicity: $\frac{\partial g(\cdot)}{\partial \theta_j} > 0, \forall j = 1, 2$

A.4 Symmetry: $g(x, y) = g(y, x)$

A.5 Supermodularity: $\frac{\partial^2 g(\cdot)}{\partial x \partial y} > 0$

A.6 Concavity: $H_g(x, y) = \begin{pmatrix} g_{xx}(x,y) & g_{xy}(x,y) \\ g_{xy}(x,y) & g_{yy}(x,y) \end{pmatrix}$ is negative-semidefinite

A.7 Schur Convexity: $(x - y)\left(\frac{\partial g}{\partial x} - \frac{\partial g}{\partial y}\right) > 0$

A.8 Multiplicative Separability: $\frac{g_u}{g_v} \leq \frac{v}{u}$

Throughout this section, and in the rest of the paper, we will assume the labor aggregator for firms to be CES, and hence to satisfy **A.1 - A.4** (we need further assumptions on the elasticity to obtain **A.5**). Firm's profit function then is:

$$\pi = \zeta(\boldsymbol{\Theta}) \cdot f(\boldsymbol{L})^{\nu} - \mathbf{w} \cdot \mathbf{L}, \quad \nu < 1$$

If $f(\cdot)$ is CES, then:

$$\pi = \zeta(\boldsymbol{\Theta}) \cdot [\delta_L l_1^{\sigma_L} + (1 - \delta_L) l_2^{\sigma_L}]^{\frac{\nu}{\sigma_L}} - \mathbf{w} \cdot \mathbf{l}$$

For a given composite quantity L, the unit cost (minimum cost of one unit of L) is the CES price index:

$$c(\mathbf{w}) = \left[\delta_L^\rho w_1^{1-\rho} + (1-\delta_L)^\rho w_2^{1-\rho}\right]^{\frac{\nu}{1-\rho}}$$

where $\rho \equiv \frac{1}{1-\sigma_L}$. Entrepreneurs then choose:

$$\max_{L \geq 0} \quad \zeta(\mathbf{\Theta})L^\nu - c(\mathbf{w})L \quad \Longrightarrow \quad \text{FOC:} \quad \nu\zeta(\mathbf{\Theta})L^{\nu-1} = c(\mathbf{w}) \quad \Longrightarrow \quad L^* = \left[\nu \cdot \frac{\zeta(\mathbf{\Theta})}{c(\mathbf{w})}\right]^{\frac{1}{1-\nu}}$$

and profits are:

$$\pi^I = (1-\nu) \cdot \underbrace{\left[\frac{\nu}{1-\nu}\right]^{\frac{\nu}{1-\nu}} c(\mathbf{w})^{-\frac{\nu}{1-\nu}}}_{=D(\mathbf{w})^{-1 \cdot \frac{1}{1-\nu}}} \cdot \zeta(\boldsymbol{\theta})^{\frac{1}{1-\nu}} = (1-\nu) \cdot \Bigg(D(\mathbf{w})^{-1} \cdot \zeta(\boldsymbol{\theta})\Bigg)^{\frac{1}{1-\nu}}$$

Assuming symmetric wages means we can write: $\pi^I = (1-\nu)\Bigg(D(w)^{-1}\zeta(\mathbf{\Theta})\Bigg)^{\frac{1}{1-\nu}}$. Working as an employee gives payoffs:

$$R(\mathbf{\Theta}; w) = \max\{h(\theta_1) \cdot w_1, h(\theta_2) \cdot w_2\} = w \, \max\{h(\theta_1)h(\theta_2)\}$$

since $w_1 = w_2 = w$. Entrepreneurship is chosen iff:

$$\zeta(\mathbf{\Theta}) \geq D(w)\Big(\frac{R(\mathbf{\Theta}; w)}{1-\nu} \cdot \Big)^{1-\nu} \tag{A.1}$$

Payoffs from team-run firms are instead given by:

$$\pi^T = \underbrace{\zeta(\psi\left(\theta_{1,i}, \theta_{1,i'}\right), \psi\left(\theta_{2,i}, \theta_{2,i'}\right))}_{\zeta^T(\mathbf{\Theta}_{i,i'})} \cdot f(\boldsymbol{L})^\nu - c(w)L$$

$$= (1-\nu) \cdot \Bigg(D(w)^{-1}\zeta\Big(\psi\left(\theta_{1,i}, \theta_{1,i'}\right), \psi\left(\theta_{2,i}, \theta_{2,i'}\right)\Big)\Bigg)^{\frac{1}{1-\alpha}}$$

Hence, the team is formed if and only if:

$$\zeta^T(\mathbf{\Theta}_{i,i'}) \geq \max\{\zeta(\mathbf{\Theta}_{\boldsymbol{i}}), \zeta(\mathbf{\Theta}_{\boldsymbol{i'}}), R(\mathbf{\Theta}_{\boldsymbol{i}}; w), R(\mathbf{\Theta}_{\boldsymbol{i'}}; w)\} \tag{A.2}$$

Now, for a general form of $\zeta(\cdot)$, what can we say about choice **Equation A.1**? Let's analyze the impact of a mean-preserving spread on each option. Define mean skill, $\bar{\theta} =$

$\frac{\theta_1+\theta_2}{2}$. Original skill levels can be recovered by adding and subtracting the individual "specialization" level $\delta \in \mathbb{R}$:

$$(\theta_1, \theta_2) \to \left(\bar{\theta} + \delta, \bar{\theta} - \delta\right), \quad \delta \in \mathbb{R}$$

What is the impact of horizontal differentiation? We can focus on the problem for agent i only and write it in terms of mean preserving spreads :

$$\zeta\left(\theta_1^T, \theta_2^T\right) \geq \max\left\{\zeta(\bar{\theta}_i + \delta_i, \bar{\theta}_i - \delta_i), \zeta(\bar{\theta}_{i'} + \delta_{i'}, \bar{\theta}_{i'} - \delta_{i'}), R(\bar{\theta}_i, \delta_i; w)\right\} \tag{A.3}$$

where $\theta_1^T = \psi(\bar{\theta}_i + \delta_i, \bar{\theta}_{i'} - \delta_{i'})$ and $\theta_2^T = \psi(\bar{\theta}_i - \delta_i, \bar{\theta}_{i'} + \delta_{i'})$

We can then prove that:

Proposition A.1. *If ψ satisfies $A.2 - A.4$ and ζ satisfies $A.3 - A.4$ the two statements are equivalent:*

- $\psi(\cdot)$ *satisfies A.7, i.e.* $(\theta_{i,j} - \theta_{i',j})\left(\frac{\partial\psi}{\partial\theta_{i,j}} - \frac{\partial\psi}{\partial\theta_{i',j}}\right) > 0$
- $\zeta^T(\mathbf{\Theta}_{i,i'})$ *is strictly increasing in* $|\delta|$

Proof.

$$\left(\implies\right)$$

Take a mean-preserving spread of ψ; by chain rule:

$$\psi'(\delta) = \psi'_{\theta_{j,i}} \cdot (+1) + \psi'_{\theta_{j,i'}} \cdot (-1) = \left[\psi'_{\theta_{j,i}} - \psi'_{\theta_{j,i'}}\right]_{(\theta_{j,i},\theta_{j,i'})=(\bar{\theta}+\delta,\bar{\theta}-\delta)} \qquad \forall j = 1, 2$$

Now, if $(\theta_{j,i}, \theta_{j,i'}) = (\bar{\theta}+\delta, \bar{\theta}-\delta)$, then $\theta_{j,i} - \theta_{j,i'} > 0$. By definition of Schur Convexity, then, $\psi'_{\theta_i} - \psi'_{\theta_{i'}} > 0$. Hence, $\psi'(\delta) \geq 0$. To prove strict inequality, observe that by **A.3** we have $\psi'_{\theta_i} \neq \psi'_{\theta_{i'}}$ whenever $\theta_i \neq \theta_{i'}$. Hence, $\psi'(\delta) > 0$. Without loss of generality, define:

$$\psi_1(\delta) = \psi(\bar{\theta}_1 + \delta, \bar{\theta}_1 - \delta) \ ; \quad \psi_2(\delta) = \psi(\bar{\theta}_2 - \delta, \bar{\theta}_2 + \delta)$$

So, obviously, we can write $\zeta^T(\delta) = \zeta(\psi_1(\delta), \psi_2(\delta))$. Then (symmetry of $\zeta(\cdot)$ makes this wlog):

$$\frac{\partial\zeta^T(\cdot)}{\partial\delta} = \left[\frac{\partial\zeta^T(\cdot)}{\partial\psi_1}\frac{\partial\psi_1}{\partial\delta} + \frac{\partial\zeta^T(\cdot)}{\partial\psi_2}\frac{\partial\psi_2}{\partial\delta}\right] > 0$$

by **A.3** for $\zeta(\cdot)$.

$$\left(\Longleftarrow\right)$$

Now, suppose

$$\frac{\partial \zeta^T(\cdot)}{\partial \delta} > 0$$

Then by **A.4** (symmetry) and **A.3** (monotonicity) it follows that $\partial\psi(\cdot)/\partial\delta > 0$. To close the proof, we need to show that if a mean preserving spread increases ψ, then Schur-convexity needs to follow. To show this, we only need to use **A.2** and **A.4** to calculate:

$$\psi'(\delta) = \psi'_{\theta_1} \cdot (+1) + \psi'_{\theta_2} \cdot (-1) = \left[\psi'_{\theta_1} - \psi'_{\theta_2}\right]_{(\theta_1,\theta_2)=(\bar{\theta}+\delta,\bar{\theta}-\delta)}$$

and we know this is strictly positive. In addition, because $\theta_{j,i} > \theta_{j,i'}$, we can write:

$$(\theta_{j,i} - \theta_{j,i'}) \cdot \left[\psi'_{\theta_1} - \psi'_{\theta_2}\right]_{(\theta_1,\theta_2)=(\bar{\theta}+\delta,\bar{\theta}-\delta)} > 0$$

which is the definition of Schur convexity. QED. □

To discuss the role of vertical dissimilarity, we face a conceptual issue: while it is possible to increase horizontal differentiation without changing the relative average productivity of the two team members, any change in relative average productivity has also an impact that goes through horizontal differentiation. Understanding the impact of vertical differentiation then requires unpacking these channels. To do so, we need to express payoffs in a slightly different way. Start from an equal team, i.e. with $\bar{\theta}_i = \bar{\theta}_{i'} = s$. The "equal team" is a special case of teams for which $\bar{\theta}_i = s + d/2$ and $\bar{\theta}_i = s - d/2$.

Proposition A.2. *Assume ζ satisfies $A.2 - A.6$, while ψ satisfies $A.2, A.4,$ and $A.7$. Then team productivity decreases with vertical dissimilarity, net of its effect of horizontal differentiation*

Proof. Let's assume, without loss of generality, a constant within-individual spread across skills, i.e. $\delta_i = \delta_{i'} = \delta$. This allows us to define:

$$x_U = \psi\left(s + \frac{d}{2} + \delta, s - \frac{d}{2} + \delta\right), \quad y_U = \psi\left(s + \frac{d}{2} - \delta, s - \frac{d}{2} - \delta\right)$$

while obviously $x_E = \psi(s+\delta, s+\delta)$, $\quad y_E = \psi(s-\delta, s-\delta)$. Simplify further using $u = s + \delta$ and $w = s - \delta$, so:

$$x_U = \psi\left(u + \frac{d}{2}, u - \frac{d}{2}\right), \quad y_U = \psi\left(w + \frac{d}{2}, w - \frac{d}{2}\right)$$

and $x_E = \psi(u,u) = c \cdot u; \quad y_E = \psi(w,w) = c \cdot w, \quad c \geq 0$. By Schur convexity, $x_U > x_E$ and $y_U > y_E$.

Now, assume:

$$\zeta_{1,1} + \zeta_{2,2} \leq 2 \cdot \zeta_{1,2} \quad \forall x, y > 0$$

Then $\zeta(x,y) \leq \zeta(\frac{S}{2}, \frac{S}{2})$ whenever $x + y = S$. We can now decompose the role of horizontal and vertical differentiation:

$$\zeta(x_U, y_u) - \zeta(x_E, y_E) = \underbrace{\left[\zeta(x_U, y_U) - \zeta\left(\frac{S_U}{2}, \frac{S_U}{2}\right)\right]}_{<0: \quad \textit{supermodularity effect}} + \\ + \underbrace{\left[\zeta\left(\frac{S_U}{2}, \frac{S_U}{2}\right) - \zeta\left(\frac{S_E}{2}, \frac{S_E}{2}\right)\right]}_{>0: \quad \textit{convexity effect (between)}} + \underbrace{\left[\zeta\left(\frac{S_E}{2}, \frac{S_E}{2}\right) - \zeta\left(x_E, y_E\right)\right]}_{>0: \quad \textit{convexity effect (within)}}$$

The two convexity effects capture the impact of a higher d via horizontal differentiation, so the first term represents the "pure" effect vertical differentiation. $\square$

The first and second term depend entirely on d and δ: while the second term captures the way in which increasing d contributes to overall team skills, the first captures the "*penalty*" that origins from the concavity of ζ. Finally, the third term depends entirely on the contribution of δ, i.e. the within-individual heterogeneity: intuitively, as individual skills are more unbalanced, aggregating through ψ improves team productivity. Intuitively, Schur convexity of ψ plus the monotonicity of ζ imply the total effect is positive even if $\delta = 0$.

We're going to make two assumptions over distributions, allowing us to make claims over the population of entrepreneurs.

B.1 (Mirror Matching): An individual with $\{\bar{\theta}, \delta\}$ meets a potential partner for team formation with probability q, the second individual having equal talent $\bar{\theta}$, but opposite specialization, i.e. the matched indvidual has $\{\bar{\theta}, -\delta\}$.

B.2 (Independence) The two skills θ_1 and θ_2 are independently distributed across the population. Equivalently, $\bar{\theta}$ and δ are distributed independently.

Call E the indicator function for whether the individual prefers to be a worker in one of the two occupations, with $E = 1$, or an entrepreneur, whether it is solo or in a team (conditional on a finding a suitable match) - then $E = 0$. Let's define $p_E = \mathbb{P}(E = 0)$. The next lemma establishes the existence of a unique threshold for productivity, below which individuals will choose paid employment.

Lemma A.1. *If ζ satisfies $A.1 - A.4$ then, for every level of specialization δ, there exists a unique individual average ability cutoff:*

$$\bar{\theta}_E(|\delta|): \quad \zeta^I(\bar{\theta}, \delta) = w \cdot (\bar{\theta} + |\delta|)$$

with $\bar{\theta}'_E(|\delta|) > 0$.

Proof. Let's call $m \equiv |\delta|$ - we will analyze the role of m, but the analysis carries through without loss of generality because of assumption $A.4$ on $\zeta(\cdot)$ and $\psi(\cdot)$. The difference between entrepreneurial payoff and paid employment is then:

$$g(\bar{\theta}, m) \equiv \zeta(\bar{\theta}, m) - w \cdot \big(\bar{\theta} + m\big)$$

We then want to prove that:

1. $g(\cdot, m)$ is continuous

   Let's rewrite ζ^I exploiting **A.1** to factor out scale. Use a continuous, increasing in $[0, 1]$, function $\varphi(\cdot)$. Also assume $\varphi(0) = \zeta(1, 0) = 0$ and $\varphi(1) = \zeta(1, 1) = 1$. Then:

   $$\zeta^I(\bar{\theta}, m) = \big(\bar{\theta} + m\big) \cdot \varphi(r(\bar{\theta}, m)), \quad \text{where:}$$

   $\varphi(u) \equiv \zeta(1, u)$, and $r(\bar{\theta}, m) \equiv (\bar{\theta} - m)/(\bar{\theta} + m)$. Then:

   $$g(\bar{\theta}, m) = \big(\bar{\theta} + m\big) \big[\varphi(r(\bar{\theta}, m)) - w\big]$$

   Continuity of $g(\cdot, \cdot)$ is immediate since $\varphi(\cdot)$ is continuous, and $r(\cdot)$ is too.

2. $g(m, m) < 0$, and $\lim_{\bar{\theta} \to +\infty} g(\bar{\theta}, m) > 0$ whenever $w < \zeta^I(1, 1)$

   We now compute the end-point signs:

   - at $\bar{\theta} = m \Rightarrow r = 0$ and:

     $$g(m, m) = 2m\,(\varphi(0) - w) = -2mw < 0$$

   - at $\bar{\theta} \longrightarrow \infty \Rightarrow r = 1$ and:

     $$\lim_{\bar{\theta} \longrightarrow \infty} \frac{g(\bar{\theta}, m)}{\bar{\theta} + m} = \varphi(1) - w = \zeta^I(1, 1) - w > 0$$

Hence, g switches sign at least once.

3. $\exists! \quad \bar{\theta}_E(m): \quad g(\bar{\theta}_E(m), m) = 0$, with:

$$
\begin{aligned}
g(\bar{\theta}_E(m), m) < 0 &\quad \text{for } \bar{\theta} < \bar{\theta}_E \\
g(\bar{\theta}_E(m), m) > 0 &\quad \text{for } \bar{\theta} > \bar{\theta}_E
\end{aligned}
$$

We cannot prove that g is monotonic everywhere in $\bar{\theta}$, but we can look at the derivative of g at the root. Let's call the root $\bar{\theta}_E$ the point where $\varphi(r) = w$. At $\bar{\theta} = \bar{\theta}_E$:

$$
\left.\frac{\partial g(\bar{\theta}, m)}{\partial \bar{\theta}}\right|_{(\bar{\theta}_E, m)} = \underbrace{(\varphi(r) - w)}_{=0} + 2m \left.\underbrace{\frac{\varphi'(r)}{\bar{\theta} + m}}_{>0}\right|_{(\bar{\theta}_E, m)} > 0 \tag{A.4}
$$

Hence, g crosses 0 with a strictly positive slope. To prove that the root is unique, suppose by contradiction that there are two roots, $\bar{\theta}_E$ and $\bar{\theta}_K$ with (wlog) $\bar{\theta}_E < \bar{\theta}_K$. Rolle's theorem states that if a function is continuous on a closed interval, differentiable on the open interval, and has the same value at both endpoints of the interval, then there must exist at least one point within that interval where the derivative of the function is zero. But by (A.4) we know that $g'(\bar{\theta}) > 0$ at every point in which $g = 0$. Also, the derivative of g cannot turn negative between those zeroes, because both summands of (A.4) are positive once $\varphi(r) > w$. It follows that only one root exists.

4. $\partial\bar{\theta}_E/\partial m > 0$

To do so, we can simply evaluate g at its root and use Dini's Theorem:

$$
\left.\frac{\partial \bar{\theta}_E}{\partial m}\right|_{g(\cdot)=0} = -\frac{\frac{\partial g}{\partial m}}{\frac{\partial g}{\partial \bar{\theta}_E}} = -\frac{(\varphi(r) - w) + \left(\bar{\theta}_E + m\right) \cdot \frac{\partial \varphi(r)}{\partial r}\frac{\partial r}{\partial m}}{(\varphi(r) - w) + 2 \cdot m \frac{\varphi'(r)}{\bar{\theta}_E + m}} > 0
$$

because $\partial r/\partial m = -2\bar{\theta}_E/\left(\bar{\theta}_E + m\right)^2 < 0$, and $(\varphi(r) - w) = 0$ if $\bar{\theta} = \bar{\theta}_E$, and $\varphi'(r) > 0$.

QED □

If an individual is not choosing *ex-ante* to be a worker, then $E = 0$. Under **B.1**, individuals with $E = 0$ who would prefer to start a team can do so with probability q. Most importantly, assuming mirror matching allows to denote entrepreneurial teams' productivity by: $\zeta^T(\bar{\theta}, \delta)$, since the other member's productivity is implied. We will define as "*specialists*" those who would start an entrepreneurial team under the right circumstances, and use the label $S = 1$ to indicate this group. The result below defines the two-dimensional threshold for average talent and skill specialization that characterizes the specialists.

Lemma A.2. *Assume that ψ satisfies $A.2 - A.4$, that ζ satisfies $A.3 - A.4$ and that $B.1$ holds. For every average ability level $\bar{\theta} > 0$:*

1. $\exists! \quad \delta^*(\bar{\theta}) > 0$ *s.t.*

$$\zeta^T(\bar{\theta}, \delta^*(\bar{\theta})) = Z^I(\bar{\theta}, \delta^*(\bar{\theta}))$$

with $|\Delta| < \delta^*(\bar{\theta}) \Longrightarrow \zeta_T(\cdot) \leq \zeta^I(\cdot)$, *and* $|\Delta| > \delta^*(\bar{\theta}) \Longrightarrow \zeta_T(\cdot) > \zeta^I(\cdot)$;

2. *The threshold is weakly decreasing in individual's average ability $\bar{\theta}$:*

$$\frac{\partial \delta^*(\bar{\theta})}{\partial \bar{\theta}} \leq 0$$

Proof. We already proved that $\frac{\partial \zeta^I(\bar{\theta}, \bar{\delta})}{\partial \delta} < 0$ as it follows intuitively from super-modularity. By **Proposition A.1**, we also know that ζ^T is strictly increasing in $|\delta|$. Now, define:

$$f(\bar{\theta}, \delta) \equiv \zeta^T(\bar{\theta}, \delta) - \zeta^I(\bar{\theta}, \delta)$$

We know that $f(\bar{\theta}, \delta) = 0$ when $\delta = 0$, since both earn $\bar{\theta}\,\zeta(1, 1)$. Obviously, $f(\bar{\theta}, \delta) > 0$ whenever $\delta \neq 0$. Hence, it crosses zero once and only once. Denote this unique root by $\delta^*(\bar{\theta})$.

We again use Dini's Theorem to calculate:

$$\left.\frac{\partial \delta^*(\bar{\theta})}{\partial \bar{\theta}}\right|_{f(\cdot)=0} = -\frac{\frac{\partial f}{\partial \bar{\theta}}}{\frac{\partial f}{\partial \delta}} \leq 0$$

The sign of the denominator is obvious, since it follows from ζ^I being decreasing and ζ^T being increasing in δ. Why is $\frac{\partial f}{\partial \bar{\theta}} \geq 0$?

Notice that, if we take any $\delta > 0$, we can say that $\psi\left(\bar{\theta}, \delta; \bar{\theta}, -\delta\right)$ will majorize $\left(\bar{\theta}, \delta\right)$. For $\delta = 0$, the derivative is equal to zero and hence the threshold does not move. Formally, $\psi\left(\bar{\theta}, \delta; \bar{\theta}, \delta\right) \succcurlyeq \left(\bar{\theta}, \delta\right)$. By $B.1$, average talent is $\bar{\theta}$ both for the solo entrepreneur and the team member with their mirror match, but the vector of skills of the latter majorises the one of the former individual.

Now, because ζ is supermodular, symmetric, and differentiable, notice that $g = f'(\bar{\theta})$ is Schur convex, because:

$$g_{1,1} = g_{2,2} \quad \text{by symmetry, and} \quad g_{1,2} > 0 \quad \text{by supermodularity of } \zeta$$

When a function g is Schur convex, then majorisation of x over y implies $g(x) \geq g(y)$. It follows that: $x \succcurlyeq y \implies \zeta_1(x) + \zeta_2(x) \geq \zeta_1(y) + \zeta_2(y)$. QED

$\square$

We can now make some claims about relative performance. Let's first define $p_E = \mathbb{P}(E = 0)$, $p = \mathbb{P}(S = 1|E = 0)$, and $\pi = \mathbb{P}(F = 1|S = 1, E = 0)$, where $R = w * \max\left\{\bar{\theta} + \delta, \bar{\theta} - \delta\right\}$ - remember we assumed wages to be symmetric - and $F = 1(\zeta^I < R)$. The probability π is relevant to the case in which the individual would start a firm only as part of a team, but does not meet the right match, and then resorts to paid employment.

We can also define observed group means, as:

$A = \mathbb{E}\left(\zeta^T | S = 1, E = 0\right)]$, the observed average productivity of teams

$B = \mathbb{E}\left(\zeta^I | S = 1, E = 0, F = 0\right)]$, the observed average productivity of solo firms run by specialists

$C = \mathbb{E}\left(\zeta^I | S = 0, E = 0\right)]$, the observed average productivity of solo firms run by generalists

By supermodularity, it is generally true that $C > B$; we also know that $A > B$ because it follows from **Proposition A.1**. We are now ready to show under what conditions we might observe a positive relationship between team productivity and specialization. Call σ^2_Δ the dispersion in δ across the population.

Proposition A.3. *If ψ satisfies $A.2 - A.4$ and $A.7$, and ζ satisfies $A.3 - A.4$, if in addition $B.2$ holds, then a mean-preserving spread in individual skills is associated with an increase in the observed productivity of entrepreneurial teams.*

Proof. Remember that because $A = \mathbb{E}\left[\zeta^T | S = 1, E = 0\right]$, we need to assess the direct impact of an increase in δ, which goes through ζ^T, together with the impact on the set $\{S = 1, E = 0\}$. The direct impact is positive, by **Proposition A.1**.

To compute the selection impact, define the eligibility region, i.e.

$$\mathcal{R} \equiv \left\{\left(\bar{\theta}, \delta \geq 0\right) : \quad \delta > \delta^*(\bar{\theta}) \quad , \text{and} \quad \bar{\theta} \geq \bar{\theta}_E(\delta)\right\}$$

Since the threshold $\delta^*(\bar{\theta})$ is monotonic in its argument, we can invert it to obtain the threshold $\tilde{\theta} = \left(\delta^*(\bar{\theta})\right)^{-1}$. This yields the lower bound of the eligibility region for team membership, i.e.:

$$L(\delta) \equiv \max\left\{\bar{\theta}_E(\delta), \tilde{\theta}(\delta)\right\}$$

which is increasing in δ because of $\bar{\theta}_E(\delta)$. Independence in the distribution of $\bar{\theta}$ and δ implies we can write the joint distribution inside the eligibility set as:

$$g_t(\bar{\theta}, \delta) \equiv \frac{f_\Theta(\bar{\theta}) f_\Delta(\delta) 1_{\bar{\theta} \geq L(\delta)}}{\int \int_{\mathcal{R}} f_\Theta f_\Delta d\Theta d\delta}$$

An increase in σ^2_Δ (from f_{Δ_0} to f_{Δ_1}) adds probability mass to larger δ realizations, which is to say $f_{\Delta_1}(\delta) > f_{\Delta_0}(\delta) \quad \forall \delta > \hat{\delta}$ for any $\hat{\delta} > 0$. Take the marginal cumulative distribution function:

$$\mathbb{P}_k\left(|\Delta| \leq b | S = 1, E = 0\right) = \frac{\int_0^b f_k(\delta) F_\Theta(L(\delta)) d\delta}{\int_0^\infty f_k(\delta) F_\Theta(L(\delta)) d\delta} \quad \text{for } k = 0, 1$$

Then intuitively we see $\mathbb{P}_1\left(|\delta| \leq b | S = 1, E = 0\right) \leq \mathbb{P}_0\left(|\delta| \leq b | S = 1, E = 0\right)$ because numerator decreases in δ as we add mass to the right tail. This implies the distribution of δ after the increase in σ^2_Δ first-order stochastically dominates the pre-increase distribution. In addition, the marginal density of $\bar{\theta}$ is unchanged by the increase in σ^2_Δ:

$$g(\bar{\theta}) = \frac{f_\Theta(\bar{\theta}) 1_{\bar{\theta} \geq L(\delta)}}{1 - F_\Theta(L(\delta))}$$

but now there is a higher lower bound $L(\delta)$, as shown above. In sum, the increase in σ^2_Δ generates coordinate-wise first-order dominance in the joint conditional distribution of $\bar{\theta}$ and δ. By the monotone mapping theorem,

$$A(\sigma^2_{\Delta,1}) > A(\sigma^2_{\Delta,0}) \iff \sigma^2_{\Delta,1} > \sigma^2_{\Delta,0}$$

Selection and direct effect then go in the same direction. QED □

We now want to discuss to the impact of a mean preserving spread on the observed average productivity of solo firms run by generalists. In order to do this, we first need to prove an intermediate result. Define the following property:

Definition 1.1 (Weak Scale Property): For $\bar{\theta} = \bar{\theta}^E$, the function $\zeta^I(\cdot)$ satisfies the weak scale property if:

$$\partial_{\bar{\theta}} \zeta^I(\cdot)\big|_{\bar{\theta} = \bar{\theta}^E} \leq \left|\partial_{|\delta|} \zeta^I(\cdot)\right| \left.\frac{\partial \bar{\theta}^E}{\partial |\delta|}\right|_{\bar{\theta} = \bar{\theta}^E}$$

The next result relates the weak scale property to a more transparent restriction on ζ:

Lemma A.3. *The weak scale property holds if $\zeta(\cdot)$ satisfies assumption A.8.*

Proof.
Denote $\zeta^I(\bar{\theta}, |\delta|) = \zeta^I(\bar{\theta}, \delta)$, with $u = \bar{\theta} + |\delta|, \quad v = \bar{\theta} - |\delta|$. At the frontier:

$$\zeta^I(\bar{\theta}^E, |\delta|) = w \, \left(\bar{\theta}^E + |\delta|\right) = w \cdot u$$

Remember that, at the frontier (Dini's Theorem, as always):

$$\frac{d\bar{\theta}^E}{d|\delta|} = \frac{w - (\zeta_u - \zeta_v)}{(\zeta_u + \zeta_v) - w}$$

Define $a = \zeta_u + \zeta_v$ and $b = |\zeta_u - \zeta_v|$. We know $\zeta_u - \zeta_v$, since for symmetric, concave $\zeta(\cdot)$: $u > v \Longrightarrow \zeta_u < \zeta_v$. Also, $a - w > 0$, since:

$$\zeta(u, v) \underbrace{=}_{\text{homogeneity of degree 1}} u\zeta_u(u, v) + v\zeta_v(u, v) \underbrace{=}_{\text{at } \bar{\theta} = \bar{\theta}^E} w\, u \Longrightarrow \zeta_u + \frac{v}{u}\zeta_v = w$$

Rearranging terms:

$$\zeta_u + \zeta_v = w + \underbrace{\left(1 - \frac{v}{u}\right)\zeta_v}_{>0} \Longrightarrow \zeta_u + \zeta_v > w$$

The weak scale property then can be written as:

$$(\zeta_u + \zeta_v) \leq |(\zeta_u - \zeta_v)| \cdot \frac{w - (\zeta_u - \zeta_v)}{(\zeta_u + \zeta_v) - w} \quad \Longrightarrow \quad a \leq |b| \cdot \frac{w - b}{a - w}$$

Divide both sides by $|b|^2$ and multiply by $a - w$ (both are positive):

$$\frac{a}{|b|^2} \cdot (a - w) \leq \frac{w}{|b|} - \frac{-|b|}{|b|} = \frac{w}{|b|} + 1$$

The last term comes from $b < 0 \Longrightarrow |b| = -b$, hence $\frac{b}{|b|} = -1$. Define $R = \frac{a}{|b|}$, and rewrite the inequality as:

$$R^2 - \frac{R}{b} w \leq \frac{w}{b} + 1$$

Add $\frac{w^2}{4b^2}$ to both sides and write:

$$R^2 - \frac{R}{b} w + \frac{w^2}{4b^2} \leq \frac{w}{b} + 1 + \frac{w^2}{4b^2} \tag{A.5}$$

These are both quadratic forms, so we can take the square root:

$$R - \frac{w}{2|b|} \leq \frac{w}{2|b|} + 1 \Longrightarrow R \leq \frac{w}{|b|} + 1, \text{ or: } \quad \frac{\zeta_u + \zeta_v}{|\zeta_u - \zeta_v|} \leq \frac{w}{|\zeta_u - \zeta_v|} + 1$$

This can also be written as:

$$\zeta_u + \zeta_v - w \leq |\zeta_u - \zeta_v| \Longrightarrow \zeta_v \left(1 - \frac{v}{u}\right) \leq |\zeta_u - \zeta_v|$$

where the last holds because, at the frontier, $w = \zeta(\cdot)\, u = \frac{u\zeta_u + v\zeta_v}{u} = \zeta_u + \frac{u}{v}\zeta_v$. Finally, after some algebra, we can write the condition in **Equation A.5** as:

$$\frac{\zeta_u}{\zeta_v} \leq \frac{v}{u} \qquad \text{QED}$$

□

Under constant-returns normalisation, assumption $A.8$ requires ζ to be Cobb–Douglas as long as it is symmetric. In the quantitative section, we will relax symmetry, and allow for ζ to take a more general CES form.

Proposition A.4. *Assume $\zeta(\cdot,\cdot)$ to satisfy $A.2 - A.6$ and $A.8$, and that $B.2$ holds. Let the marginal distribution of δ undergo a mean-preserving spread that increases its variance from $\sigma^2_{\Delta,0}$ to $\sigma^2_{\Delta,1}$ while the distribution of $\bar{\theta}$ remains fixed. Then $C(\sigma^2_{\Delta,1}) \leq C(\sigma^2_{\Delta,0})$.*

Proof. Under $A.2 - A.6$ we have:

(i) ζ^I is *strictly decreasing* in $|\delta|$;

(ii) along the wage frontier the weak scale property holds;

(iii) $L(\delta) := \max\{\bar{\theta}_E(\delta), \underline{\bar{\theta}}(\delta)\}$ is strictly increasing in δ.

A mean-preserving spread (MPS) shifts conditional mass inside the balanced region toward *larger* $|\delta|$ and, because $L(\delta)$ rises, toward *larger* $\bar{\theta}$. By (ii) the directional derivative of ζ^I along that shift is non-positive; by (i) it is negative for any positive-measure move. Hence the post-MPS joint distribution $(\bar{\theta}, |\delta|) \mid (S = 0, E = 0)$ first-order stochastically dominates the pre-MPS one only in directions where ζ^I is weakly lower, implying the stated inequality for $C(\sigma^2_{\Delta})$. □

The intuition for this result is simple: higher $|\delta|$ pushes balanced solos toward states with *larger* individual imbalance, generating a higher threshold on average ability. The weak scale property guarantees that the imbalance penalty outweighs the ability gain, so the average balanced-solo profit falls. An easy consequence of **Proposition A.4** is the following:

Corollary A.1. *Horizontal differentiation lowers* specialist-*solo mean profit*

Proof. The specialist set is the complement of the balanced set: $\mathcal{S} = \{(\bar{\theta}, \delta) : \delta > \delta(\bar{\theta})\}$. A mean-preserving spread (MPS) in Δ shifts conditional mass inside $\mathcal{S}$ *further to the right* (larger $|\delta|$). To satisfy $\bar{\theta} > \bar{\theta}^E$, such draws must also move *upwards*, which is a *steeper* filter than in the balanced region because $\bar{\theta}'_E(\delta) > 0$ and $\delta > \delta(\bar{\theta})$ already.

Along this north-east diagonal strip the directional derivative of $\zeta^I(\cdot)$ is *strictly negative* by the same weak-scale inequality used in **Proposition A.4**. Hence every point to which probability mass is transferred yields a solo payoff no larger (and generically strictly smaller) than the point from which the mass is taken. First-order stochastic dominance toward lower $\zeta^I(\cdot)$ therefore lowers the conditional mean B. $\square$

Before proving our next result, let's introduce an important quantity: the share of individuals who start solo firms. This is:

$$
\begin{aligned}
D = \quad & p_E \left(1 - \underbrace{p \cdot q}_{\text{teams}} - \underbrace{p \cdot (1-q) \cdot \pi}_{\text{specialists who prefer paid work}} \right) = \\
= \quad & \underbrace{p_E \cdot (1-p)}_{\text{non-specialists who prefer solo firms to employment}} + \underbrace{p_E \cdot p \cdot (1-q) \cdot (1-\pi)}_{\text{specialists who prefer solo firms to employment}}
\end{aligned}
$$

Define μ_T as the average observed productivity of teams, and μ_I as the average observed productivity of solo firms. We can now state the following proposition, which is almost a corollary:

Proposition A.5. *For any ψ that satisfies $A.1 - A.4$ and $A.7$, and ζ that satisfies $A.1 - A.5$ and $A.8$, and if $B.1 - B.2$ hold, we have that:*

$$\mu_T > \mu_I \iff q < q^*, \quad \textit{where:}$$

$$q^* = 1 - \frac{(1-p)\,(C-A)}{p\,(1-\pi)\,(A-B)}$$

with: $\partial q^* / \partial \sigma^2_\Delta \geq 0$

Proof. We want to see under what conditions $\mu^T - \mu^I > 0$. Notice that $\mu^T = A$ in this context. For solo teams, instead:

$$\mu^I = \frac{p_E\,(1-p)\,C + p_E\,p\,(1-q)\,(1-\pi)B}{D}$$

After a little bit of algebra, we obtain q^*.

To prove $\partial q^*/\partial\sigma_\Delta^2 \leq 0$, notice that $\partial p/\partial\sigma_\Delta^2 > 0$ (as skills become more dispersed, more individuals are specialists). To calculate the sign of the numerator, we need $\partial A/\partial\sigma_\Delta^2$ and $\partial C/\partial\sigma_\Delta^2$. We know $\partial A/\partial\sigma_\Delta^2 > 0$ from **Proposition A.3**, $\partial A/\partial\sigma_\Delta^2 < 0$ from **Proposition A.4**. Hence, the numerator falls. For the denominator, things are less straightforward, since the probability π can increase when σ_Δ^2 grows.

Still assuming distributions of $(\bar{\Theta}, \delta)$ to be *independent*, for any mean-preserving spread in δ that raises σ_Δ^2, we need to show that:

$$\frac{d}{d\sigma_\Delta^2}\Big[\, p\,(1-\pi)\,(A-B)\Big] \;\geq 0,$$

For CES with $\rho \leq 0$one solves $\delta(\bar{\theta}) = \lambda\,\bar{\theta}$ and $\theta_F(\delta) = \alpha\,\delta$ with constants $0 < \lambda < \alpha < 1$ that depend only on (w, ρ).[30] Hence the specialist region in $(\bar{\theta}, \delta)$-space is a wedge bounded by two straight rays $\delta = \lambda\bar{\theta}$ and $\delta = \alpha\bar{\theta}$.

Independence of $\bar{\theta}$ and δ implies

$$p = \mathbb{P}[\delta > \lambda\bar{\theta}] = \mathbb{E}\big[\,\overline{F}_\delta(\lambda\bar{\theta})\big], \qquad \pi = \mathbb{P}[\delta > \alpha\bar{\theta} \mid \delta > \lambda\bar{\theta}],$$

where $\overline{F}_\Delta$ is the survival function of δ. A mean-preserving spread shifts probability from δ_- to $\delta_+ > \delta_-$ and:

$$\frac{dp}{p} = \epsilon\,\frac{\overline{F}_\delta(\lambda\bar{\theta};\delta_+) - \overline{F}_\delta(\lambda\bar{\theta};\delta_-)}{p}, \qquad \frac{d\pi}{\pi} = \epsilon\,\frac{\overline{F}_\delta(\alpha\bar{\theta};\delta_+) - \overline{F}_\delta(\alpha\bar{\theta};\delta_-)}{\overline{F}_\delta(\alpha\bar{\theta};\,\cdot\,)}.$$

Because $\alpha > \lambda$, every tail probability at $\alpha\bar{\theta}$ is *strictly smaller* than at $\lambda\bar{\theta}$, hence

$$\frac{d\pi}{\pi} \;\leq\; \frac{dp}{p}, \tag{M}$$

with strict $<$ when positive mass moves. Assumption $A.8$ implies the *excess-gap inequality* $|\zeta_u - \zeta_v| \geq (\zeta_u + \zeta_v) - w$, so the weak-scale bound holds. **Proposition A.4** and **Corollary A.1** give $dA > 0, \quad dB < 0 \quad \Longrightarrow \quad d(A-B) > 0$. Let $X := p(1-\pi),\ Y := A - B$. Then

$$d(XY) = X\,dY + Y\,dX, \quad dX = (1-\pi)\,dp - p\,d\pi.$$

Divide by XY and substitute:

$$\frac{d(XY)}{XY} = \frac{dY}{Y} + \frac{(1-\pi)\,dp - p\,d\pi}{p(1-\pi)} \;\geq\; \frac{dY}{Y} \;+\; 0,$$

so $d(XY) \geq 0$ with strict inequality unless the spread moves no mass in the specialist

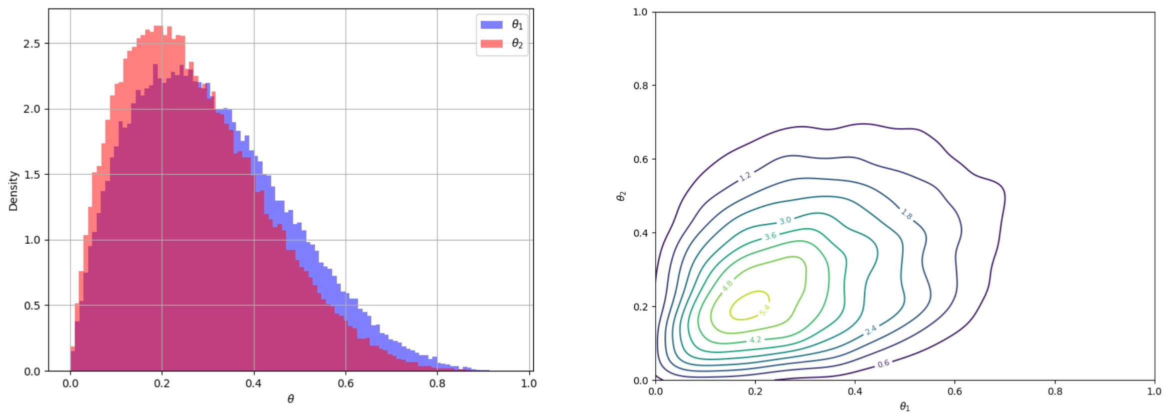
[30] Remember $A.8$ requires $\rho = 0$

band. Hence $p(1-\pi)(A-B)$ is non-decreasing (strictly increasing generically). To sum up, we now know that the denominator increases when σ^2_Δ grows. Hence the ratio declines, and the threshold q^* grows. $\square$

When q is high, specialists disappear from the solo pool, so solo firms are run mostly by balanced founders whose payoff C can exceed A. To see a within-group advantage for teams some search friction (low q) that drags the conditional solo mean down is needed.

A.2 Tables and Figures

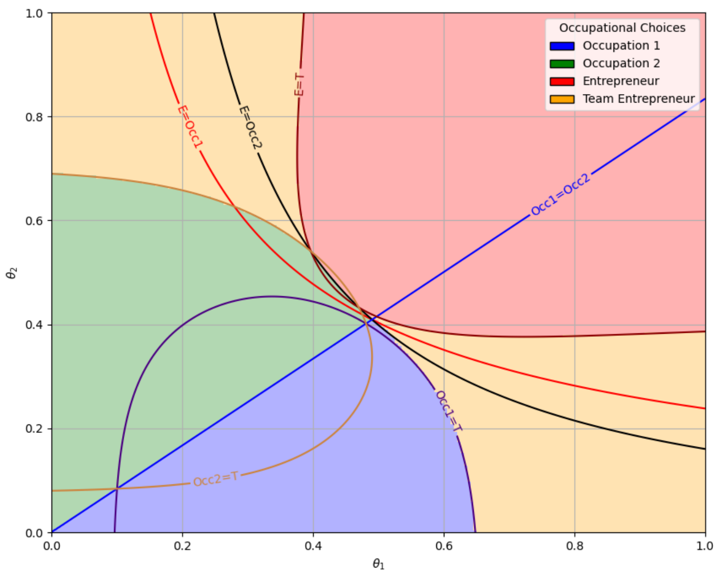
Figure A.1: Skills Distribution in 2-Dimensional Model



(a) Marginal Distributions

(b) Joint Distribution

Figure A.2: Bilateral Meeting with $\theta_1, \theta_2 = [0.45, 0.45]$ and Occupation Choices



B Data Appendix

B.1 Quadros de Pessoal

The main data source is the *Quadros de Pessoal* (hereafter QP) for the 1985-2019 period. The data are gathered annually by the Portuguese Ministry of Employment through an questionnaire that every establishment is obliged by law to fill in. The dataset does not cover the public administration and non-market services, whereas it covers partially or fully state-owned firms, provided that they offer a market service. The dataset covers virtually the entire population of firms with at least one employee. The dataset contains a snapshot of firms' employment in October each year, and when relevant firms also report the identity of the individuals self-identifying as employers. It contains information on industry, hiring date, the kind of job contract (fixed-term or open-ended), the effective number of hours worked, and different types of compensation. This implies that jobs (hence earnings, days worked and daily wages) are not recorded for a worker who is not employed in October. The dataset is hierarchically composed by a firm-level dataset, an establishment-level dataset and a worker-level dataset.

The firm level dataset made available to us contains information on the firm location at NUTS 2 level,industry of operation (CAE rev. 1 until 1994, rev. 2 until 2002, rev. 2.1 until 2006 and rev. 3, based on NACE-Rev. 2 Statistical classification of economic activities in the European Community), total employment, total sales, ownership structure and legal incorporation. Analogous information is available on the establishment-level dataset. The worker level dataset provides detailed information on worker characteristics and contracts. Information included comprehends workers' gender, age, nationality, detailed occupational code (the *Classificação Nacional de Profissões* (CNP94) up to 2009 and the *Classificação Portuguesa das Profissões* (CPP2010) from 2010 onward, which is based on ISCO08 International Occupational Classification Codes), detailed educational level, qualification within the firm[31]. At the contract level it is possible to know the precise hiring date, the kind of contract (various typologies that generally define the contract as fixed-term or open-ended, from 2000), the hours arrangement (full-time versus part-time), the effective number of hours worked, and information on the compensation. More specifically, for each worker it is possible to obtain information on the base pay, any extra paid in overtimes or other extra-ordinary payments and other irregularly paid components. There is no information on social security contributions. As

[31]As regards the qualification categories, the Portuguese Decree-Law 380/80 established that firms should indicate the qualification level as in the Collective Agreement. If this is not available, firms should select the qualification level of the worker. These categories are based on the degree of complexity of tasks that the worker performs within the firm (from more basic, routine tasks to more discretionary managerial ones). The categories are defined within a 9 levels hierarchy, that we simplify into three broad categories.

regards employers, the dataset reports detail on their hierarchy and occupation within the firm, but information on compensation is almost entirely missing.

We perform several minimal checks on the data to eliminate inconsistencies in individuals identification and demographic characteristics over time. We follow Caliendo et al. (2020) and Mion, Opromolla and Sforza (2022) in harmonizing the sectoral codes across years, and use firms own changes in occupational definitions for continuing contracts to create a frequency-based transition table between occupational codes. For each worker, we select the main job as the highest paid job during the year. We report in **Table C.1** descriptive statistics for workers in the sample, covering all years from 1991 to 2019.

B.2 Sistema de Contas Integradas das Empresas

The *Sistema de Contas Integradas das Empresas* (henceforth SCIE) is a firms level balance-sheet and income statements database, created by the Instituto Nacional de Estatisticas (hereby INE), combining several administrative and survey sources from various other Portuguese institutions. Our dataset consists of a repository of yearly economic and financial information on the universe of non-financial corporations operating in Portugal from 2004 to 2019. It includes information on sales, balance-sheet items, profit and loss statements, and cash flow statements (after 2009) for private firms in Portugal (with the sxclusion of the public sector, finance and insurance businesses).[32]

The dataset contains a great amount of information on enterprises' balance sheets and income statements, but has limited information on sole proprietorships. We use the dataset to obtain information on total assets, fixed assets, interest expenditures, cash-flow and capital expenditures (after 2009), cash balances, exports and export status, value added and profits.

The coverage of SCIE in the QP is not complete, but is extremely high. Firms present in both datasets account for 98% of the total number, 96% of employment and 96% of sales, for the years in which the data exists.

B.3 Variables definition for the entrepreneurs dataset

We identify as owners all individuals who are identifies as "employers" in the QP worker level records. Of these, we identify as founders all owners present in the firm within three years of its foundation date.

Entrepreneurs can be further characterized as *serial* when they own multiple enterprises

[32]After 2009, in order for the data to comply with international accounting standards, there has been a major overhaul of the variables definitions in the dataset, from the *Plano Oficial de Contabilidade* (POC) to the *Sistema de Normalização Contabilística* (SNC). In all our computations, unless otherwise noted, we have personally gone through a variables' harmonization process.

at the same time, and/or *sequential*, if they ever own more enterprises but not necessarily at the same time.

For all entrepreneurs with a work history, we obtain characteristics regarding their past work career *before* their first spell as entrepreneurs.[33] We calculate quantiles of several characteristics for their work careers upon becoming entrepreneurs: size of the firm, sales, last five years of earnings, cumulative career earnings, tenure, age of the firm for the last employer. We also calculate, when possible conditional of belonging to the relevant connected set, worker and firm fixed effects as in Abowd, Kramarz and Margolis (1999).

Eventually, we are able to identify owners for 65% of firms, covering 66% of sales and 76% of employment in the QP.

B.4 AKM specifications

In order to extract worker and firms fixed effects (hereafter: AKM) as in Abowd, Kramarz and Margolis (1999), we run the following regression:

$$\log(w_{i,t}) = X_{i,t}'\beta + \alpha_i + \psi_{j(i)} + \epsilon_{i,t}$$

where $X_{i,t}$ include age^2 and year FE, α_i measures latent worker quality, and $\psi_{j(i)}$ measures latent workplace quality. The estimation of the fixed effects relies on the concept of connected set, that is the set of all firms connected by worker mobility. In order to properly disentangle the individual and workplace effects one needs to have workers moving across different firms. This in turn implies that if firms do not experience worker flows with firms in the connected set, no estimation is feasible for them. Given the presence of some very small (and isolated) firms in our dataset, the connected set does not cover the entirety of the labor market.

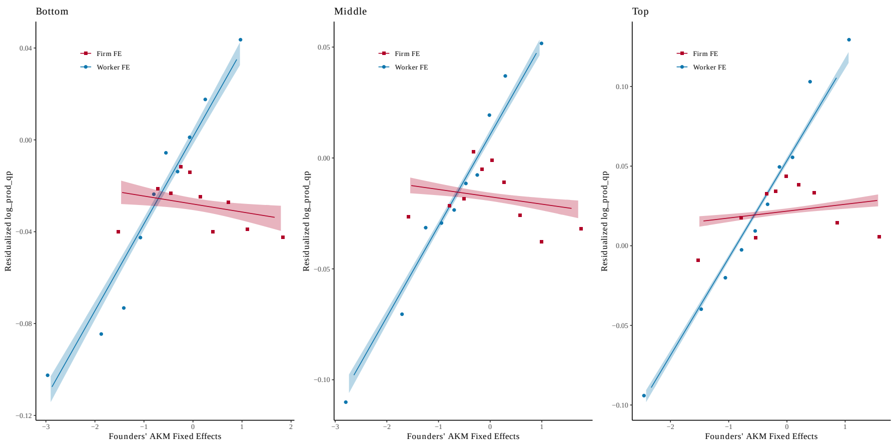
One way to overcome this limitation is to give up the estimation of workplace effects, and aim at estimating effects corresponding to more broadly defined categories that can expand the connected set. That is the approach in Bonhomme, Lamadon and Manresa (2019*b*), who employ a K-means clustering algorithm (MacQueen et al., 1967, Lloyd, 1982) to the empirical cumulative distribution function of wages at the firm level to characterize broadly defined "firm-types". We use for robustness analysis the same technique to identify 10 clusters of firm types, by pooling all years in the datasets for the clustering procedure.[34]

[33] We can identify work histories for 44% of owners in the data.

[34] The procedure is typically proposed to attenuate the so-called "limited mobility bias" problem (Andrews et al., 2008), which is however relevant for variance-decompositions and calculation of sorting with the estimates. We mainly use it to expand our connected set of estimation.

As we want individual and workplace effects for entrepreneurs to be proxies of their talent and career characteristics *before* their entrepreneurial career starts, we estimate them only for the years before the first entrepreneurial spell. This amounts to estimating our AKM model or backward-looking rolling windows of years. Specifically, for every year in the data we run the AKM specification on the connected set estimated on the current year of analysis and the five years prior. Then, for entrepreneurs, we assign to them the most recently estimated individual fixed effect as a proxy of skill or talent on the workplace, and the most recent firm effect as a proxy of the unobserved quality of the last workplace before the decision of undertaking an entrepreneurial activity.

Figure B.1: Entrepreneurs' AKM Fixed Effects and Firm TFP



Note: The figure plots the correlations between log firm-level productivity – residualised by sector and year – and the estimated worker and firm fixed effects for founders by terciles of firm size. Productivity is estimated following Gandhi, Navarro and Rivers (2020) in each one-digit sector.

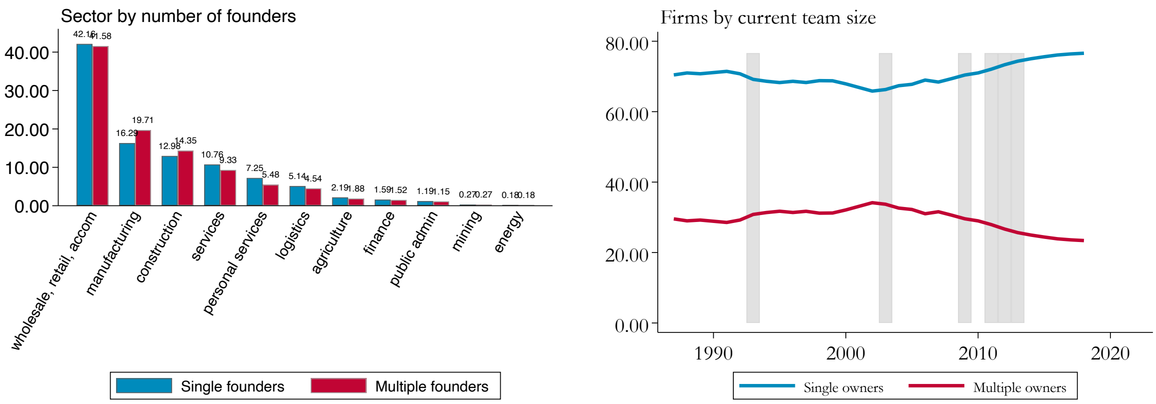
C Appendix Tables and Figures

Table C.1: Descriptive Statistics from *Quadros de Pessoal*, workers

	Mean	SD	Median	P25	P75	N
Age	37.2	11.2	36	28	45	55,436,196
Sh. Female	.413	.492	0	0	1	55,436,196
Sh. High educated	.105	.307	0	0	0	54,197,088
Sh. Managers	.0562	.23	0	0	0	49,044,808
Sh. Temp. contracts	.283	.451	0	0	1	36,586,988
Sh. Part-time	.129	.335	0	0	0	55,427,944
Tenure	7.83	8.66	5	1	12	55,436,196
Yearly wage	11,985	10,046	9,100	6,356	14,440	55,436,196
Firm size	1,164	3,533	59	12	417	55,436,196
Num. jobs	1.02	.404	1	1	1	55,436,104

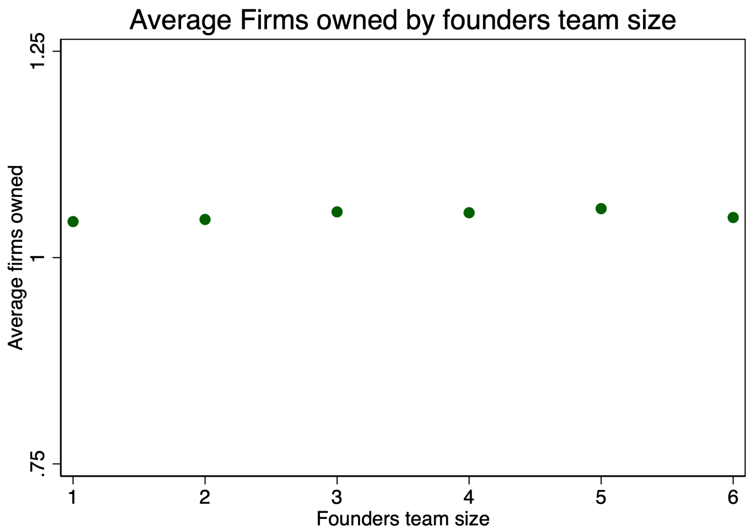
Note: The table reports descriptive statistics for workers in the sample, covering all years from 1991 to 2019. Wages are deflated by the 2010 CPI. The detail on temporary vs. permanent contract is only available from 2000 onwards.

Figure C.1: Industry and Time Trends of Firms by Team Ownership



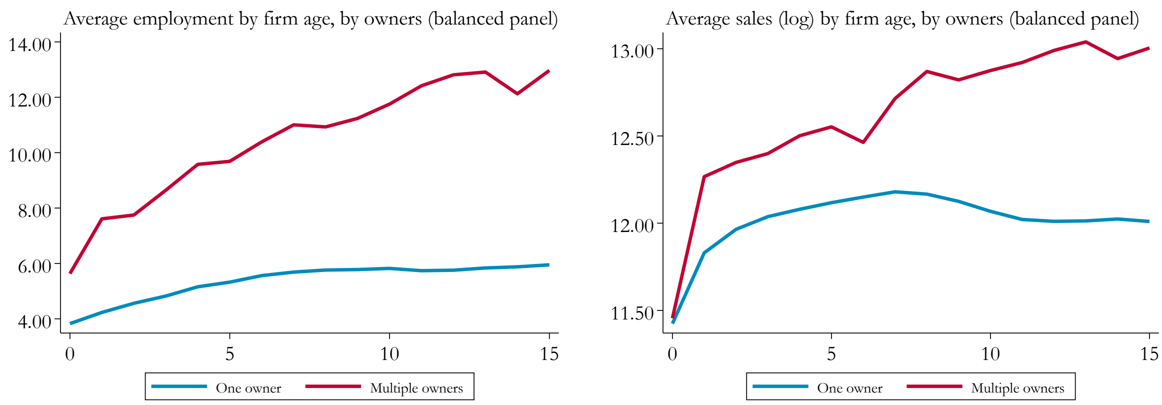
Note: The figure presents the percent of firms in each sector of the economy, using 1-digit NACIS codes to define sectors. The blue bars cover exclusively the subset of firms founded by one entrepreneur, while the red bars cover the subset of firms founded by more than one entrepreneur. The data are from the Portuguese *Quadros de Pessoal*, and range from 1991 to 2019.

Figure C.2



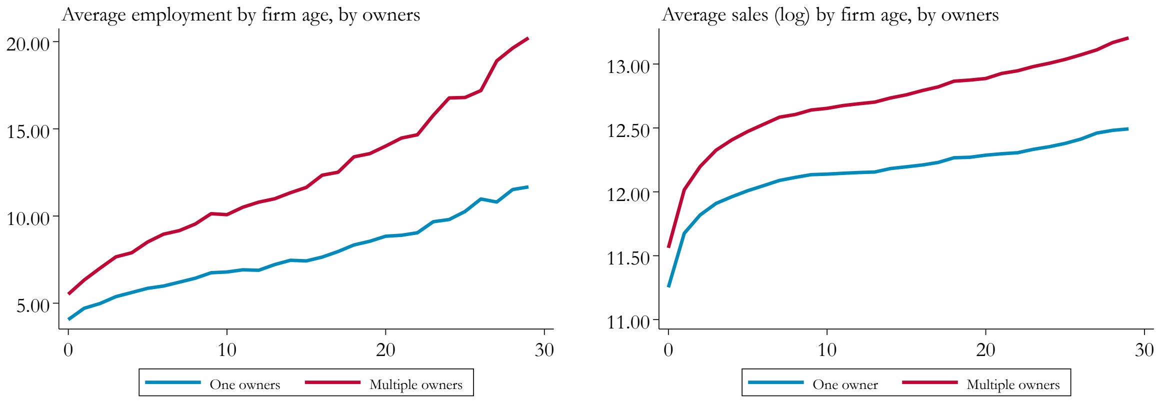
Note: The figure presents the average number of firms owned per founder, given the founders' team size. The data are from the Portuguese *Quadros de Pessoal*, and range from 1991 to 2019.

Figure C.3: Average Life-Cycle Employment and Sales for a Balanced Panel of Firms



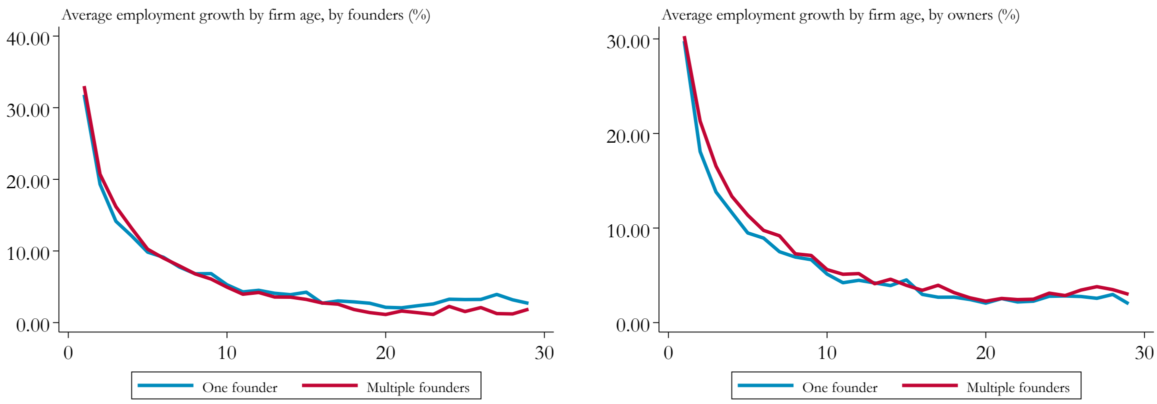
Note: The figure shows the average number of workers per firm (left) and average logged sales (right) of firms by firm age, measured in years. In both cases, the blue line represents firms owned by only one entrepreneur, while the red line represents firms owned by more than one entrepreneur. The data are from the Portuguese *Quadros de Pessoal*, and range from 1991 to 2019.

Figure C.4: Average Life-Cycle Employment and Sales by Number of Entrepreneurs



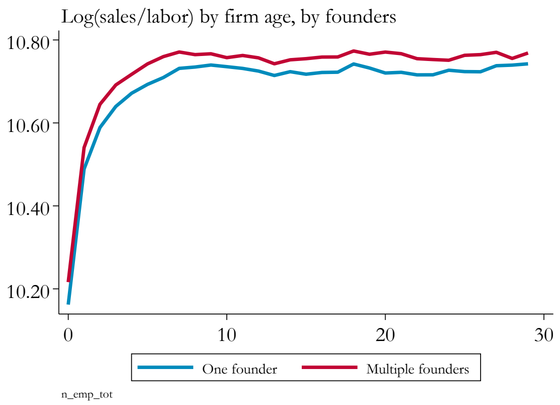
Note: The figure shows the average number of workers per firm (left) and average logged sales (right) of firms by firm age, measured in years. In both cases, the blue line represents firms owned by only one entrepreneur, while the red line represents firms owned by more than one entrepreneur. The data are from the Portuguese *Quadros de Pessoal*, and range from 1991 to 2019.

Figure C.5: Life-Cycle Employment and Sales Growth by Number of Entrepreneurs



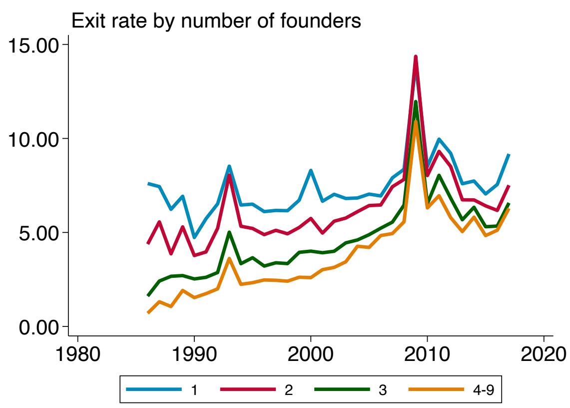
Note: The figure shows the growth rate, in percent terms, of the number of workers per firm, by firm age measured in years. The left-hand-side figure divides total firms by number of entrepreneurs that founded them, while the right-hand-side figure divides total firms by number of entrepreneurs that own them. In both figures, the blue line represents firms with only one founder/ owner, and the red line firms with more than one founder/ owner. The data are from the Portuguese *Quadros de Pessoal*, and range from 1991 to 2019.

Figure C.6: Average Life-Cycle Labor Productivity by Number of Entrepreneurs



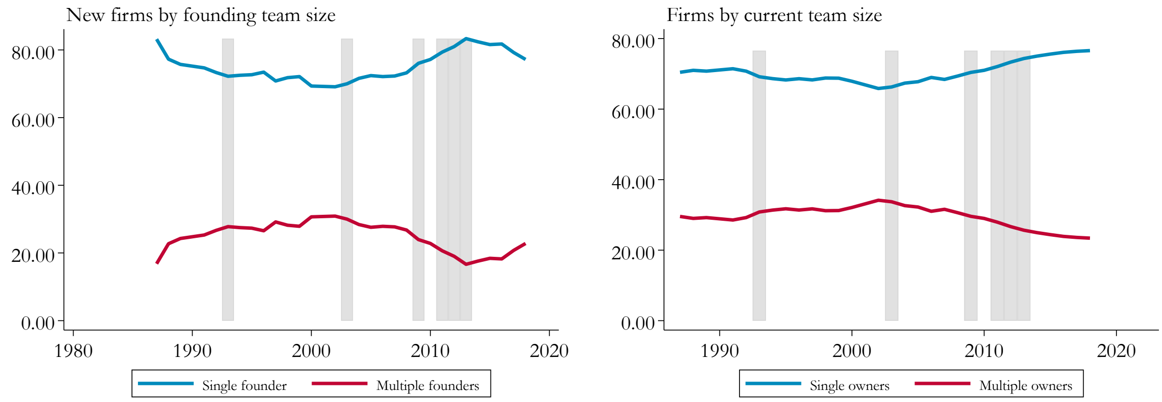
Note: The figure presents the average logged total sales over number of workers of firms, by firm age. In the left-hand-side figure, the number of workers includes the entrepreneur, while it is excluded in the right-hand side figure. In both cases, the blue lines presents the statistic for the subset of firms that have been founded by only one entrepreneur, while the red line is for firms that have been founded by more than one entrepreneur. The data are from the Portuguese *Quadros de Pessoal*, and cover all years from 1991 to 2019.

Figure C.7: Exit Rates by Number of Entrepreneurs



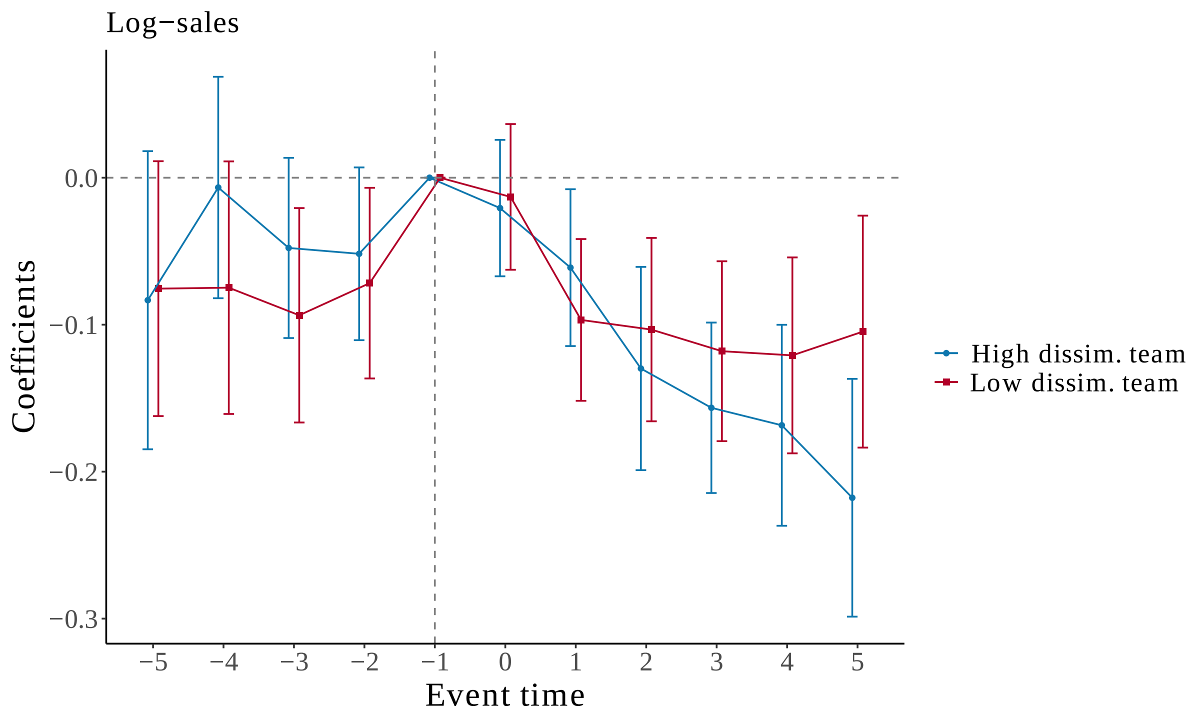
Note: The figure shows the exit rate, defined as the number of firms that exit the economy over total firms in the economy, multiplied by 100. Both charts present this statistic for all firms, by the the number of entrepreneurs that founded a firm. The left-hand-side chart presents yearly exit rates, while the right-hand-side presents exit rates by firm age, measured in years. The data are from the Portuguese *Quadros de Pessoal*, and cover all years from 1991 to 2019.

Figure C.8: Flow and Stock of Firms by Entrepreneurial Team Size



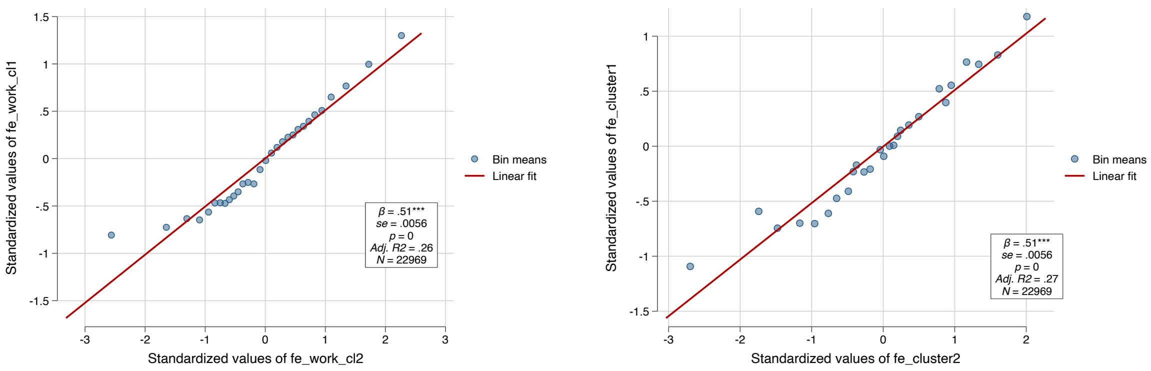
Note: The figure presents the percent of firms in the economy that have been founded by one (blue) vs multiple (red) entrepreneurs. The left-hand-side chart show this information for only new firms, defined as firms founded that year. The right-hand-side chart shows this for the entire population of firms. The data are from the Portuguese only Quadros de Pessoal, covering all years from 1986 to 2018. The gray shaded areas in the background indicate the years in which Portugal was in recession, using *OECD based Recession Indicators for Portugal from the Peak through the Trough [PRTRECDM]*, retrieved from FRED, Federal Reserve Bank of St. Louis.

Figure C.9: Event study: founders early separations



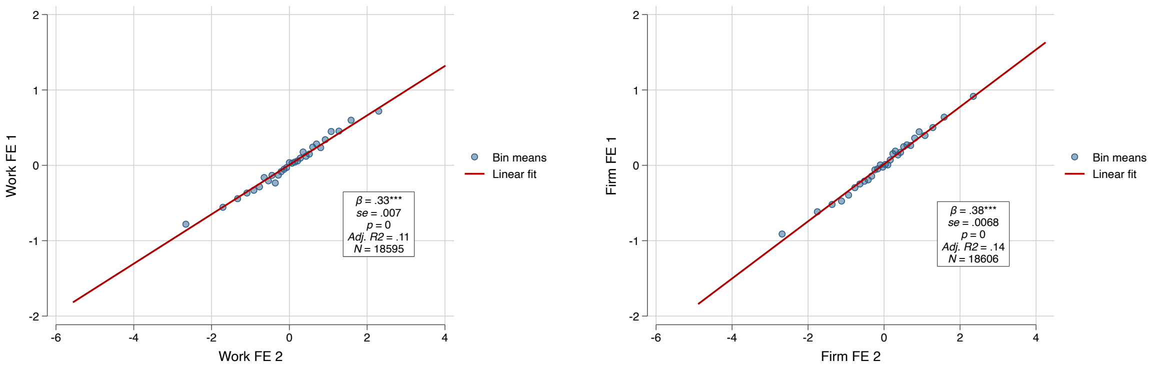
Note: The regression reports the coefficient from the event study in **Equation** 7. Controls for separated founders are obtained by nearest neighbor propensity score matching of on founder age, gender, education, firm size (sales and employment), sector, number of owners, avg. founders' types, cumulative earnings and Skills' PC dissimilarity. Time period: 1995 to 2018, event window:(-5,+5). Firms are split in high and low founders' dissimilarity depending on being above or below the median in the year before the separation event. Errors clustered at the sector by year level.

Figure C.10: Correlation of Worker and Past Workplace Types for Entrepreneurial Teams, clustered workplaces



Note: The figures present binned scatterplots of standardized individuals' (left) and workplaces (right) AKM fixed effects for entrepreneurs in two-member teams. For this estimation a K-means clustering is used to identify 10 clusters of firms types, based on the empirical cumulative distribution functions of earnings within firms, pooled across all years, as in Bonhomme, Lamadon and Manresa (2019*a*). Fixed effects are estimated for every year on a 5 years backward looking rolling window. The fixed effects come from the last year before the first entrepreneurial spell.

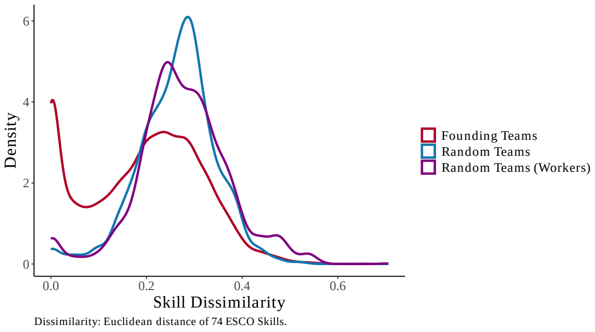
Figure C.11: Correlation of Worker and Past Workplace Types for Entrepreneurial Teams, residualized effects



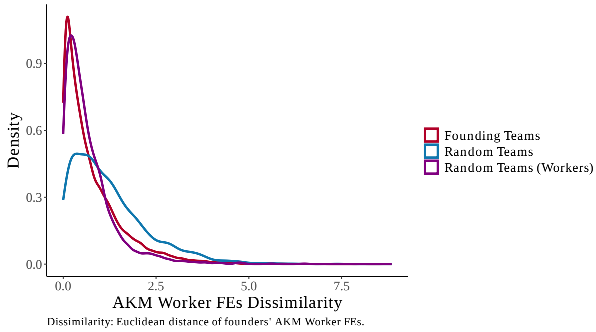
Note: The figures present binned scatterplots of standardized individuals' (left) and workplaces (right) AKM fixed effects for entrepreneurs in two-member teams. Fixed effects are estimated for every year on a 5 years backward looking rolling window. We plot residuals obtained by regressing fixed effects on age, year, gender, college education, dummies for same sector, profession, qualification, earnings quintiles, firm size, being a "sequential" entrepreneur and being colleagues, for both members of the teams. The fixed effects come from the last year before the first entrepreneurial spell.

Figure C.12: Similarities in two-entrepreneurs founding teams and random pairs of entrepreneurs

(a) ESCO Skills



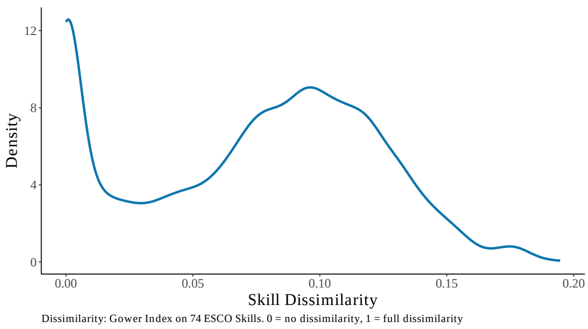
(b) AKM Worker Fixed Effects



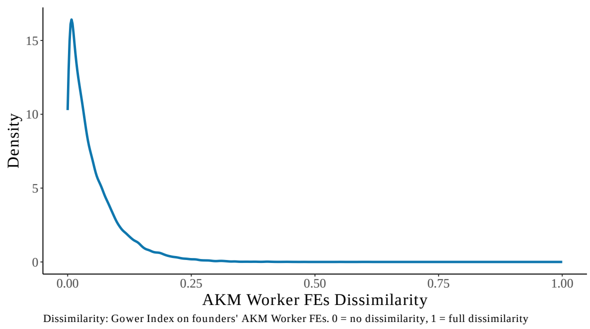
Note: The figure plots the densities of the Skill dissimilarities between founders and a sample of random pairs of entrepreneurs and workers.

Figure C.13: Horizontal (Skills) and vertical (Talent) dissimilarities, Gower Indexes

(a) ESCO Skills



(b) AKM Worker Fixed Effects



Note: The figure reports the distributions for the average pairwise Gower Indexes between seventy-four ESCO skills (a) and the estimated AKM worker fixed effects in (b) for each founding team in our sample.

Figure C.14: Full Distributions of Skills in Two-members Teams

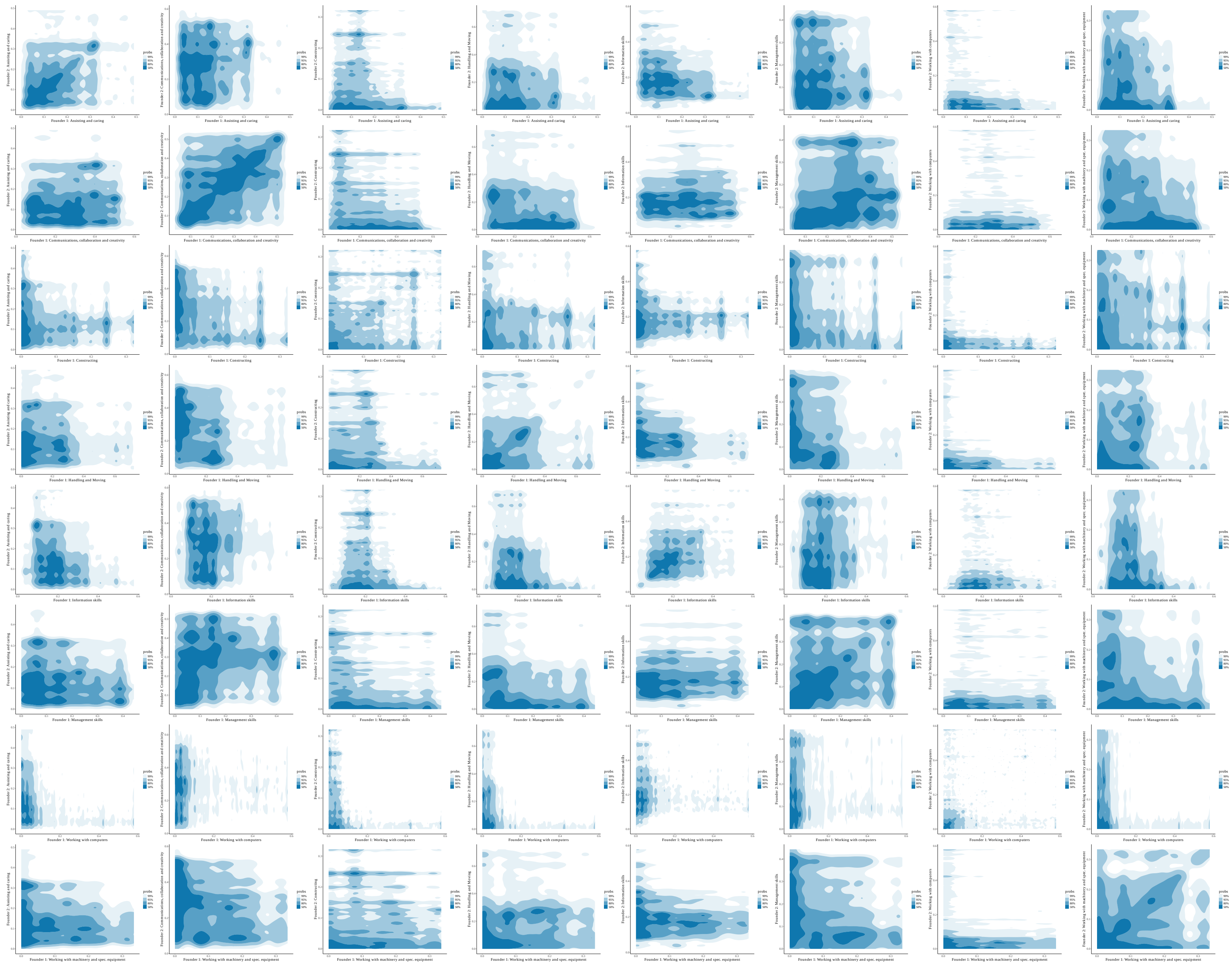
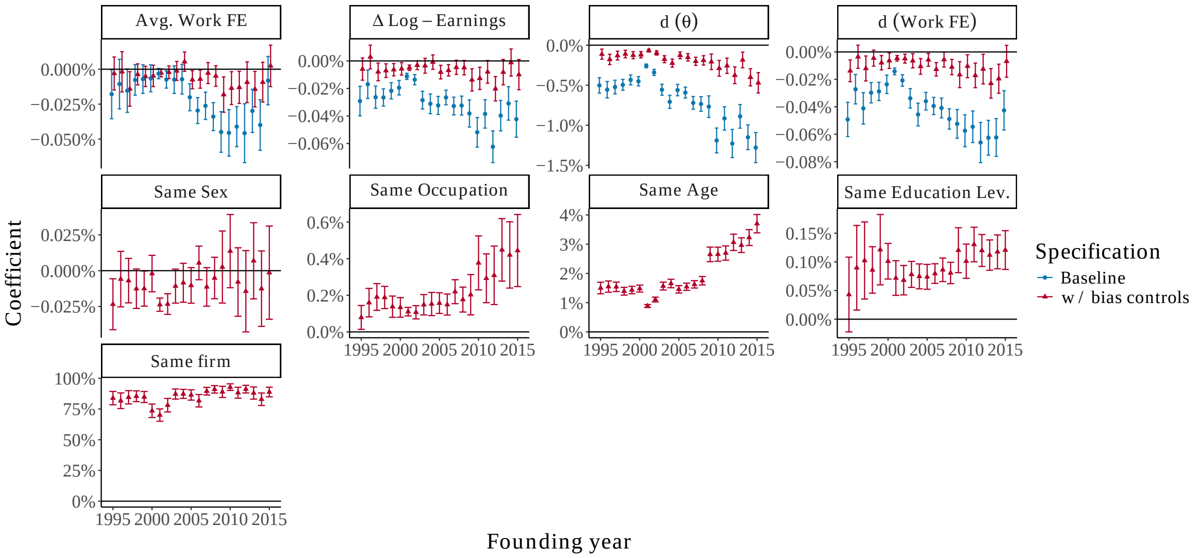


Figure C.15: Dyadic regressions with and without bias controls



Note: The figure reports the dyadic regression coefficients from **Equation 5**, with and without controls for entrepreneurs having the same age or sex, being colleagues, having worked in the same occupation or having the same educational level.

Table C.2: Dyadic Regression: Average coefficients (percentage points

Dependent Variable:	$\mathbb{I}\{\text{Team}_{i,j}\}$	
Model:	(1)	(2)
Variables		
Log-Earnings	-0.031^{***}	-0.007^{***}
	(0.001)	(0.001)
Average Work FE	-0.022***	-0.006***
	(0.002)	(0.001)
Skill Dissimilarity (HD)	-0.707***	-0.199***
	(0.012)	(0.008)
Worker FE Dissimilarity (VD)	-0.042***	-0.010***
	(0.001)	(0.001)
Same Age		1.975***
		(0.021)
Same Education		0.094***
		(0.004)
Same Firm		85.047***
		(0.509)
Same Occupation		0.219***
		(0.012)
Same Sex		-0.008^{***}
		(0.002)
Bias Controls	No	Yes

Clustered (dyad members, two-way) standard errors in parentheses.
Signif. Codes, *** : 0.01, ** : 0.05, * : 0.1.

Note: The table reports the average – in percentage points – for the main coefficient of interest from the linear probability model in **Equation** 5. The sample is based on entrepreneurial teams with only two members and conditional on surviving for at least 3 years, augmented with a random 1/4 of all possible non-team combinations between entrepreneurs.

Table C.3: Founding team characteristics and firm performance, different age cutoffs

Dependent Variable:	Log Sales					
	Firm Age ≤ 2		Firm Age ≤ 3		Firm Age ≤ 10	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Avg. Work FE	0.180***	0.140***	0.181***	0.135***	0.178***	0.137***
	(0.009)	(0.013)	(0.008)	(0.011)	(0.005)	(0.007)
Worker FE dissimilarity	-0.012	-0.014	-0.009	-0.014*	-0.013***	-0.028***
	(0.008)	(0.010)	(0.007)	(0.008)	(0.004)	(0.005)
Skill dissimilarity	0.191***	0.117	0.200***	0.128*	0.254***	0.207***
	(0.055)	(0.085)	(0.051)	(0.076)	(0.048)	(0.058)
Fixed-effects						
Incorporation type	Yes	Yes	Yes	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes	Yes	Yes	Yes
Log Total Earnings, quintiles	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
Log Fixed Assets, quintiles		Yes		Yes		Yes
Fit statistics						
Observations	42,896	13,447	57,885	18,191	130,325	37,763
R^2	0.289	0.327	0.284	0.323	0.273	0.321
Within R^2	0.016	0.013	0.017	0.012	0.016	0.013
No Firms	22,079	6,666	23,860	7,345	26,490	8,941

Clustered (Sector × Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table reports the relationship between founding team characteristics and firm performances based on **Equation 6** for samples with different firm age cut offs. *Avg. Work FE* is the average AKM worker FEs of founders, *Worker FE dissimilarity* is the average of pairwise Euclidean distance of founders' AKM worker FEs, and *Skill dissimilarity* is the average of founders' pairwise Euclidean distances across 74 ESCO skill categories.

Table C.4: Founding team characteristics and firm performance, control for initial employees skills

Dependent Variable:	Log Sales				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Avg. Work FE	0.200***	0.141***	0.139***	0.197***	0.099***
	(0.006)	(0.005)	(0.008)	(0.006)	(0.008)
Worker FE dissimilarity	-0.019***	-0.016***	-0.022***	-0.034***	-0.018***
	(0.006)	(0.004)	(0.007)	(0.007)	(0.006)
Skill dissimilarity	0.192***	0.223***	0.148**	0.259***	0.206***
	(0.051)	(0.044)	(0.068)	(0.079)	(0.066)
Fixed-effects					
Team Characteristics	Yes	Yes	Yes	Yes	Yes
Sector trends	Yes	Yes	Yes	Yes	Yes
Initial Size, Employment quintiles		Yes			Yes
Total Previous Earnings, quintiles			Yes		Yes
Initial Assets, quintiles			Yes		Yes
Additional Controls					
Initial Team Dissimilarities (w/ workers)				Yes	Yes
Fit statistics					
Observations	83,916	83,916	26,141	83,898	26,141
R^2	0.273	0.526	0.319	0.274	0.534
Within R^2	0.021	0.016	0.013	0.021	0.010
No Firms	25,401	25,401	8,072	25,394	8,072

Clustered (Sector × Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table reports the relationship between founding team characteristics and firm performances based on **Equation 6**. *Avg. Work FE* is the average AKM worker FEs of founders, *Worker FE dissimilarity* is the average of pairwise Euclidean distance of founders' AKM worker FEs, and *Skill dissimilarity* is the average of founders' pairwise Euclidean distances across 74 ESCO skill categories. In columns (4) and (5) adds as control the average of pairwise Euclidean distances across 74 ESCO skill categories for employees present in the firm during the initial three years from foundation.

Table C.5: Founding team characteristics and firm performance, additional financial controls

Dependent Variable:	Log Sales		
Model:	(1)	(2)	(3)
Variables			
Avg. Work FE	0.099***	0.060***	0.061***
	(0.008)	(0.006)	(0.005)
Worker FE dissimilarity	-0.015***	-0.009	-0.009**
	(0.005)	(0.005)	(0.004)
Skill dissimilarity	0.088***	0.077***	0.050**
	(0.034)	(0.028)	(0.022)
Fixed-effects			
Incorporation type	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes
Log Total Earnings, quintiles	Yes	Yes	Yes
Initial size, Employment quintiles	Yes	Yes	Yes
Log Initial Tang. Assets, quintiles	Yes		
Sector $\times$ Year	Yes	Yes	Yes
Sector $\times$ Founding Year	Yes	Yes	Yes
Whited-Wu Index, quintiles		Yes	
Log Initial Total Assets, quintiles			Yes
Fit statistics			
Observations	25,960	21,095	43,223
R^2	0.537	0.680	0.623
Within R^2	0.010	0.006	0.005
No Firms	8,006	7,721	13,193

Clustered (Sector $\times$ Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table reports the relationship between founding team characteristics and firm performances based on **Equation 6** augmented with other measuers of financial frictions. *Avg. Work FE* is the average AKM worker FEs of founders, *Worker FE dissimilarity* is the average of pairwise Euclidean distance of founders' AKM worker FEs, and *Skill dissimilarity* is the average of founders' pairwise Euclidean distances across 74 ESCO skill categories. The estimation sample is based on firms surviving up to 5 years.

Table C.6: Founding team characteristics and firm performance, "sequentials" sample

Dependent Variable:	Log Sales			
Model:	(1)	(2)	(3)	(4)
Variables				
Avg. Work FE	0.200***	0.099***	0.230***	0.132***
	(0.006)	(0.008)	(0.011)	(0.016)
Worker FE dissimilarity	-0.020***	-0.017***	-0.046***	-0.019*
	(0.006)	(0.006)	(0.009)	(0.011)
Skill dissimilarity	0.124***	0.117***	0.159***	0.202***
	(0.031)	(0.036)	(0.043)	(0.066)
Fixed-effects				
Incorporation type	Yes	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes
Log Total Earnings, quintiles		Yes		Yes
Log Fixed Assets, quintiles		Yes		Yes
Initial size, Employment quintiles		Yes		Yes
Additional Controls				
Initial Team Dissimiliraties		Yes		Yes
Sample	Full	Full	Only Seq.	Only Seq.
Fit statistics				
Observations	83,916	26,141	33,738	9,703
R^2	0.273	0.534	0.294	0.551
Within R^2	0.021	0.010	0.024	0.016
No Firms	25,401	8,072	10,222	3,019

Clustered (Sector × Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table reports the relationship between founding team characteristics and firm performances based on **Equation 6**, on the full sample and on a sample of firms featuring a "sequential" entrepreneur among founders. Sequential etrepreneurs are defined as individuals who, throughout their working career, will own more than one business. *Avg. Work FE* is the average AKM worker FEs of founders, *Worker FE dissimilarity* is the average of pairwise Euclidean distance of founders' AKM worker FEs, and *Skill dissimilarity* is the average of founders' pairwise Euclidean distances across 74 ESCO skill categories. The estimation sample is based on firms surviving up to 5 years. In columns 2 and 4 controls for quintile of initial size, initial fixed assets and the dissimilarity of the initial team of employees are added.

Table C.7: Founding team characteristics and firm performance, different similarity measures

Dependent Variable:	Log Sales			
Model:	(1)	(2)	(3)	(4)
Variables				
Avg. Work FE	0.200***	0.148***	0.182***	0.139***
	(0.006)	(0.008)	(0.006)	(0.008)
Worker FEs dissimilarity, Gower Index	-0.311***	-0.451***	-0.173**	-0.328***
	(0.082)	(0.101)	(0.082)	(0.098)
Skill dissimilarity, Gower Index	0.693***	0.298*	0.749***	0.397**
	(0.140)	(0.171)	(0.137)	(0.171)
Fixed-effects				
Incorporation type	Yes	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes
Log Fixed Assets, quintiles		Yes		Yes
Log Total Earnings, quintiles			Yes	Yes
Fit statistics				
Observations	83,916	26,141	83,916	26,141
R^2	0.274	0.316	0.280	0.319
Within R^2	0.021	0.016	0.017	0.013
No Firms	25,401	8,072	25,401	8,072

Clustered (Sector × Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table reports the relationship between founding team characteristics and firm performances based on **Equation 6**. *Avg. Work FE* is the average AKM worker FEs of founders, *Worker FE dissimilarity* is the average of pairwise Gower index of founders' AKM worker FEs, and *Skill dissimilarity* is the average of founders' pairwise Gower indexes across 74 ESCO skill categories. The estimation sample is based on firms surviving up to 5 years.

Table C.8: Founding team characteristics and firm performance, full similarity measure

Dependent Variable:	Log Sales			
Model:	(1)	(2)	(3)	(4)
Variables				
Avg. Work FE	0.299***	0.207***	0.268***	0.189***
	(0.008)	(0.011)	(0.009)	(0.012)
Avg. Firm FE	0.180***	0.104***	0.145***	0.083***
	(0.009)	(0.012)	(0.010)	(0.013)
AKM FEs dissimilarity	-0.017***	-0.027***	-0.013***	-0.023***
	(0.004)	(0.006)	(0.004)	(0.006)
Skill dissimilarity	0.199***	0.113*	0.229***	0.154**
	(0.049)	(0.067)	(0.048)	(0.067)
Fixed-effects				
Incorporation type	Yes	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes
Log Initial Fixed Assets, quintiles		Yes		Yes
Log Total Earnings, quintiles			Yes	Yes
Fit statistics				
Observations	83,916	26,141	83,916	26,141
R^2	0.280	0.319	0.283	0.321
Within R^2	0.029	0.019	0.022	0.015
No Firms	25,401	8,072	25,401	8,072

Clustered (Sector × Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table reports the relationship between founding team characteristics and firm performances based on **Equation 6**. *Avg. Work FE* is the average AKM worker FEs of founders,*Avg. Firm FE* is the average AKM employer FEs of founders, *Worker FE dissimilarity* and *Firm FE dissimilarity* are the average of pairwise Euclidean distance of founders' AKM worker and employer FEs, and *Skill dissimilarity* is the average of founders' pairwise Euclidean indexes across 74 ESCO skill categories. The estimation sample is based on firms surviving up to 5 years.

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