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SORTING INTO ENTREPRENEURIAL TEAMS



EDOARDO MARIA ACABBI
ANDREA ALATI
LUCA MAZZONE
MARTA MORAZZONI

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Sorting into Entrepreneurial Teams[*]

Edoardo Maria Acabbi[†], *Andrea Alati*[‡], *Luca Mazzone*[§], *Marta Morazzoni* [**]

Abstract

This paper studies how entrepreneurs sort into founding teams and how team composition shapes the firm distribution. We develop a theory of career choice and team formation in which skill complementarities make team entrepreneurship attractive for agents with unbalanced skill profiles, while talent similarity makes teaming preferable to other career options. Using matched employer-employee and balance-sheet data from Portugal, we show that teams combining similar talent with diverse specializations create larger, more productive, and longer-lived firms; yet founders with dissimilar skills are less likely to start firms together. We calibrate the model to reproduce these patterns and use it to quantify the cost of imperfect founder matching. Counterfactuals show that reducing founders' biased exposure reallocates activity from low-productivity solo firms toward more productive teams. An optimal-assignment benchmark reveals that even unbiased random search leaves substantial gains unrealized because high-surplus matches fail to form.

Résumé

Cet article examine comment les entrepreneurs s'associent pour former des équipes fondatrices et comment la composition de ces équipes façonne la distribution des entreprises. Nous développons une théorie du choix de carrière et de la formation des équipes dans laquelle les complémentarités entre compétences rendent l'entrepreneuriat en équipe attrayant pour les individus aux profils de compétences déséquilibrés, tandis que la similitude des niveaux de

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† Acabbi: edoardo.maria.acabbi@uni-mannheim.de, University of Mannheim

‡ Alati: andrea.alati@bankofengland.co.uk, Bank of England

§ Mazzone: luca.mazzone@umontreal.ca, University of Montreal

** Morazzoni: m.morazzoni@ucl.ac.uk, University College London, IFS and CEPR

talent rend cette option préférable à d'autres choix de carrière. À partir de données portugaises appariant employeurs et employés ainsi que de données de bilan, nous montrons que les équipes combinant des niveaux de talent similaires et des spécialisations diversifiées créent des entreprises plus grandes, plus productives et dont la durée de vie est plus longue. Pourtant, les fondateurs aux compétences différentes sont moins susceptibles de créer une entreprise ensemble. Nous calibrons le modèle pour reproduire ces régularités et l'utilisons pour quantifier le coût des imperfections de l'appariement entre fondateurs. Des simulations contrefactuelles montrent qu'une réduction des biais dans l'exposition des fondateurs à des partenaires potentiels réoriente l'activité des entreprises individuelles à faible productivité vers des équipes plus productives. Un scénario de référence fondé sur un appariement optimal révèle que même une recherche aléatoire sans biais laisse des gains substantiels inexploités, parce que des appariements susceptibles de générer un surplus élevé ne se concrétisent pas.

Mots-clés/Keywords : Entrepreneuriat, appariement, frictions de recherche/Entrepreneurship, sorting, search frictions.

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1 Introduction

A large share of firm heterogeneity is determined at birth: firms enter with different technologies, workforces, and growth prospects, and these differences persist over the life-cycle (Sterk, Sedláček and Pugsley, 2021, Bhandari et al., 2022, Choi et al., 2023). Our paper studies one aspect of firm formation that has received comparatively little attention: how entrepreneurs sort into founding teams. This margin is quantitatively important, since roughly 30% of privately held firms in advanced economies are multi-owned and account for a large share of employment and sales. Yet the forces determining who starts firms with whom remain not fully understood. We empirically and theoretically ask how entrepreneurs select co-founders, along which dimensions they match, and whether these patterns shape the equilibrium distribution of firms. Characterizing these channels in a quantitative model of entrepreneurial team formation, we then quantify the aggregate consequences of complementary founders failing to match and start a firm together.

We propose a theory of career choice and team formation in which individuals are endowed with multidimensional skills and choose between different paid occupations, solo entrepreneurship, and team entrepreneurship. The key trade-off is simple. Agents with relatively balanced skill bundles are better positioned to found firms on their own. By contrast, those with more uneven skill profiles have more to gain from partnering with a co-founder whose strengths offset their weaknesses. While team formation is driven by complementarities in specialization, teams do not mechanically form whenever skills are complementary. A match must generate enough surplus to beat both founders' outside options, which depend on what each could earn in paid employment or in solo entrepreneurship. This makes similarity in overall talent valuable within teams even when heterogeneity in specialization is productive. Team formation is also frictional: potential founders do not choose from the full population of possible partners, facing instead limited meeting opportunities. The equilibrium team structure is therefore shaped jointly by skill complementarities, other career options, and search frictions.

Our model yields four main implications. First, conditional on talent, agents with more unbalanced skill profiles are more likely to sort into team entrepreneurship. Second, among teams, firms perform better when founders bring more complementary specializations. Third, conditional on specialization, firms perform better when founders have more similar talent. Fourth, in the presence of search frictions, team-founded firms can outperform solo-founded firms on average because realized teams are positively selected and many potentially complementary matches fail to form. This last point is important for the aggregate analysis: the distribution of firms depends not only on who enters entrepreneurship, but also on how effectively potential founders are matched.

We test these mechanisms using Portuguese administrative data covering the

universe of employer-employee matches from 1991 to 2018, merged with balance-sheet information for privately held firms. The data allow us to observe workers before they become entrepreneurs and link founders to the firms they start, including team-founded ones. Using detailed occupational histories, together with official occupation-skill crosswalks, we construct individual multidimensional skill profiles. In addition, we use wage records before entrepreneurial entry to estimate a measure of individuals' latent talent based on worker fixed effects – following methods in Abowd, Kramarz and Margolis (1999). This lets us characterize entrepreneurs not just by their average human capital, but separately by their overall talent and by the composition of their skills.

The data reveal that entrepreneurs are positively selected on talent relative to workers – a view dating back to Lucas (1978) and expanded in Levine and Rubinstein (2017). More novel, entrepreneurs who found firms in teams are more positively selected on talent than solo entrepreneurs. At the same time, co-founders tend to be more similar in talent than in skill specialization. Finally, these sorting patterns matter for firm outcomes: teams whose founders are closer in talent and more diverse in specialization create larger, more productive, and longer-lived firms. These relationships are visible from the earliest stages of the firm life-cycle, suggesting that founder sorting is an important source of firm heterogeneity at entry rather than merely an outcome of later organizational choices.

We also document evidence of search frictions in entrepreneurial team formation. In the data, pairs of potential founders who are more dissimilar in skills are less likely to form a team, even though teams with greater skill complementarity perform better once they form. This tension is central to the paper: the same characteristic that raises the surplus from teaming up also predicts a lower probability of founding a firm together. We interpret this as a wedge in co-founding, which the quantitative model assigns to founders' exposure being biased toward similar types. This result disciplines the matching function in the quantitative model and becomes the basis for our counterfactual analysis.

In particular, we calibrate the model to match occupational shares, moments of the earnings distribution, the share of solo and team entrepreneurs, and the impact of skill distance on the probability to form a team. We then validate it against key dimensions that are not directly imposed in the estimation, including moments of the firms' sales distribution and of the skills composition of founders. Indeed, our quantitative framework is asked to account jointly for who becomes an entrepreneur, who becomes a team entrepreneur, and how founder characteristics map into firm outcomes. We show that, in our calibrated economy as in the data, more specialized individuals are also more likely to found firms in teams, and firms perform better when founders are more different in specialization but more similar in talent. Together, these exercises show that the model captures the micro sorting patterns that motivate our theory, but also the broader empirical link between founder composition and the distribution of firms.

Finally, we exploit the general-equilibrium nature of our model to quantify how imperfect founder matching shapes aggregate outcomes. We distinguish between two inefficiencies. The first is distance-dependent pairing, which makes founders disproportionately likely to meet others with similar skill profiles, interpreted primarily as exposure bias. The second is random search, which prevents potential founders from systematically reaching their highest-surplus partners. In a set of counterfactuals, we progressively lower η, the parameter that tilts meetings toward founders with similar skill profiles, while preserving random search and bilateral participation. At the empirically interpretable point at which skill distance no longer predicts realized co-founding, activity reallocates from low-productivity solo firms toward more productive teams, raising average wages by 6% and output by 4%. We also compare the baseline economy with an optimal-assignment benchmark that allocates founders across teams to maximize entrepreneurial surplus. Baseline output is about 36% below this allocation, capturing the joint cost of biased exposure and random search. Our analysis complements evidence that facilitating business links improves young firms' outcomes (Cai and Szeidl, 2018) by isolating founder-to-founder matching as an aggregate margin. Within the long-standing debate on fostering entrepreneurial activities, our exercises therefore shift the focus from how many individuals enter entrepreneurship to how effectively entrepreneurial talent is matched and allocated across firms.

Related Literature. Our work relates to five strands of research. First, we contribute to the literature on the labor-market determinants of entrepreneurship. Gendron-Carrier (2025), Humphries (2022), and Queiró (2022) document how human capital accumulation and career trajectories shape selection into entrepreneurship, while Lazear (2004) shows that entrepreneurs tend to be generalists relative to workers. We build on this work by focusing not only on the level of human capital, but also on its composition across skill dimensions, and by showing that skill specialization predicts selection into team entrepreneurship. Argan, Indraccolo and Piosk (2024) provide related evidence from Denmark, showing that workers with specialized skills are less likely to become entrepreneurs; our results complement theirs by showing that, conditional on entrepreneurship, specialists are more likely to found firms in teams.

Second, we relate to the literature on multidimensional skills, complementarities, and sorting. Lise and Postel-Vinay (2020) show that multidimensional skills generate rich sorting patterns between workers and firms, an insight that motivates our distinction between talent and specialization. Our analysis also connects to work on human-capital accumulation and learning within teams (Acabbi, Alati and Mazzone, 2026, Jarosch, Oberfield and Rossi-Hansberg, 2021, Herkenhoff et al., 2024). The closest related paper is Freund (2022), though he analyzes teams of workers inside firms, while we analyze teams of firm founders. This changes both the model economics and the empirical focus. In our

setting, team formation is embedded in a career-choice problem between employment, solo and team entrepreneurship, and depends on bilateral surplus sharing given founders' outside options. As a result, we study how founder matching shapes firm heterogeneity at birth, rather than how coworker matching shapes inequality across existing firms.

Third, we contribute to the literature on entrepreneurial teams. While Choi et al. (2023) and Becker and Hvide (2022) show that the premature death of a founding team member causes persistent declines in firm performance, we document that founder exits are especially costly when teams display strong ex-ante skill complementarities. In a similar spirit, D'Acunto, Tate and Yang (2024) study complementarities among workers with similar prior industry experience, while Calder-Wang, Gompers and Huang (2021) analyze how diversity affects team performance. We build on these contributions by studying both the formation and the composition of entrepreneurial teams, along the vertical dimension of talent and the horizontal dimension of skill specialization, and by linking these sorting patterns to firm performance in both the data and the model.

Fourth, our model connects three macro frameworks. On the career choice side, our model speaks to the classic Roy (1951) set up. On the production side, we build on the span-of-control model of Lucas (1978) by introducing multiple skill dimensions and endogenous team formation. On the matching side, our theory is informed by multidimensional sorting models such as Eeckhout and Kircher (2011) and Lindenlaub (2017). The closest related paper is Boerma, Tsyvinski and Zimin (2025), who study complementarities within teams but focus on worker teams assigned to projects. Boerma et al. (2023) and Mukoyama and Sahin (2005) also analyze environments in which positive and negative sorting coexist, but do not embed team formation in a model of career choice or connect sorting to the equilibrium distribution of firms.

Finally, our paper relates to a growing literature showing that firm heterogeneity at birth is highly persistent and shapes the equilibrium distribution of firms (Sterk, Sedláček and Pugsley, 2021, Bhandari et al., 2022, Choi et al., 2023). We contribute to this literature in two ways. First, we use our calibrated model to quantify the role of meeting bias in team formation. Second, following Galichon (2016), we solve an optimal assignment problem to compare equilibrium team formation with the output-maximizing allocation of founders across teams. We show that facilitating complementary matches between co-founders, rather than simply lowering barriers to entry, yields aggregate gains by shifting the entrepreneurial composition toward fewer but more productive firms.

The remainder of the paper is organized as follows. Section 2 describes our data and institutional setting and documents the importance of entrepreneurial teams. Section 3 presents a model of career choice and team formation. Section 4 takes the model predictions to the data. Section 5 calibrates the quantitative model and Section 6 uses it to quantify the aggregate cost of search frictions and meeting bias. Section 7 concludes.

2 Empirical Setting and Motivating Facts

This section describes the administrative data and sample construction that underpin our analysis, focusing on how we identify founders, founding teams, and founders' characteristics before entering entrepreneurship. It then documents three suggestive facts: (i) team-founded firms are quantitatively important, and (ii) exhibit better firm outcomes than solo-founded firms; moreover, (iii) co-founders tend to have similar pre-entry earnings, but relatively different pre-entry occupations. Together, these patterns will motivate and help discipline the model's two central ingredients: selection into team entrepreneurship and sorting in talent and competences within teams.

2.1 Data Sources and Sample Construction

Our main data source is Quadros de Pessoal (QP), a matched employer-employee administrative dataset covering the universe of Portuguese individual-firm matches from 1991 to 2018, with roughly 4 millions observations per year. QP records workers' demographics, occupations,[1] earnings, working hours, and employment status. On the firm side, it includes information on their sector, region, total employment, sales, founding year and legal status, which we use to identify privately-owned firms – our specific focus. Moreover, for the subset of firms observed between 2004 and 2018, we can link QP to balance-sheet data from Sistema de Contas Integradas das Empresas (SCIE), which we exploit for productivity measurement and capital/debt structure.

The advantage of using QP is twofold: first, agents are characterized as either "employees" or "employers", which makes it possible to identify entrepreneurs within privately-held firms. Second, because individuals are observed longitudinally, we can reconstruct agents' labor-market histories before entry into entrepreneurship and relate those histories to the subsequent outcomes of their firms. Our analysis restricts to firms with ≥ 2 employees at some point in time, following the employer-firm focus common in this literature and abstracting from very small own-account businesses, many of which have limited growth ambitions (Haltiwanger, Jarmin and Miranda, 2013, Hurst and Pugsley, 2011). In our baseline specifications, we work with founders rather than time-varying employers, to ensure consistency with our theoretical framework. Founders are defined as individuals listed as owners within the first three years of a firm's stated founding year, and we define a firm to be team-founded if it has more than one founder.[2] Indeed, we keep for our analysis all privately-held firms of which we can

[1] 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.

[2] This team/solo distinction operates on a different dimension from the QP self-employed/employer one: a firm classified as "employer" (i.e. with ≥ 2 workers) can still be solo-founded if only one individual is listed as owner over its first three years, and conversely a small firm may be team-founded.

identify one or more founders.[3] These make up for 65% of all firms in QP over the period considered, covering 66% of aggregate sales and 76% of overall employment.[4]

Finally, to characterize founders' pre-entry backgrounds, we complement QP with information on the skill content of occupations. We link 3-digit occupation codes in QP to O*NET, which measures the skill requirements of each occupation, through the European Skills, Competences, Qualifications and Occupations (ESCO) crosswalk, and build each founder's skill endowment from their pre-entry occupational history. Separately, we use founders' pre-entry wage histories to construct measures of latent talent. These data allow us to move beyond a simple comparison of solo and team entrepreneurship, and to study both the aggregate importance of founding teams and the composition of the individuals who form them.

2.2 Aggregate Relevance of Team-founded Firms

We begin by documenting that entrepreneurial teams are quantitatively important in the Portuguese economy. Using our founder-based definition and over the entire sample period, firms with more than one founder represent about 28% of privately-held firms, but account for roughly 40% of both aggregate employment and sales,[5] as reported in **Figure 1**. Team-founded firms are also overrepresented in the upper tail of the firm-size distribution, as they account for 43% of the top 10% largest firms in the data. Note that, despite its relatively smaller size, Portugal's firm distribution compares to that of several other OECD countries, as summarized in **Figure C.4** in the Appendix.[6]

Interestingly, the prevalence of entrepreneurial teams is broad-based across industries and cohorts (**Appendix Figure C.6**). Moreover, **Appendix Figure C.5** clarifies that the aggregate relevance of team-founded firms is not driven by large entrepreneurial teams only: more than three quarters of team-founded firms have exactly two founders.[7] Taken together, these patterns show that team entrepreneurship is not a niche organizational

[3]The analysis sample contains 453,636 unique identified founders. Of these, 230,380 (51%) appear as employees in QP for at least one year prior to entrepreneurship, enabling reconstruction of pre-entry earnings and occupational histories; 203,560 (88% of those with pre-entry observability) fall inside the connected set required for the firm- and worker-fixed-effect estimation we will perform in **Section 4**.

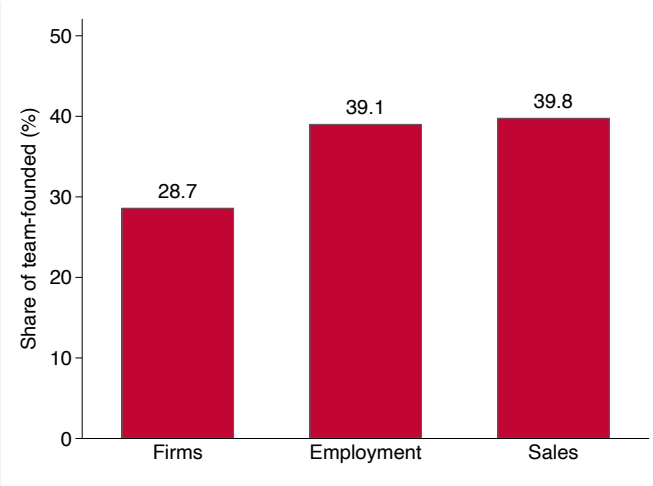
[4]See **Appendix B.1-B.2** for further details on the QP and SCIE data, and **Appendix B.3** for variable construction. **Tables C.1-C.3** report entrepreneur- and worker-level descriptive statistics.

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

[6]Harmonised OECD firm-level evidence points the same way: over 2016–2019 the start-up rate in Portugal was above the cross-country average (13% of manufacturing and 19% of services firms, against 11% and 17%), within a firm-size distribution typical of Southern-European economies (OECD, 2025). Portugal is also a producer of high-growth ventures: it has hosted the Web Summit, one of the world's largest technology conferences, since 2016, and Portuguese founders have built several technology companies that have reached billion-dollar valuations, such as Farfetch, OutSystems, and Talkdesk. The Portuguese employer–employee sample is thus adequate as a laboratory for firm-dynamics and entrepreneurship questions (Cabral and Mata, 2003, Caliendo et al., 2020, Queiró, 2022).

[7]**Figure C.7** shows no relationship between team size and number of firms owned, that is, most entrepreneurs own one firm only, regardless of team size, which will map consistently in our framework.

Figure 1: Share of Team-founded Firms, Employment and Sales



The figure shows the share of team-founded firms (defined as firms with more than one founder) in total firms, employment, and sales. Data is from the matched employer-employee sample of *Quadros de Pessoal*, covering all years from 1991 to 2018. *Cited on p. 6.*

form: team-founded firms are a minority of firms, but account for a disproportionately large share of aggregate activity. We next exploit the rich micro-level structure of the QP to investigate further the performance of solo-founded and team-founded firms.

2.3 Performance of Team and Solo-founded Firms

This section documents that team-founded firms differ systematically from solo-founded firms along standard performance margins. Using QP data, **Table 1** suggests that team-founded firms are on average larger and more productive than solo-founded firms. Specifically, it shows that firms founded by teams have higher employment (both headcount and total wage bill), higher sales, higher labor productivity (defined as sales over headcount employment) and survival rates at different age horizons. These differences are already visible right after entry and remain present later in the life-cycle, as documented in Appendix **Figures C.8**, **C.9**, and **C.10**. The same patterns hold with a stricter definition of entrepreneurs based on firm incorporation, positive turnover, and a top-management role of founders (**Appendix C.3**), and also when we restrict to firms whose founders' pre-entry backgrounds are not observed (**Appendix C.1**).

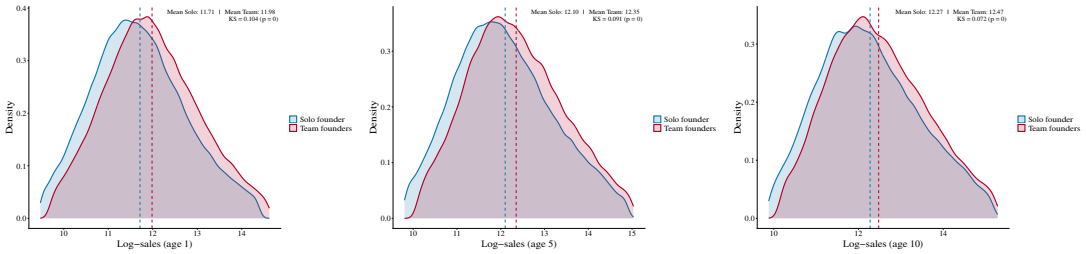
To stress this point further, **Figure 2** plots the sales distributions of solo and team-founded firms residualized by sector, founding year, legal form, and region fixed effects, at firm age 1, 5, and 10. The sales distribution of firms founded by teams shows a higher mean and a fatter right tail than the distribution of firms by solo entrepreneurs, and again these differences are present from the earliest stages of the firm life-cycle and persist over

Table 1: Team vs. Solo-founded Firms: Performance at Different Horizons

	Firm Age = 1			Firm Age = 5			Firm Age = 10		
	Solo	Team	Δ	Solo	Team	Δ	Solo	Team	Δ
Log Employment	0.82	0.93	0.11***	1.00	1.13	0.13***	1.14	1.27	0.13***
Log Wage Bill	9.35	9.55	0.20***	9.80	9.98	0.18***	10.06	10.23	0.17***
Log Sales	11.65	11.94	0.29***	12.04	12.32	0.28***	12.22	12.44	0.22***
Log Productivity	10.86	11.03	0.17***	11.08	11.20	0.12***	11.12	11.19	0.07***
Survival Rate	0.89	0.92	0.03***	0.92	0.93	0.01***	0.94	0.95	0.01***

Note: The table compares mean outcomes for solo-founded (one founder) and team-founded (more than one founder) firms at different firm age horizons. Δ is the difference (Team − Solo); stars denote significance from a two-sample t-test: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The *Survival Rate* at a given horizon is the share of firms observed at that age that are still active – i.e. not recorded as exiting in that year – computed among the firms that reached the corresponding age. Data is from *Quadros de Pessoal*, 1991–2018. *Cited on p. 7, 43.*

Figure 2: Distribution of Residualized log-Sales: Solo vs Team-Founded Firms



Note: Kernel density estimates of residualized log-sales for solo-founded (blue) and team-founded (red) firms at firm age 1 (left), firm age 5 (centre), and firm age 10 (right). We control for sector, founding year, legal form, and region fixed effects. Data is from *Quadros de Pessoal*, 1991–2018. *Cited on p. 7.*

time, despite the selection induced by greater exit rates for solo-founded firms (see also **Figure C.1** in the Appendix for the corresponding wage-bill distributions). Overall, this evidence suggests that team-founded firms differ from solo-founded ones not only in economic relevance but also observed performance, at and after entry. A natural question is whether these differences may be related to agents' sorting at the time of firm formation.

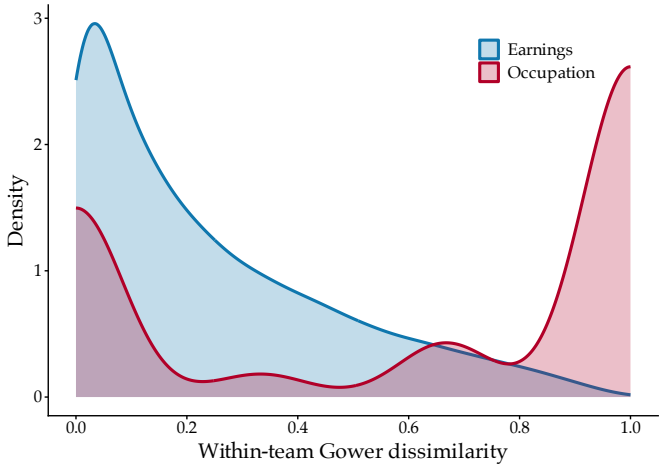
2.4 Sorting of Founders in Teams

Our third motivating pattern concerns the composition of founding teams. We focus on two-founder teams and compare co-founders along two pre-entry dimensions: their earnings percentile rank in the year before entrepreneurial entry, and their most frequently held occupation.[8] For each team, we compute a Gower dissimilarity index on each dimension: the absolute difference in within-year earnings percentile ranks (normalized to $[0, 1]$), and a hierarchical occupational distance that equals zero when

[8] **Table C.2** in the Appendix reports further descriptive statistics on team-founders demographics.

co-founders held the same three-digit occupation, one-third when they shared only the two-digit code, two-thirds when they shared only the one-digit code, and one otherwise.[9]

Figure 3: Within-team dissimilarity in pre-entry earnings and occupation



Note: Density estimates of within-team Gower dissimilarity for two-founder teams. The earnings index (blue) is the absolute difference in co-founders' within-year earnings percentile ranks, normalized to $[0, 1]$. The occupation index (red) is a hierarchical distance based on three-digit occupation codes: 0 if co-founders held the same three-digit occupation, 1/3 if they shared only the two-digit code, 2/3 if only the one-digit code, and 1 otherwise. The universe of identified two-founder teams over 1991–2018 contains 60,634 teams; the sample used here is the subset of 19,888 teams (33%) for which pre-entry earnings *and* a three-digit occupation are observed for *both* co-founders. Data from *Quadros de Pessoal*, 1991–2018. *Cited on p. 9.*

Figure 3 plots the within-team density of each index. The earnings dissimilarity distribution is concentrated near zero: co-founders tend to come from nearby positions in the pre-entry earnings distribution, consistent with positive assortative matching along a vertical dimension. The occupation dissimilarity distribution, by contrast, is more dispersed and shifted to the right, indicating that co-founders could be more likely to differ in occupational backgrounds than earnings rank.[10] Although suggestive, this pattern of vertical similarity combined with horizontal diversity motivates a formal decomposition in **Section 4**, where we separate a talent component – captured by unobserved individual types – from a specialization component – captured by occupation-based skill vectors – and we measure their distance among co-founders.

[9]Note that the Gower dissimilarity between two observations i and j is defined as $D_{ij} = \frac{\sum_{k=1}^{K} w_{ijk} d_{ijk}}{\sum_{k=1}^{K} w_{ijk}}$, where $d_{ijk} \in [0, 1]$ is the variable-specific normalized distance for characteristic k, and w_{ijk} is an indicator for non-missing comparability. In our setting, since each index is constructed on a single characteristic, this reduces to a normalized pairwise distance in $[0, 1]$: for pre-entry earnings, $d_{ij} = |p_i - p_j|$, where p_i denotes the founder's within-year earnings percentile rank; for occupation, $d_{ij} \in \{0, \frac{1}{3}, \frac{2}{3}, 1\}$ is the hierarchical distance implied by the finest occupational code shared by the two co-founders.

[10]**Appendix Figure C.3** compares both distributions to a random matching benchmark. Co-founders sort positively on both dimensions – actual dissimilarity is shifted left of random for both earnings and occupation – but the gap is larger for earnings, consistent with stronger sorting on the vertical dimension.

3 Model

In this section, we develop a static model of career choice and entrepreneurial team formation. The economy is populated by a continuum of risk-neutral agents, each endowed with one unit of time and a vector of skills over N dimensions – their human capital.

Agents choose among three career paths: paid employment, solo entrepreneurship, and team entrepreneurship. Workers supply labor to one of N occupations, each of which rewards a different dimension of their skill vector. Solo entrepreneurs operate a firm on their own. Team entrepreneurs instead search for a potential co-founder and form a firm only when the expected gains from partnering exceed the value of their outside options.

A firm's output depends on the human capital of its founder or founders, the labor it hires from the external market, and the production technology. Moreover, firms demand workers from different occupations depending on their founders' skill composition and prevailing wages. This framework generates two margins that will be central throughout the paper: selection into team entrepreneurship and sorting within entrepreneurial teams.

3.1 Environment and Payoffs

Agent Heterogeneity. Each agent is characterized by an N-dimensional skill vector, $\boldsymbol{\theta}_i$. We refer to differences in the overall level of skills across $\boldsymbol{\theta}_i$ as *vertical* heterogeneity, and to differences in the balance of skills across dimensions as *horizontal* heterogeneity. In the language we use throughout the paper, the former captures how agents differ in talent, while the latter captures how they differ in specialization, close in spirit to the terminology in Freund (2022). The joint distribution of $\boldsymbol{\theta}_i$ represents the heterogeneity in individuals' skill endowments as a multivariate probability distribution over $\mathbb{R}^N$.

Occupational Choices. Agents choose among three career paths: paid employment, solo entrepreneurship, and team entrepreneurship. There are N occupations in paid employment, each pricing individual skills separately, so that workers select them according to their comparative advantage (Edmond and Mongey, 2021). Let w_j denote the wage per efficiency unit in occupation j. An agent with skill vector $\boldsymbol{\theta}_i$ who works in occupation j supplies efficiency units $h(\theta_{i,j})$. The value of paid employment is given by:

$$R_i(\boldsymbol{\theta}_i) = \max_{j \in \{1,\dots,N\}} \{w_j \, h(\theta_{i,j})\} \,. \tag{1}$$

An individual who becomes a solo entrepreneur operates instead a firm using her own skill vector, hired labor, and the production technology. Entrepreneurial productivity is

$\zeta(\boldsymbol{\Theta_i})$, increasing in each skill dimension, so that the profit of a solo-founded firm is:

$$\pi_i^S\left(\boldsymbol{\theta_i}, \boldsymbol{l}, \boldsymbol{w}\right) = \zeta\left(\boldsymbol{\theta}_i\right) \cdot f(\boldsymbol{l})^{\nu} - \sum_{j=1}^{N} w_j l_j - \kappa \tag{2}$$

where $\boldsymbol{l} = (l_1, \ldots, l_N)$ denotes labor demand across occupations, $f(\cdot)$ is increasing and concave, and $\nu < 1$ captures decreasing returns to scale, whilst κ represents constant opening and operating production costs. Let $\pi_i^{S*}(\boldsymbol{\theta}_i)$ denote the optimized payoff from solo entrepreneurship. As in standard span-of-control models, entrepreneurial output depends on the founder's human capital and on hired labor. For an appropriate specification of $h(\cdot)$ that collapses worker heterogeneity into a single type, and for skill-dimensionality $N = 1$, our framework boils down to the original span of control model by Lucas (1978).[11]

As a third occupational option, individuals can form two-person entrepreneurial teams. If agents i and i' start a firm together, team productivity depends on the skill vectors of both founders. Specifically, each skill dimension is combined across founders through a team aggregator $\psi(\cdot, \cdot)$, so that the team's effective skill vector is given by:

$$\boldsymbol{\theta}_{i,i'}^T = \left[\psi(\theta_{i,1}, \theta_{i',1}), \psi(\theta_{i,2}, \theta_{i',2}), \ldots, \psi(\theta_{i,N}, \theta_{i',N})\right]. \tag{3}$$

The team's profit maximization problem is analogous to that of a solo firm, except that productivity depends on $\boldsymbol{\theta}_{i,i'}^T$ rather than on the skill vector of a single founder, allowing teams to combine similarity in talent with heterogeneity in specialization. Let $\pi_{ii'}^{T*}(\boldsymbol{\theta}_{i,i'}^T)$ denote the optimized team-level profit, which is distinct from founder i's individual payoff from team entrepreneurship. In particular, we assume that the gains from team formation are divided through Nash bargaining. Also, let i's outside option be defined as:

$$\overline{V}_i(\boldsymbol{\theta}_i) = \max\left\{R_i(\boldsymbol{\theta}_i), \pi_i^{S*}(\boldsymbol{\theta}_i)\right\}, \tag{4}$$

that is, the value of the best individual alternative between paid employment and solo entrepreneurship. If individuals i and i' meet, i's share of team profits $s_i \in [0, 1]$ solves

$$s_i = \arg\max_{s_i} \left(s_i \pi_{ii'}^{T*}(\boldsymbol{\theta}_{i,i'}^T) - \overline{V}_i\right)^{\beta} \left((1 - s_i)\pi_{ii'}^{T*}(\boldsymbol{\theta}_{i,i'}^T) - \overline{V}_{i'}\right)^{1-\beta}, \tag{5}$$

where $\beta \in (0, 1)$ indexes their bargaining power. The bilateral surplus from the match is

$$S_{ii'} = \pi_{ii'}^{T*}(\boldsymbol{\theta}_{i,i'}^T) - \overline{V}_i - \overline{V}_{i'}.$$

A team forms only if $S_{ii'} \geq 0$. When this condition holds, Nash bargaining implies that

[11] Gyetvai and Tan (2023) provide recent evidence on how workers' skills transfer to entrepreneurship.

founder i receives her outside option plus a share of the match surplus, namely:

$$V_i^T = \overline{V}_i + \beta S_{ii'}.$$

For a matched pair (i, i'), individual i chooses the career with the highest value among $\{R_i(\boldsymbol{\theta}_i),\ \pi_i^{S*}(\boldsymbol{\theta}_i),\ V_i^T(\boldsymbol{\theta}_i, \boldsymbol{\theta}_{i'})\}$, where the team option is available only if $S_{ii'} \geq 0$. Team formation therefore requires bilateral agreement and depends jointly on the productivity gains from combining skills and on the outside options each agent brings into the match.

Matching. Team formation is frictional because individuals cannot choose from the full population of potential co-founders. Before making occupational choices, agents are instead assigned to disjoint potential-founder pairs according to an exogenous meeting measure M on $\Theta \times \Theta$. The measure is symmetric and has marginal-type distribution G, so $\int_\Theta M(d\theta, d\theta') = G(d\theta)$. These conditions ensure that every individual is assigned exactly one potential partner and that every meeting is counted consistently from the perspective of both participants. Conditional on meeting, the pair forms a team if and only if team profit is preferable to both founders' stand-alone outside options. Otherwise, each individual chooses between paid employment and solo entrepreneurship.

A useful interpretation of our meeting technology is random exposure within constrained social environments: entrepreneurs tend to encounter business partners through schools, workplaces, and networking institutions, where contacts are local and biased yet still partly shaped by assignment, timing, and incidental proximity, rather than pure optimization (Kacperczyk, 2013, Nanda and Sørensen, 2010, Aldrich and Kim, 2007).[12] The meeting measure is left otherwise unrestricted in this section, as the model's qualitative predictions require only that agents face a restricted set of potential partners, so that some technologically valuable pairs fail to meet. Section 5 will specify and estimate a distance-dependent meeting process for the quantitative analysis.

Timing. There are two sub-periods. First, every agent meets one potential co-founder, and, conditional on that meeting, the pair decides whether to form a team. If the match generates positive surplus for both under Nash bargaining, the team is formed; else each agent is free to choose between working and solo-entrepreneurship. All other decisions are then taken simultaneously: each firm demands its optimal amount of labor from each occupation, and workers sort into occupations based on their skills and prevailing wages.

Market Clearing. Recall the standalone value defined in **Equation 4**. For a meeting $(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'})$, we define the team-formation policy:

$$d^T(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w}) = \mathbf{1}\left\{\pi^T(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w}) \geq \overline{V}_i(\boldsymbol{\theta}_i) + \overline{V}_{i'}(\boldsymbol{\theta'}_{i'})\right\}.$$

[12]Related evidence comes from random exposure in MBA cohorts and post-business-school networks (Lerner and Malmendier, 2013), randomized business-network interventions (Fafchamps and Quinn, 2018), and how co-worker mobility lowers search costs for start-ups (Rocha, Carneiro and Varum, 2018).

Under Nash bargaining with interior bargaining weights, nonnegative joint surplus ensures the "double coincidence" condition is naturally satisfied. The team region is

$$\mathcal{E}_T(w) = \left\{(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}) \in \Theta^2 : d^T(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w}) = 1\right\}.$$

This is naturally a set of pairs. If the team does not form, each individual chooses her best stand-alone occupation. For the first member of the ordered meeting, define policies:

$$\begin{aligned} d^S(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w}) &= [1 - d^T(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w})]\mathbb{1}\{\pi^S(\boldsymbol{\theta_i}; \boldsymbol{w}) \geq R(\boldsymbol{\theta_i}; \boldsymbol{w})\}, \\ d^W_j(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w}) &= [1 - d^T(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w})]\mathbb{1}\left\{w_j h(\theta^j_i) = R(\boldsymbol{\theta_i}; \boldsymbol{w}) > \pi^S(\boldsymbol{\theta_i}; \boldsymbol{w})\right\} \end{aligned}$$

If the team forms, neither founder becomes a worker or solo entrepreneur. The indicators describing the occupational choice of individual i can be defined as:

$$\begin{aligned} e^S(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}) =& \left[1 - d^T(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w})\right]\mathbb{1}\left\{\pi^{S*}(\boldsymbol{\theta_i}; \boldsymbol{w}) \geq R(\boldsymbol{\theta_i}; \boldsymbol{w})\right\}, \\ e^W_j(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}) =& \left[1 - d^T(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w})\right]\mathbb{1}\left\{w_j\, h(\theta^j_i) \geq \pi^{S*}(\boldsymbol{\theta}; \boldsymbol{w})\right\}\mathbb{1}\left\{w_j\, h(\theta^j_i) \geq w_k\, h(\theta^k_i)\ \forall k\right\}. \end{aligned}$$

The corresponding realized regions are

$$\mathcal{E}_S(\boldsymbol{w}) = \{(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}) : d^S(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w}) = 1\}; \qquad \mathcal{W}_j(\boldsymbol{w}) = \{(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}) : d^W_j(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}; \boldsymbol{w}) = 1\}.$$

We use $e^{W,j}_i(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'})$ to indicate i becoming a worker in occupation j. Integrating across agents, the labor supply for occupation j becomes:

$$LS_j = \iint e^{W,j}_i(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}) h(\theta^j_i) M(d\boldsymbol{\theta_i}, d\boldsymbol{\theta'}_{i'}) \tag{6}$$

Solo-firm and team demand are finally:

$$LD_j = \iint e^S(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}) l^S_j(\boldsymbol{\theta_i}) M(d\boldsymbol{\theta_i}, d\boldsymbol{\theta'}_{i'}) + \frac{1}{2}\iint d^T(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}) l^T_j(\boldsymbol{\theta_i}, \boldsymbol{\theta'}_{i'}) M(d\boldsymbol{\theta_i}, d\boldsymbol{\theta'}_{i'}) \tag{7}$$

Equilibrium wages are given by the vector $\boldsymbol{w} = [w_1, ..., w_N]$ and, together with occupational and entrepreneurial choices, they clear the labor market, so that $LS_j = LD^S_j + LD^T_j$.

Definition. *Static Equilibrium.* A static equilibrium consists of a stand-alone payoff function $B : \Theta \to \mathbb{R}_+$, a solo profit function $\pi^S : \Theta \to \mathbb{R}_+$, a solo firm labor demand function $l^{S*} : \Theta \to \mathbb{R}^n_+$, a team operating policy $d^* : \Theta \times \Theta \to \{0, 1\}$, a team profit function $\pi^T : \Theta \times \Theta \to \mathbb{R}_+$, a surplus sharing function $s : \Theta \times \Theta \to \mathbb{R}_+$, a team-firm labor demand function $l^{T*} : \Theta \times \Theta \to \mathbb{R}^n_+$, and a wage vector $\boldsymbol{w} \in \mathbb{R}^n_+$ such that:

1. Given $\boldsymbol{w}$, the solo profit function satisfies **Equation 2** for every $\boldsymbol{\theta} \in \Theta$, and $l^{S*}(\boldsymbol{\theta})$ is an associated optimal solo-firm labor demand;

2. Given $\boldsymbol{w}$, the stand-alone payoff function satisfies, for every $\boldsymbol{\theta} \in \Theta$, $B(\boldsymbol{\theta}) = \max\left\{\boldsymbol{w}\, h(\boldsymbol{\theta}), \pi^S(\boldsymbol{\theta}; w)\right\}$

3. Given $\boldsymbol{w}$, the team profit function satisfies the team analogue of **Equation 2** for every $\{\boldsymbol{\theta}, \boldsymbol{\theta}'\} \in \Theta \times \Theta$, and $l^{T*}(\boldsymbol{\theta}, \boldsymbol{\theta}')$ is an associated optimal team-firm labor demand;

4. Given $\boldsymbol{w}$ and stand-alone payoffs B, the sharing rule s satisfies **Equation 5**;

5. Given $\boldsymbol{w}$, stand-alone payoffs B, and the team profit π^T, the policy $d^*(\boldsymbol{\theta}, \boldsymbol{\theta}')$ is an associated optimal team decision, and satisfies

$$d^*(\boldsymbol{\theta}, \boldsymbol{\theta}') = \begin{cases} 1 & \text{if } \pi^T(\boldsymbol{\theta}, \boldsymbol{\theta}') \geq B(\boldsymbol{\theta}) + B(\boldsymbol{\theta}') \text{ for the pair } \{\boldsymbol{\theta}, \boldsymbol{\theta}'\} \\ 0 & \text{otherwise} \end{cases}$$

6. Given stand-alone payoff functions B, team policy d, and labor demand for solo firms l^{S*} and team firms l^{T*}, wages $\boldsymbol{w}$ clear labor markets in each occupation j with aggregate labor demand defined as in **Equation 7** and aggregate labor supply defined as in **Equation 6**.

3.2 A Two-Skill Illustration

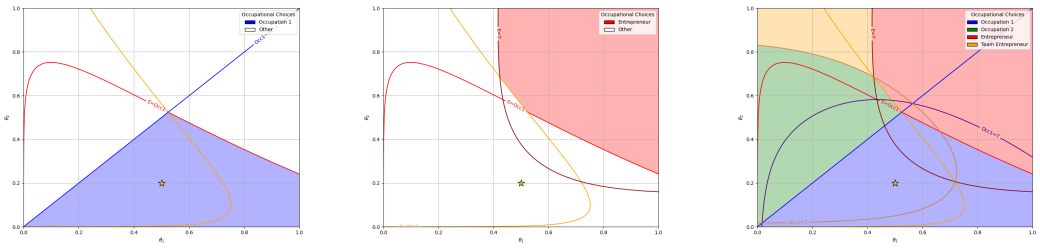
To illustrate the basic mechanics of our model, we impose a 2×2 skill-occupation structure and a set of functional forms to discuss how horizontal differentiation (specialization), vertical differentiation (talent), and bilateral agreement shape occupational choice and team formation. On functional forms, our core assumptions include entrepreneurial productivity $\zeta(\cdot)$ to be homogeneous of degree one, monotonic, concave, and supermodular, and the skill-aggregator for teams $\psi(\cdot)$ to be monotonic, symmetric, and Schur-convex. For this exposition, we also assume no wage heterogeneity, i.e. $\boldsymbol{w} = \mathbf{1}$, and describe agents' two-dimensional skill vector explicitly in terms of an average talent $\bar{\theta}$, and a "*specialization*" constant δ. As we want to focus on team formation based on skills and talent, we also temporarily set the fixed cost κ to 0.

A Fixed Match. In **Figure 4**, a representative agent i meets a potential partner i' with fixed skill bundle $(\theta_1, \theta_2) = (0.5, 0.2)$ – the star in the figure – who is relatively specialized in skill 1. The question is what characteristics of agent i would make her prefer to work (and in which occupation), found a firm alone, or form a team with this potential match.

Panel (a) of **Figure 4** shows the occupational margin. The downward-sloping boundary (dark blue line) separates agents who prefer occupation 1 from those who

Figure 4: Individual Choices Upon Meeting with [0.5,0.2]

(a) Occupation 1 **(b)** Solo Founders **(c)** All Career Choices



prefer occupation 2. Workers sort according to their strongest skill: agents with relatively high θ_1 choose occupation 1, while those with relatively high θ_2 choose occupation 2. Panel (b) of **Figure 4** introduces the entrepreneurial margin: the region in which solo entrepreneurship is preferred is concentrated among individuals with relatively balanced and sufficiently high skills (red-shadowed area). Note that the yellow line, anticipated from Panel (c), separates high-θ_2 types for whom θ_1 is high enough that they will prefer team entrepreneurship once that margin is introduced, from those whose θ_1 is not high enough for solo entrepreneurship and hence remain in occupation 2.

Panel (c) of **Figure 4** combines these margins and makes the role of team formation more transparent. The additional boundaries show that some individuals with more uneven skill profiles may prefer team entrepreneurship, because partnering allows them to compensate for the dimensions in which they are relatively weak. Relative to workers who sort into occupation 2, agents who end up in teams are similar in being specialized toward θ_2, but differ in one important dimension: those who form a team have higher overall talent. Taken together, the panels of **Figure 4** highlight the joint role of horizontal and vertical differentiation in the model. Specialization helps determine which occupation or entrepreneurial mode is attractive, while talent helps determine which specialized individuals can profitably become entrepreneurs rather than workers.

As a final remark, we stress that the boundaries of the choice regions depend on the type of match agents draw. A more talented or less specialized potential partner changes the set of individuals for whom teaming up is attractive, because the gains from team-complementarity and the scope for agreement change with partner type (see **Figure C.2** for an example). This is why team entrepreneurship is selective along several margins. Whether an agent becomes part of a founding team depends on her own skills, on the type of partner she meets, and on the outside options available to both sides of the match (which in turn depend on equilibrium wages). Indeed, all these forces are central for the model's main implications on selection and sorting in teams, as further discussed below.

3.3 More General Model Implications

We here summarize the model implications that guide our empirical analysis; note that we keep this exposition informal, but **Appendix A** proves formal counterparts to these statements in a two-skill, partial-equilibrium benchmark. The latter keeps wages fixed, sets fixed costs to zero, and uses the special case of cross-specialized teams – where each founder has a strict advantage in at least one skill dimension – to isolate the mechanisms analytically, although our model allows for teams outside this class if they generate positive bilateral surplus. While we establish the implications that follow under restrictive hypotheses, the general-equilibrium model in **Section 5** relaxes these assumptions and does not mechanically inherit those properties, which is why we will establish its corresponding implications in the numerical exercise. Still, the insights of this simplified case should clarify which primitives drive the main model's properties.

Selection into Team Entrepreneurship. Starting with team formation, individuals with uneven skill profiles have more to gain from a complementary co-founder – conditional on their overall talent – because a team can combine the dimensions in which each founder is relatively strong. By contrast, individuals with more balanced skills are better positioned to operate alone, in the spirit of Lazear (2004)'s insight that many entrepreneurs are talented *generalists*. When the team technology rewards combining different comparative strengths strongly enough that these gains outweigh the increase in the wage outside option, we obtain a clean sorting result – our **Model Prediction I**: *conditional on talent, individuals with unbalanced skills are more likely to sort into entrepreneurial teams.* This intuition also guides our quantitative specification of the team skill aggregator ψ: we use a smooth-max function, which makes team productivity depend mainly on the founder who is strongest in each dimension, thereby capturing the idea that specialization is particularly valuable within teams.

Team Composition and Performance. Team performance depends on two distinct features of founder composition. First, teams are more productive when founders bring different comparative strengths: the within-team skill aggregator ψ rewards combinations in which each founder is relatively strong in a different dimension. **Model Prediction II** summarizes this: *firms run by founders with more complementary specializations are more productive and, through higher labor demand, larger.* This result is not only technological, but extends to the whole economy when aggregate skills become more dispersed (or individuals more specialized), extending the scope for complementarity in teams.

Second, talent similarity generates a vertical-balance channel. Consider cross-specialized founders with the same average team talent and fixed opposite specialization profiles. A larger talent gap makes the effective team skill bundle more uneven, because the more talented founder increasingly dominates one skill dimension relative to the other. The idea that entrepreneurial productivity rewards balance across

effective skills, is contained in **Model Prediction III**: *among cross-specialized teams, greater talent similarity raises productivity and optimal labor demand conditional on the mean level of effective team skills.* This prediction does not necessarily sign the effect of talent dissimilarity on raw team productivity, because a larger talent gap may also change the mean level of effective team skills. In the calibrated model, we verify that the negative vertical-balance effect dominates this scale effect, generating a negative relationship between talent dissimilarity and raw productivity and sales.

This coexistence of horizontal complementarity and vertical similarity echoes the mixed sorting patterns in Boerma, Tsyvinski and Zimin (2025). The arguments above are valid pointwise, namely at the firm level: they compare the productivity of a given potential team as specialization and talent gaps change. Translating these forces into observed averages requires, however, an additional restriction on the distribution of individual skill profiles $G(\boldsymbol{\theta})$, because participation cutoffs also change the composition of selected teams and solo entrepreneurship. This leads to the next model's prediction.

Teams Overperform Solo Entrepreneurs. The comparison between team-founded and solo-founded firms is an average statement, not a claim that every team dominates every solo firm. Realized teams are positively selected, because they form only when both founders obtain enough surplus relative to their outside options. At the same time, search frictions leave some specialized individuals unmatched. These individuals may operate alone, but solo entrepreneurship does not exploit the complementarities that made them valuable potential teammates. The solo-entrepreneurs pool therefore contains both balanced generalists and specialized "failed matches." This mechanism yields **Model Prediction IV**: *in the presence of search frictions, entrepreneurial teams are on average more productive than solo entrepreneurs.* For this average ranking to hold, the unmatched specialists who become solo entrepreneurs cannot be so positively selected on talent that they offset the lost team complementarities. In **Appendix A**, this is expressed as a local restriction on the distribution of individual skill profiles, $G(\boldsymbol{\theta})$: average talent among inframarginal entrepreneurs must not change too sharply when participation cutoffs move. This rules out very thick-tailed distributions, such as Pareto-like tails, where selection could overturn the pointwise productivity effect; the condition holds for a scalar lognormal and can be verified numerically for the Gaussian-copula lognormal.

Several insights from Predictions I–IV complement the broader multidimensional matching literature. The fact that multidimensional heterogeneity generates richer sorting patterns is familiar from Lindenlaub (2017); the positive selection of realized matches under search frictions is a standard feature of frictional matching models following Shimer and Smith (2000) and, in team settings, Herkenhoff et al. (2024). The prediction that productive teams combine diversity in task-specific skills with similarity in overall talent is the founder-team counterpart of the within-worker-team logic of

Freund (2022). Our distinct contribution is to embed these forces in a career-choice model in which specialization governs endogenous selection into paid employment, solo entrepreneurship, and team entrepreneurship, while talent and specialization jointly discipline sorting within teams and firm outcomes. These general predictions provide the bridge between the model and the empirical analysis in **Section 4** and **Section 5**.

4 Model Predictions in the Data

This section explores the key predictions of the simplified model from **Section 3** in the administrative Portuguese data, proceeding as follows: first, we describe the measurement strategy at the core of our characterization of individual heterogeneity in talent and competences. Then, we empirically review how agents select and sort into team entrepreneurship, and the relation between founders' traits and firm outcomes.

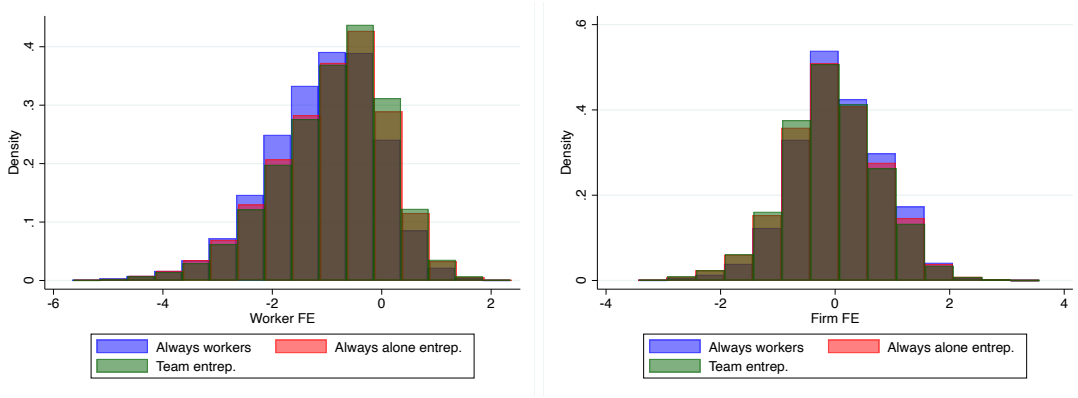
4.1 Measuring Talent and Skill Specialization

The first task in our quantitative exercise is to map the model's individual characteristics into observable empirical measures. We need to define and measure three main objects: agents' (i) talent, (ii) skill specialization, (iii) and the similarity of (i) and (ii) among agents in entrepreneurial teams. We explain how we construct these variables below.

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, including for future entrepreneurs. Because the average age at first entrepreneurial spell is 42 years old, we often have more than 20 years of pre-entrepreneurship wage histories. This allows us to estimate unobserved worker and workplace heterogeneity via the Abowd, Kramarz and Margolis (1999) (AKM) regression, estimated yearly on rolling backward-looking 5 years windows. For individuals that become entrepreneurs at least once in their career, worker and firm AKM fixed effects (FEs) measure their type as workers and the quality of their last employer before their first entrepreneurial spell (**Appendix B.4** contains more details on the estimation). Indeed, the worker FE should capture what occupation-level measures cannot: variation in quality *within* occupational histories, which keeps the vertical and horizontal dimensions of the analysis empirically distinct. Note that, consistent with Lucas (1978) and Levine and Rubinstein (2017), we interpret worker FEs as a proxy for entrepreneurial talent, not as a structural counterpart of the overall firm-level productivity $\zeta(\boldsymbol{\theta})$. Nevertheless, we observe individuals with higher AKM FEs to be on average founders of more productive firms (**Appendix Figure C.16**).

Figure 5 plots the distribution of the estimated worker and workplace FEs. We

Figure 5: 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 model. 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". *Cited on p. 18, 20.*

observe positive selection into entrepreneurship based on worker qualities, and a small negative selection based on past workplace qualities. Furthermore, entrepreneurs who open a firm with a team at least once tend to be more positively selected on their worker type compared to single entrepreneurs and individuals who will always be workers.

Skills. Exploiting the ESCO-O*NET crosswalk and the O*NET mapping between 3-digit occupations and the skills each occupation requires, we build individuals' skill endowment.[13] We proxy skill acquisition with exposure to occupations that demand different skill bundles: each agent's endowment is built from their occupational history, weighting skill levels by the time spent in each occupation. For workers who become entrepreneurs, we use employment histories prior to their first entrepreneurial spell.

To give a straightforward description of agents' specialization and operationalize it later in the quantitative model, we follow Lise and Postel-Vinay (2020) and collapse the multidimensional skill vector into three dimensions by selecting the first three principal components (PC), computed under a non-negativity constraint on the loadings.[14] We look at the highest loadings within each component and interpret them as representing

[13] **Appendix B.3** provides more details. For a description of O*NET, see: `O*NET`. For a description of ESCO, see: European Commission (2019). For a description of their crosswalk, see: `ESCO-O*NET`.

[14] **Appendix Figure B.1** reports the loadings on each skill. As an example, "*Managerial and Analytical*" includes Critical Thinking, Judgment and Decision Making, Time Management, Management of Personnel, Complex Problem Solving; "*Manual and Physical*" relates to Troubleshooting, Repairing, Equipment Maintenance, Operations Monitoring; while "*Interpersonal*" focuses on Negotiation, Persuasion, Social Perceptiveness. Together, these account for 89% of the variance in skills in our sample.

"*Managerial and Analytical*", "*Manual and Physical*", and "*Interpersonal*" skill requirements – with labels M, P, I, which we use again for the model calibration in **Section 5**. For each group, we measure the *market value* of its skills as the average annual labor earnings (in real 2010 euros) that the market attaches to the corresponding skill bundle, after accounting for age, gender, qualification, and year. **Table 2** shows that, consistent with the intuition from **Figure 5**, the correlation between more valued skills and entrepreneurial entry is strongly positive.

Table 2: Skill Prices and Prevalence

Specification	Managerial & Analytical	Physical & Manual	Interpersonal
Main specification	€11,995	€8,070	€8,853
No age/educ FE	€15,208	€7,664	€8,696
Occupation shares	13.7%	52.7%	33.6%
Share into solo firms	29.6%	36.0%	34.4%
Share into team firms	26.2%	40.0%	33.8%

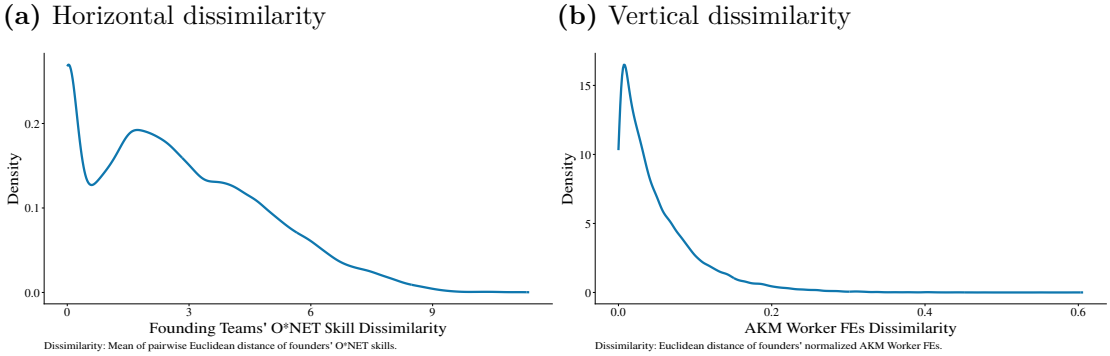
Real Euros.

Note: *Market value*: The market value of a skill type is the average real annual labor income (2010 Euro) the market pays for that type's skill bundle — the exponential of mean log earnings plus the group's skill-price deviation estimated from a pre-entry, worker-level regression of log annual earnings on the three non-negative skill principal components, so the three figures differ only in skill content, with year, age, gender, and qualification composition held fixed. *Occupation shares*: average share of workers in each skill category. *Share solo entrepreneurs*: average share of solo entrepreneurs in each skill category. *Share team entrepreneurs*: average share of entrepreneurs with at least one co-entrepreneur in each skill category. *Cited on p. 20, 27.*

Similarities. Having defined individual-level measures of talent and skill specialization, we characterize the composition of entrepreneurial teams. For our baseline measures of team dissimilarity, we rely on the average of pairwise Euclidean distances between co-founders, computed separately along two dimensions. The first captures differences in AKM worker FEs, which we label *Vertical Dissimilarity (VD)*; the second captures differences in skill specialization vectors, which we label *Horizontal Dissimilarity (HD)*.[15] We average across all pairs within a team, so that lower values indicate more homogeneous co-founder teams (**Appendix B.3** reports further details on the construction of both measures). **Figure 6** shows that the distribution of VD is relatively more concentrated near zero with a long right tail, suggesting that teams are composed of co-founders with similar talent levels. HD exhibits greater dispersion, indicating more heterogeneity in skill composition across teams. Co-founders are more similar to each other than two randomly drawn entrepreneurs would be (**Figure C.15**).

[15]We exploit the HD computed on 35 O*NET skill categories. As our specialization measure is based on occupations, the mass at 0 is due to pairs with a common history – i.e. have worked in the same occupations for the same number of years. Results are robust to computing HD on the three main PCs reported in **Table 2**, which we use to calibrate the quantitative model.

Figure 6: Dissimilarities measures in co-founders teams



Note: The figure displays the distribution of team dissimilarity measures across entrepreneurial teams in our sample. Panel (a) reports Horizontal Dissimilarity (HD), defined as the average pairwise Euclidean distance between co-founders' skill specialization vectors. Panel (b) reports Vertical Dissimilarity (VD), defined as the average pairwise Euclidean distance between co-founders' worker fixed effects. *Cited on p. 20.*

4.2 Team Formation and Performance

Individual level analysis. We validate **Model Prediction I** regarding which characteristics are good predictors of joining a team of founders as opposed to starting a firm solo, by running the following linear probability model at the founder level:

$$\mathbb{I}\{|\text{Co-founders}|_{f(i)} > 0\} = \beta_0 \text{Log-Earnings}_i + \beta_1 \hat{\alpha}_i + \beta_3 \Delta \cos(\boldsymbol{\theta}_i, \bar{\boldsymbol{\theta}}) + \boldsymbol{\beta}' \mathbf{X}_i + \Phi + \epsilon_i, \quad (8)$$

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 firm f. On the right-hand side, we include the log of (cumulative) previous labor earnings, the AKM FEs as workers, $\hat{\alpha}_i$, and $\Delta \cos(\boldsymbol{\theta}_i, \bar{\boldsymbol{\theta}})$ the cosine dissimilarity of each entrepreneur skill-bundle relative to the average bundle in the economy – our proxy of individual specialization. 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.[16] We report the results of this estimation in **Table 3**.

[16]The baseline FE set includes an indicator for serial entrepreneurs (i.e., founders holding ownership stakes in multiple firms simultaneously, following the convention adopted on the same data by De Vera et al. (2024); in the earlier entrepreneurship literature this concept is typically termed *portfolio* entrepreneurship, while *serial* refers to sequential ownership, see Westhead and Wright 1998), whose prior entrepreneurial experience may independently affect both team formation decisions and firm outcomes. We also control for the AKM worker and firm FEs from **Section 4.1**, sex, age at founding, sector, founding year, and college education. We control for the latter because schooling shifts both the propensity to enter entrepreneurship and the pool of potential co-founders an individual is likely to meet, and is a first-order dimension of founder human capital (Queiró, 2022). Column (1) additionally includes 35 O*NET skill levels; Column (2) replaces them with a FE for the last occupation held as a worker.

Table 3: Predictors of Team formation

Dependent Variable:	$\mathbb{I}\{\lvert\text{Co-Founders}\rvert > 0\}$	
	(1)	(2)
Main variables		
Prev. Log-Earnings	-0.004^{**}	-0.006^{***}
	(0.002)	(0.002)
Cosine Dissim. in Skills	0.699^{***}	0.424^{***}
	(0.168)	(0.155)
Controls		
Baseline FE set	Yes	Yes
Worker FE	Yes	Yes
Firm FE	Yes	No
Skill Levels	Yes	No
Prev. Occupation	No	Yes
Observations	185,901	180,289

Note: The table reports the correlations between the probability of having at least one co-founder and entrepreneurs' characteristics based on **Equation 8**. *Prev. Log-Earnings* are the cumulative earnings before becoming an entrepreneur; *Cosine Dissim. in Skills* is the cosine dissimilarity relative to the average skill bundle in the economy for each entrepreneur. The baseline FE set includes serial entrepreneur, college, sex, age at founding, sector, and founding year. Column (1) additionally includes the 35 O*NET skill levels; Column (2) replaces them with a FE for the last occupation held as a worker. Both columns control for AKM worker and firm FEs. Data from *Quadros de Pessoal*, 1991–2018. Clustered (sector × founding date) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 21.*

High labor market earnings reduce the likelihood of joining a founding team with a fellow entrepreneur. Our intuition from **Section 3** suggests that team entrepreneurs could be both positively and negatively selected compared to solo entrepreneurs – the relative importance of these two channels depending on the number of "*inefficient*" solo entrepreneurs induced by search frictions. Crucially, the degree of skill specialization 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).[17] These findings are in line with **Model Prediction I**.

Dyadic analysis. We extend the study of team predictors and analyze the joint role of founders' characteristics on the probability that a dyad is observed co-founding. The shift to the dyad level allows us to distinguish characteristics associated with founding in a team from those associated with whom founders match. We take founders in region r for whom prior labor market history is observed and estimate a linear probability model on the set of realized two-founder teams augmented, for computational tractability, with a random $1/4$ sample of all counterfactual pairings drawn from workers in the same region.[18]

[17]Roughly 90% of entrepreneurs is employed in two or fewer occupations, and 50% report only one.

[18]We estimate **Equation 9** year by year from 1995 to 2015, restricting the sample to founders of firms that survive at least three years. The counterfactual pool is defined *ex ante* by geography rather

Pooling these counterfactual samples, we estimate:

$$\mathbb{I}\{\text{Team}_{i,i'}\} = \beta_1 d(\boldsymbol{\theta}_{i,i'}) + \beta_2 d(\hat{\boldsymbol{\alpha}}_{i,i'}) + \beta_3 \Delta(\text{Log-Cum.Earnings})_{i,i'} + \Psi_{i,i'} + \Phi_{i,i'} + \phi_r + \varepsilon_{i,i'}, \tag{9}$$

where $\mathbb{I}\{\text{Team}_{i,i'}\}$ is equal to 1 if the dyad (i, i') is a founding team and 0 otherwise, and $d(\hat{\boldsymbol{\alpha}}_{i,i'})$ and $d(\boldsymbol{\theta}_{i,i'})$ are Euclidean distances in talent and skills – measuring vertical and horizontal dissimilarity among members of each dyad, respectively. $\Psi_{i,i'}$ is a set of dummy variables to control for possible biased matches, taking value 1 when the members of the dyad have the same sex, age, college attainment, occupation, and shared at least one previous employer. $\Phi_{i,i'}$ controls for the average talent in the dyad as well as individual FEs for each member's occupation, sex, and college attainment, while ϕ_r are region fixed effects, and $\Delta(\text{Log-Cum.Earnings})_{i,i'}$ is the difference in past cumulated labor earnings between members of each dyad, proxying potential differences in seniority and wealth.

Table 4: Dyadic regressions: Average coefficients

Dependent Variable:	$\mathbb{I}\{\text{Team}_{i,i'}\}$	
	(1)	(2)
Variables		
Log-Cum.Earnings	-0.064^{***}	-0.039^{***}
	(0.002)	(0.002)
Skill Dissimilarity (HD)	-0.186^{***}	-0.048^{***}
	(0.003)	(0.002)
Worker FE Dissimilarity (VD)	-0.067^{***}	-0.042^{***}
	(0.003)	(0.003)
Dyadic Proximity Controls	No	Yes
Avg. obs. per year	239,992	
Yearly regressions	20 (1995–2015)	

Note: The table reports the average – in percentage points – for the main coefficient of interest from the linear probability model in **Equation** 9 estimated year by year from 1995 to 2015. The coefficients are reported in units of 1 SD of the random-founder-pair distributions. The sample is based on entrepreneurial teams in region r 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 workers active in region r at the time of founding. **Figure C.17** reports the full time series of estimated coefficients for both specifications. The coefficients on the dissimilarities Bias controls include dummies that are equal to one when dyad members have: at least one shared employer, the same past occupation, same sex, same educational attainment and same age. Clustered (dyad members, two-way) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 23, 29, 38, 39.*

We report estimates of the main coefficient of interest averaged across all years in **Table 4**. Three main points are worth emphasizing. First, the coefficient on VD is

than by industry of the eventual venture: the latter is realized jointly with the team, so conditioning on it would absorb the sorting the regression is meant to measure. Restricting counterfactual pairs to industry × region cells, as in the study of political affiliation and employer-worker matching probabilities by Colonnelli, Neto and Teso (2025), would remove most of the skill-dissimilarity variation, since co-founders in the same narrow industry share occupational histories almost by construction.

significantly negative, albeit small, indicating that dissimilarities in talent decrease the likelihood of co-founding a firm. Second, the coefficient on the difference in labor earnings is negative, indicating that it is unlikely for founding teams to be formed by capital-rich entrepreneurs simply providing funding to talented ones. As such, differences in pre-entry resources do not appear to be a main driver of team formation, a pattern consistent with the complementarity story we emphasize. Third, the coefficient on HD is negative: between heterogeneous work histories and potential complementarity gains, the first has a stronger effect, deterring team formation. We attribute this distance dependence in realized co-founding, conditional on the model's productivity, occupational-choice, and bilateral-participation mechanisms, to a bias in exposure to potential partners towards individual with similar work history.

Equation 9 thus measures a reduced-form gradient in realized co-founding. Because the data observe completed founding teams rather than encounters between potential founders, the coefficients β_1 and β_2 combine differences in opportunities to interact with differences in willingness to form a team conditional on interaction. Since a major determinant of the likelihood of forming a team is whether two potential founders were colleagues in a previous job,[19] we test our exposure interpretation directly by allowing the distance gradients to vary with pre-entry exposure and plot the resulting coefficients for HD and VD in **Appendix C.2**. Relative to each group's co-founding rate, the skill-distance gradient falls monotonically as exposure gets closer: about -35% per standard deviation among unconnected pairs, -14% within region–occupation pools, and -3 to -6% among former coworkers. Skill distance thus deters co-founding mainly where opportunities to interact are scarce, yet a residual penalty survives among former colleagues, presumably resulting from workplace segmentation by occupation or team. We accordingly assign the remaining distance dependence to the pairing stage, and our counterfactuals in **Section 6** will remove only part of this wedge in founders' matching. Our findings suggest that search frictions can be more severe for specialized individuals, who may find it harder to obtain exposure to partners with a different specialization.

Team Performance. Having established that entrepreneurial teams are characterized by HD in founders' skills and VD in founders' talent, we quantify the effect of these sorting patterns on firm performance. To this end, we estimate the following regression:

$$\log(y)_{f,t} = \beta_0 \overline{\hat{\alpha}}_f + \beta_2 \Delta_f(\hat{\boldsymbol{\alpha}}) + \beta_3 \Delta_f(\boldsymbol{\theta}) + \Phi_{f,t} + \epsilon_{f,t}, \tag{10}$$

[19] This is consistent with evidence by Rocha, Carneiro and Varum (2018). See **Figure C.17** for a comparison of coefficients in **Equation 9** controlling for whether team founders were colleagues or not. Removing dyadic proximity controls for the matching process, 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 dissimilarity even more negative.

where $\log(y)_{f,t}$ denotes log sales in year t, $\overline{\hat{\alpha}}_f$ is the average AKM worker FE across 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. Finally, $\Phi_{f,t}$ absorbs sector-by-year and sector-by-founding-year fixed effects, the firm's incorporation type, and indicators for whether the team includes at least one college-educated founder and for mixed-gender teams. Across specifications, we progressively add controls for firm size via quintiles of total employment, and for financial resources available to the founding team via quintiles of founders' cumulative labor earnings and total assets at incorporation.

Table 5: Founding Team Characteristics and Firm Performance

Dependent Variable:	Log Sales		
	(1)	(2)	(3)
Main variables			
Avg. Work FE	0.181***	0.111***	0.056***
	(0.006)	(0.005)	(0.005)
Worker FE dissimilarity (std.)	−0.021***	−0.008***	−0.007**
	(0.004)	(0.003)	(0.003)
O*NET skill dissimilarity (std.)	0.036***	0.039***	0.010*
	(0.007)	(0.006)	(0.006)
Controls			
Baseline FE	Yes	Yes	Yes
Size / employment	No	Yes	Yes
Total earnings	No	Yes	Yes
Initial size	No	No	Yes
Initial assets	No	No	Yes
Fit statistics			
Observations	83,915	83,915	43,199
R^2	0.285	0.543	0.633
Within R^2	0.018	0.011	0.004
No. Firms	25,397	25,397	13,183

Note: The table reports the relationship between founding team characteristics and firm performances based on **Equation 10**. *Avg. Work FE* is the average AKM worker FEs of founders, *Worker FE dissimilarity* is the average of pairwise Euclidean distances of founders' AKM worker FEs, and *Skill dissimilarity* is the average of founders' pairwise Euclidean distances across 35 O*NET 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 common FE set includes incorporation type, at least one college founder, mixed-gender team, serial entrepreneur, sector × year, and sector × founding year. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 25, 28, 36, 44, 46, 56, 57, 58, 59, 61, 62.*

Table 5 shows the main coefficients of interest. Column (1) reports our baseline model: firms founded by entrepreneurs with higher average worker fixed effects – our proxy for talent – perform better. In addition, higher *vertical dissimilarity* in founders' latent types is associated with worse firm performance, while the positive and significant β_3 coefficient indicates that *horizontally-dissimilar* founders tend to perform better than less heterogeneous ones, consistent with **Model Predictions II-III**. These findings

survive to progressively absorbing firm size and financial controls across columns, while additional analysis is included in **Appendix C**: the point estimates hold under three other checks: a rank of pre-founding earnings in place of the AKM talent measure, which avoids connected-set estimation (**Appendix Table C.22**); skills measured on the ESCO taxonomy rather than O*NET (**Appendix Table C.24**); and the stricter entrepreneur definition of **Appendix C.3** (**Appendix Table C.10**). Nor do the vertical and horizontal sorting premia simply reflect familiarity among founders: among teams whose members worked at the same firm at the same time before founding, the skill-dissimilarity coefficient is, if anything, twice as large (**Appendix Table C.23**).

One interpretation of the positive correlation between firm sale and founder-skill dissimilarity is that the latter simply proxies for the composition of the workforce hired by the firm. Since both Freund (2022) and D'Acunto, Tate and Yang (2024) emphasize that the composition of a firm's workforce can significantly shape its performance, we also verify that our results hold when controlling for the talent and skill dissimilarities of employees hired in the firm's first three years of operations, constructed analogously to the founder-level ones. **Appendix Table C.20** clarifies that the founder-composition gradient is not mechanically absorbed by the skill diversity of the early workforce.

In addition, identification concerns for **Equation 10** revolve around the possibility that team composition is endogenous to the (unobserved) quality of the project proposed by one founder, who then "*recruits*" others. To partially address this issue, we exploit permanent separations of founding members as a source of exogenous variation in team composition. The exercise is informative about the loss associated with founder departure, although it does not by itself isolate a structural technology parameter. A growing literature uses the death of key individuals – entrepreneurs (Becker and Hvide, 2022), founding members (Choi et al., 2023), and top-executives (Sauvagnat and Schivardi, 2024) – to gauge at the effect of losing talent on firm performance. Adapting this strategy to our setup, we define permanent separations as founders under 60 who exit their firm and are never subsequently observed in the employer-employee data – neither as entrepreneurs nor as workers – while the firm survives at least three years after the event. These criteria should select exits driven by mortality or emigration rather than voluntary career transitions.[20] We combine this with a matching strategy and a difference-in-differences framework. Nearest-neighbor propensity score matching on founder demographics (age, gender, education), pre-event measures of talent and skills (cumulative earnings, average worker FE, worker FE and skill dissimilarities), and firm traits (employment, age, sales, number of owners) selects a control firm for each treated one (**Appendix Tables C.13** and **C.14** report the resulting covariate balance

[20]Portugal experienced significant emigration waves, particularly after the 2010–2012 sovereign debt crisis. Our data cover the universe of formal employment in Portugal, so a founder who is never observed again in any capacity has most likely died or left the country.

and the profile of the exiting founders). We then run:

$$Y_{i,j,t} = \beta \left(\text{Post}_{i,t} \times \text{Treat}_i \right) + \alpha_i + \tau_{j,t} + \varepsilon_{i,t}, \tag{11}$$

where $Y_{i,j,t}$ is log sales for firm i in industry j in year t, $\text{Post}_{i,t}$ equals one from the year of separation from a founder onward, Treat_i equals one for firms that experience a separation, α_i are firm FEs, and $\tau_{j,t}$ are industry-by-year FEs. The coefficient β captures the average post-separation effect on treated firms relative to matched controls. **Table 6** shows that the departure of a founder is associated with a persistent decrease in firm sales of approximately 5%, and up to 9% for teams in the top quartile of skill dissimilarity. Moreover, losses seem to be larger for teams with ex-ante high HD in skills, suggesting that the departure may have reduced the skill complementarity that drove firm performance. **Appendix C.4** further reports the full dynamic event-study specification, which replaces $\beta \left(\text{Post}_{i,t} \times \text{Treat}_i \right)$ with event-time interactions $\sum_{k=-5}^{5} \delta_k \, \mathbf{1}\{t - \tau_i = k\} \times \text{Treat}_i$. The event-study estimates confirm parallel pre-trends and show that the sales decline materializes at the time of separation and persists throughout the post-event window. Note that the average effect we document in **Table 6** is stable across age-at-separation cutoffs, when we drop the financial-crisis cohorts, and for Portuguese-born founders (**Appendix C.4.1**). It also concentrates among founders with an operational role in the firm (**Appendix Table C.16**), and survives both the stricter entrepreneur definition (**Appendix Table C.11**) and measuring skills with the ESCO taxonomy (**Appendix Table C.17**).

Table 6: Effect of Founder Separation on Firm Sales

Dependent Variable:	Log Sales		
	All	Top Q4	Rest
	(1)	(2)	(3)
Post × Treated	-0.045***	-0.090***	-0.040**
	(0.014)	(0.034)	(0.018)
Observations	10,777	2,510	8,043
No. firms	1,317	316	976
Sector × year and firm FE	Yes	Yes	Yes

Note: Difference-in-differences estimates of the effect of a founder's permanent separation on firm log sales, averaged over an event window of $[-5, +5]$ years around the separation; the full dynamic event-study specification is reported in **Appendix Table C.12** and **Figure C.14** (**Appendix C.4**). *Top Q4* refers to firms in the top quartile of pre-event Euclidean skill dissimilarity among founders. Treated firms matched via nearest-neighbor PSM on founder demographics, firm characteristics, and pre-event measures of talent and skill dissimilarity. Firm and sector × year FE. Clustered (sector-year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 27, 30, 46, 50, 51.*

Finally, we also re-estimate **Equation 10** restricting the sample to sequential entrepreneurs – founders who appear in more than one venture over their career. If the

performance results were driven by the mere presence of especially gifted individuals rather than by how teams are composed, conditioning on firms that all feature a sequential founder should absorb this individual-level advantage and eliminate the sorting coefficients. **Table C.26** shows that, even in this selected sample, skill and talent complementarities in founder teams remain significant, confirming that team composition matters for firm outcomes beyond the individual quality of its members.

5 Quantitative Exercise

This section discusses the functional forms, calibration, and validation strategies of our quantitative exercise. Let us be precise about two aspects: first, the quantitative specification should be viewed as a mechanism-preserving extension of the analytical benchmark rather than as an economy directly covered by the propositions in the **Appendix**. Second, we rely on the principal component decomposition of skills described in **Section 4.1**, and hence focus on an economy where agents are characterized by a three-dimensional skill vector, so that $\boldsymbol{\theta} \in \mathbb{R}^3$ represents "*managerial and analytical*", "*manual and physical*", and "*interpersonal*" skills, with labels M, P, I.

5.1 Model Calibration

Quantitative Setup. We collect all functional form choices in **Table 7**. We assume that labor supply is linear in skills, while the production function $f(\cdot)$ is constant-elasticity-of-substitution (CES) with parameter $1/(1-\sigma)$. The aggregation of individual or team skills into firm productivity is a CES with elasticity of substitution $1/(1-\gamma)$. Different values of γ and σ inform the different degree of substitutability or complementarity of the same skills when used for paid labour or entrepreneurship.

Table 7: Functional Forms

Definition	**Specification**
Labor supply	$h(\theta_j) = \theta_j \quad \text{for } j = \{M, P, I\}$
Production Function	$f(\boldsymbol{l}) = (\delta_{F,M} l_M^{\sigma} + \delta_{F,P} l_P^{\sigma} + \delta_{F,I} l_I^{\sigma})^{\frac{1}{\sigma}}$
Firm Productivity	$\zeta(\boldsymbol{\theta}) = (\delta_{E,M} \theta_M^{\gamma} + \delta_{E,P} \theta_P^{\gamma} + \delta_{E,I} \theta_I^{\gamma})^{\frac{1}{\gamma}}$
Skills Aggregator	$\psi(\theta_{j,i}, \theta_{j,i'}) = \frac{\log\left(e^{a \cdot \theta_{j,i}} + e^{a \cdot \theta_{j,i'}}\right)}{a}, \quad \text{for } j = \{M, P, I\}$
Joint Skill Distribution	$\ln(\boldsymbol{\theta}) \sim \mathbf{N}(\boldsymbol{\mu}, D_{\sigma_d} \mathbf{R} D_{\sigma_d})$
Pairing Kernel	$K_\eta(\theta_i, \theta_{i'}) = \exp\left\{-\eta \sum_{j=1}^{3} (\theta_{j,i} - \theta_{j,i'})^2\right\}$

In addition, for the within-team skill aggregator $\psi(\cdot)$ we choose a smooth-max

approximator, which converges to $\max\{\theta_{j,i}, \theta_{j,i'}\}$ as a grows. The skill distribution $G(\boldsymbol{\theta})$ is instead a three-dimensional lognormal with a Gaussian copula, where $\boldsymbol{\mu} = [\mu_M, \mu_P, \mu_I]$ are location parameters, $D_{\sigma_d} = \sigma_d \cdot I_3$ is the dispersion, and $\boldsymbol{R}$ is the correlation matrix of the copula, with off-diagonal elements $\rho_{M,P}, \rho_{M,I}$, and $\rho_{P,I}$.

Finally, we parameterize the meeting measure introduced in Section 3.1 using the distance-based pairing weights $K_\eta(\theta_i, \theta_{i'}) \exp\left\{-\eta \sum_{j=1}^{3} (\theta_{j,i} - \theta_{j,i'})^2\right\}$. Together with the population distribution G, these weights induce a symmetric meeting measure M_η through random pairing without replacement. When $\eta = 0$, all potential partners receive equal weight and M_η corresponds to uniform random pairing. We discipline the parameter η using the realized co-founding distance gradient from **Table 4**, as η governs the extent to which candidate meetings are tilted toward nearby types, capturing the idea that co-founder search may be local rather than global. The literature on entrepreneurial teams typically finds that founding teams are not assembled from the full population of potential partners: for instance, Ruef, Aldrich and Carter (2003), Aldrich and Kim (2007) and Lazar et al. (2020) show that homophily and network constraints are among the most pronounced determinants of founding-team composition. Read through this lens, η parsimoniously captures the fact that complementary but socially distant founders may exist in the population, and yet be less likely to find each other and form a team.

Estimation. The model is characterized by 18 parameters, of which 16 are internally calibrated. The ones fixed externally are the Nash bargaining weight β across founders (set to 0.5), and the parameter a governing how smoothly the within-team skill aggregator $\psi(\cdot)$ approximates the max operator. While this parameter does not have an immediate empirical target, a value of $a = 20$ allows reasonable smoothness in the skills aggregation of similar individuals. This choice is also not particularly consequential, as most teams are sufficiently differentiated in equilibrium, making our results robust to alternative calibrations. We then estimate the remaining parameters via the Simulated Method of Moments (SMM), targeting specific moments of solo and team entrepreneurship, as well as of the earnings distribution. Note that, to account for the static nature of our model, labor market statistics on the dispersion of workers earnings are extracted from a sample of prime-age workers (aged between 35 and 45 years), net of composition effects our model is not designed to capture - like age itself, contract type, gender and qualification.

While the model calibration is performed jointly, we can provide some intuitive links between the chosen empirical moments and the model parameters.[21] To start, occupational shares are especially informative about the corresponding CES weights in the production function. For instance, higher $\delta_{F,M}$ raises the demand for skill M and

[21] A formal Roy-model identification in the spirit of Heckman and Honore (1990) is difficult here because agents face multiple choice thresholds. Still, wage ratios and moments of the earnings distribution are informative about distributional parameters, especially the vector of log-normal marginals means, $\boldsymbol{\mu}$.

therefore its equilibrium employment share, while the occupational share for P is primarily informative about $\delta_{F,P}$. The wage ratios w_M/w_P and w_P/w_I help distinguish changes in production demand from changes in the locations of the underlying skill distributions. Similarly, the team employment share captures how much labor teams absorb – and the total supply of labor depends on the joint location of $\boldsymbol{\theta}$ – so that these moments discipline together the location parameters μ_1, μ_2, μ_3 in the skill distribution $G(\boldsymbol{\theta})$. The share of team founders with leading M or P skill are direct restrictions on the occupation-specific CES weights in firm productivity, i.e. $\delta_{E,M}$ and $\delta_{E,P}$.[22] The standard deviation of earnings helps instead pin down the dispersion parameter, $\sigma_{\boldsymbol{\theta}}$.

Note that, in our model, the top-decile sales share captures the concentration of economic activity among the largest firms, while the dissimilarity in teams is the empirical counterpart of the Horizontal Dissimilarity (HD), and describes the horizontal sorting margin. These two moments load heavily on the off-diagonal elements of $\boldsymbol{R}$, i.e. $\rho_{M,P}$ and $\rho_{M,I}$ in the copula, which govern the correlation of the skill that is the most-paid and most-represented in firm formation with the other two. Hence, the relationship between the leading labor market skill and the other two across agents drives the cross-sectional characteristics of team firms in the economy. The third correlation, $\rho_{P,I}$, has a different identifying moment, which is earnings skewness. Because skills P and I have lower labor market prices than M, changes in $\rho_{P,I}$ alter the joint distribution of the lower-return skill dimensions and thus the amount and dispersion of earnings below the mean. The model can improve on the skewness statistic either by increasing the positive contribution of the upper tail or by reducing the negative contribution of the lower tail. This distinction matters for economic interpretation, as we can match part of empirical earnings skewness through occupational composition and left-tail geometry without exceptionally high earners.

The extent to which productivity advantages translate into larger firm size depends on the curvature of the production function, which is why we calibrate the span-of-control parameter ν using firms' median size. For the degree of substitutability or complementarity among skills in production, governed by γ, we exploit heterogeneity in the relation between founder exit and firm sales by teams' ex-ante horizontal dissimilarity (HD). Within the model, this moment is particularly responsive to γ, because it speaks to the loss from removing one component of a complementary skill bundle among founders. We replicate the regression in **Table 6** using simulated data and target the difference in estimated semi-elasticities between the top quartile of HD pre-founder-exit and the rest of the firms in the distribution, providing an economically distinct restriction on selection and reallocation following a founder-related disruption.

[22] In our model, shares of team founders help identifying firm-productivity CES coefficients δ_E because the within-team skill aggregator ψ places a bigger role on the leading skills of entrepreneurs.

As for the remaining parameters, we jointly pin down the production-function elasticity σ and the fixed production cost κ using the shares of team and solo entrepreneurs. This is because an increase in σ lowers wages by making skills more substitutable, which affects labor demand and makes firm entry more profitable; κ determines instead the productivity threshold for entry and the characteristics of the marginal firm. Finally, the exposure bias parameter η governs the extent to which the model's candidate pairings are tilted toward similar skill profiles. We discipline η by matching the coefficient on $d(\boldsymbol{\theta}_{i,i'})$ in the dyadic regression of **Equation 9**. Because our data record realized teams rather than meetings, this identification is conditional on the model's occupational-choice and bilateral-acceptance mechanisms. To this end, **Appendix C.2** provides support to the bias-exposure interpretation, and **Figure C.13** shows the monotone mapping between η and the simulated skill-distance coefficient.

Table 8: Internally Calibrated Parameters: Values and Targets

Parameter	Estimate	95% C.I.	Target	Data	Model
$\delta_{E,M}$	0.272	[0.188, 0.356]	Team founders with leading M	32%	26%
$\delta_{E,P}$	0.376	[0.318, 0.435]	Team founders with leading P	42%	40%
$\delta_{E,I}$	0.352	–	Team founders with leading I	26%	34%
ν	0.593	[0.463, 0.723]	Median firm size (employees)	4	3.6
$\delta_{F,M}$	0.184	[0.120, 0.248]	Employment in occupation M	13.0%	9.5%
$\delta_{F,P}$	0.472	[0.407, 0.536]	Employment in occupation P	53.0%	56.0%
$\delta_{F,I}$	0.345	–	Employment in occupation I	34.0%	34.5%
η	22.348	[15.027, 29.668]	Dyadic regression coeff. (HD)	−0.05	−0.05
μ_M	−1.091	[−1.225, −0.957]	Employment in Team Firms	39%	40%
μ_P	−0.290	[−0.405, −0.176]	Wage w_P (rel. to w_M)	0.67	0.64
μ_I	−0.617	[−0.788, −0.447]	Wage w_I (rel. to w_M)	0.73	0.70
γ	0.273	[−0.059, 0.605]	Founder Sep., Post × Treated	−0.05	−0.11
$\rho_{M,P}$	0.001	[−0.071, 0.072]	Teams Firms in Sales p10	30%	30%
$\rho_{M,I}$	−0.002	[−0.165, 0.161]	HD within teams	1.34	1.29
$\rho_{P,I}$	−0.808	[−0.932, −0.684]	Skewness of log earnings	1.09	0.70
σ_d	0.415	[0.372, 0.458]	Standard Dev. of log Earnings	0.32	0.26
κ	0.394	[0.175, 0.614]	Share of solo entrepreneurs	7.6%	6.8%
σ	0.407	[0.192, 0.623]	Share of team entrepreneurs	2.1%	1.6%

Model Properties. We report the internally calibrated parameters and the fit of targeted moments in **Table 8**. The standard errors of our sixteen parameters are obtained by linearizing the simulated moment conditions around the estimated parameter vector. We compute $\widehat{J}$, the Jacobian of the simulated moments with respect to the estimated parameters, using central finite differences and fixed simulation draws. We then combine $\widehat{J}$ with the covariance matrix of the empirical moments $\widehat{\Omega}$, assuming

it to be diagonal (and hence forcing the correlations outside the marginal empirical standard errors to be 0). The resulting parameter covariance matrix is $\widehat{J}^{-1}\widehat{\Omega}, \widehat{J}^{-1\prime}$. The reported confidence intervals (C.I.) are the corresponding normal 95% intervals.

The model matches the wage moments closely, capturing both their dispersion and the overall shape of the worker earnings' distribution. We attribute the lower fit in the skewness moment to the inability of the model to generate enough right-tail inequality, lacking exceptionally high labor market earnings the model is not designed to produce. Occupational shares, the split between solo and team entrepreneurs, and the observed differences in skill prices, also follow the data closely, reflecting both relative skill scarcity and the distinct roles of skills in labor supply and entrepreneurial productivity.

Moreover, consistent with P being the most common pre-entrepreneurship occupation in the data, the corresponding skill receives the highest weight in the firm aggregator. Yet, because the supply of P is even larger, it commands the lowest wage – a standard negative-selection pattern of Roy models. Another feature of our calibration concerns the correlation structure of skills. In particular, M is not strongly correlated with either P or I: both correlations are not statistically different from zero. Skills P and I, instead, are strongly negatively correlated. This is further evidence of M being a "*special*" skill dimension, which not only commands the largest price in the labor market, but also contributes disproportionately to firm creation, both for solo- and team-entrepreneurs.

Noticeably, the experiment in **Equation 11** linking founders' separation and firm performance provides additional evidence and a useful calibrating strategy for the importance of skill complementarities, although the model-implied coefficient is larger than the empirical estimate. This finding supports the role of team complementarities but also reflects the static nature of the framework. In the data, surviving firms may replace a departed founder or adjust gradually; in the model, instead, the loss is immediate and permanent. The difference between the model-implied coefficient and the empirical one can thus be interpreted as the option value of replacing a team-founder.

Central to our calibration is also the comparison between the CES elasticities σ and γ. The labor aggregator exhibits substantial substitutability across occupation-specific labor inputs ($\sigma = 0.407$, implying an elasticity of substitution over 1.5): firms can compensate for scarcity in one type of hired labor by employing more of another. By contrast, the productivity aggregator $\zeta(\cdot)$ is relatively closer to Cobb–Douglas ($\gamma = 0.27$, implying an elasticity of about 1.3), and the confidence interval around the estimated γ cannot exclude 0, making the case for strong complementarities in entrepreneurial skills even stronger. Skill dimensions are hence less substitutable within a founder or founding team than across hired workers. This asymmetry rationalizes the sorting patterns documented in **Section 4**: since the entrepreneurial technology penalizes imbalance across skills more than the market, agents with uneven skill profiles

gain disproportionately from co-founders whose strengths offset their weaknesses.

5.2 Model Validation

Our calibration relies on occupational shares, moments of the earnings distribution, and characteristics of solo and team entrepreneurs. The only targeted moment describing who forms teams with whom is the co-founding distance gradient from **Equation 9**, disciplining the meeting-bias parameter η. While **Section 6** will discuss the aggregate cost of search frictions and the meeting bias, the exercises below provide a validation of the calibrated model's broader implications for team formation and firm performance.

To validate the selection dynamics in our framework, we first estimate the linear probability model in **Equation 8** on simulated data, and document how skills correlate with the likelihood of having co-founders. As shown in **Table 9**, the coefficient on agents' skill specialization in the model is not only qualitatively but also quantitatively close to its empirical counterpart. This supports the mechanism behind **Model Prediction I**: more specialized agents are more valuable team partners, even though team formation remains, *ceteris paribus*, less likely for pairs that are more horizontally dissimilar.

Table 9: Predictors of Team Formation

$\mathbb{I}\{\lvert\text{Co-Founders}\rvert > 0\}$		
	Model	Data
Cosine Dissimilarity in Skills	0.667	0.699
Worker Productivity	Yes	Yes

Note: Worker productivity controls for the model regression include individual productivity $\zeta(\boldsymbol{\theta})$; worker productivity controls for the empirical regressions include cumulative earnings in the 10 years before becoming an entrepreneur, plus AKM worker and firm FEs. *S.D. in Skills* in the model is the standard deviation across de-meaned components of $\boldsymbol{\theta}$; in the data is the standard deviation across ESCO skills for each entrepreneur. *Cited on p. 33.*

We next validate the relationship between team composition and firm performance by replicating in the model the regression in **Equation 10**. **Table 10** reports the simulated coefficients, together with their empirical counterparts: the model reproduces the qualitative trade-off between horizontal and vertical differentiation. In particular, the positive correlation between firm performance and teams' HD is accompanied by a negative coefficient on VD, and the latter is not a mechanical implication of the former.

Conditioning on the average talent of the team $\overline{\hat{\alpha}}_f$ in the analysis of **Table 10**, however, leaves open the question of what the two founders would have achieved separately. It also masks part of the VD effect on firm performance because a wider talent gap mechanically inflates horizontal differentiation. We thus re-estimate the same

regressions replacing $\overline{\hat{\alpha}}_f$ with the team's combined standalone scale, which is the log of the output founders would have produced had each of them run a firm on their own. The coefficient on founders' VD now measures whether a team outperforms the sum of its parts by more when its members are unequal in talent, and would be zero if teams were simply portfolios of two solo ventures. The coefficient on VD is more strongly negative, while the one on HD barely changes, suggesting that teams in our calibrated economy are neither portfolios of solo ventures nor vehicles for a single lead founder.

Table 10: Firm Performance and Team Dissimilarity

	Model		Model, alternative		Data	
	Productivity	Sales	Productivity	Sales	Productivity	Sales
Horizontal Dissimilarity: $\Delta_f(\boldsymbol{\theta})$	0.027	0.067	0.028	0.069	0.016	0.039
Vertical Dissimilarity: $\Delta_f(\hat{\boldsymbol{\alpha}})$	-0.0002	-0.0004	-0.002	-0.005	-0.007	-0.008
Talent control	$\overline{\hat{\alpha}}_f$		S_f		$\overline{\hat{\alpha}}_f$	

Note: Relationship between founding team characteristics and firm performances based on **Equation 10**. *Team Productivity* is the average AKM worker FEs of founders, and the average level of team member solo productivities $\zeta(\boldsymbol{\theta})$ in the model; *Vertical Dissimilarity* ($\Delta_f(\hat{\boldsymbol{\alpha}})$) is the average of pairwise Euclidean distances of founders' AKM worker FEs in the data and of team member solo productivities $\zeta(\boldsymbol{\theta})$ in the model. *Horizontal Dissimilarity* ($\Delta_f(\boldsymbol{\theta})$) is the average of founders' pairwise Euclidean distances across ESCO skill categories in the data and across de-meaned values of the skill vector $\boldsymbol{\theta}$ in the model. Columns (3)–(4) replace the average talent control with the team's combined standalone scale $S_f = \log \sum_{i \in f} \zeta(\boldsymbol{\theta}_i)^{1/(1-\nu)}$, the output the two founders would have produced running separate firms. Model regressors are standardized. *Cited on p. 33.*

Importantly, a tension we observe in the data is the one between the gains from skill complementarity and the relative paucity of diverse entrepreneurial teams. In our model, horizontal dissimilarity is also a negative predictor of team formation, and entrepreneurial teams do not look extremely diverse.[23] The parameter η drives this: its high value implies homophily at the meeting stage, with implied bilateral correlations across skills for candidate meetings above 60%. Indeed, the estimated model requires substantial homophily in candidate pairings to reproduce the empirical co-founding gradient, as the 95% C.I. for η excludes negative values. Still, selection into teams pushes co-founders back apart: pairs that meet but are too similar do not find it worth teaming up, which is why realized teams have $HD = 1.3$ in our calibration (**Table 8**), against the value of 0.84 for an average couple sampled at the meeting stage.

As final validation, we turn to other aggregate moments in **Table 11**. The empirical ranking of leading skills prevalence is preserved in the model, with most solo founders coming from P occupations, followed by M occupations. The table also reports

[23]To better interpret the empirical value of the dissimilarity measure, note that, under independent draws for the two founders, expected pair distance in the M, P, I space would be roughly 2.26. The observed value of 1.34 implies co-founders are far closer than they would be under random matching.

Table 11: Other Untargeted Moments

Moment	Data	Model
Solo Founder Share, M	29%	32%
Solo Founder Share, P	36%	50%
Log Earnings $p90 - p10$	0.81	0.66
Log Earnings $p90 - p50$	0.59	0.4
Log Sales: Skewness	0.59	0.906
Log Employment $p90 - p10$	2.7	1.5

Note: Share of teams in sales p90: percentage of team-owned firms in the top decile of the sales distribution. Median firm size: number of employees, excluding the founders/owners. All earnings and sales moments are calculated in logs. *Cited on p. 34.*

distributional statistics of workers' earnings and firms' size. It is important to stress that the model generates dispersion in earnings, sales and employment through the distribution of the skill vector $\boldsymbol{\theta}$ alone, and so it compresses the tails of all three: observed inequality also reflects hours, location and demographics on the worker side, and financial constraints, firm age and idiosyncratic shocks on the firm side, none of which our static environment built to study sorting is designed to reproduce. This has limited repercussions for what follows, since our counterfactual exercises in **Section 6** turn on the *composition* of the upper tail rather than on its width, and the share of team-founded firms in the top sales decile is matched closely. A more dispersed productivity distribution would, if anything, raise the gains from reallocating founders across teams, making our estimates conservative. Because the calibrated model captures untargeted macro moments linking team formation to the firm distribution, it provides a credible laboratory for quantifying how search frictions and matching bias affect the allocation of founders across teams and, through that channel, aggregate outcomes.

6 The Cost of Frictions in Team Formation

We now use the calibrated model to study the impact of two sources of inefficiency in team formation. The first is distance-dependent pairing, which we interpret primarily as *exposure bias*: in our estimated economy, meetings are skewed toward founders with similar skill profiles, so that, for instance, a manual specialist is disproportionately likely to meet another manual specialist rather than a managerial or analytical complement. As highlighted in the discussion of **Equation 9**, the skill-distance gradient in team formation observed empirically can combine resource-seeking with interpersonal attraction, and teams whose members' background is more heterogeneous may face lower cohesion, higher attrition, and more difficult bargaining over equity and control (Forbes et al., 2006, Lazar et al., 2020, Hellmann and Wasserman, 2017). While a lower probability of skill-distant co-

founders may reflect lower willingness to team up conditional on meeting, **Appendix C.2** shows that, among former coworkers who demonstrably had the chance to meet, the skill-distance penalty on co-founding is indeed an order of magnitude smaller (though not zero). Through the lens of our theory, skill complementarities should generate a positive co-founding gradient absent distance-dependent pairing.

The second inefficiency this section studies is the misallocation induced by *search frictions*: even if potential team members meet across the whole economy without any exposure bias ($\eta = 0$), meetings remain random, so founders may still fail to encounter the partner with whom they would generate the highest surplus. In fact, the empirical results of **Section 4** and the quantitative framework in **Section 5** suggest that both exposure-bias and search frictions play a non-negligible role in team formation process. That is why we compare the calibrated economy to two counterfactual scenarios: (i) an economy with smaller or no skill-distance penalty on team formation (i.e., $\eta \to 0$), and (ii) an Optimal Assignment (henceforth, OA) benchmark. Under OA, matches can be reallocated globally and founders can be assigned to partners so as to maximize total entrepreneurial surplus, subject to feasibility. Specifically, what we do is to solve an optimal transport problem in the spirit of Galichon (2016), according to:

$$\max_{\Gamma \geq 0} \sum_{i,i'} \Gamma_{i,i'} S_{i,i'} \qquad \text{subject to} \qquad \sum_{i'} \Gamma_{i,i'} \leq a_i, \qquad \sum_{i} \Gamma_{i,i'} \leq a_{i'},$$

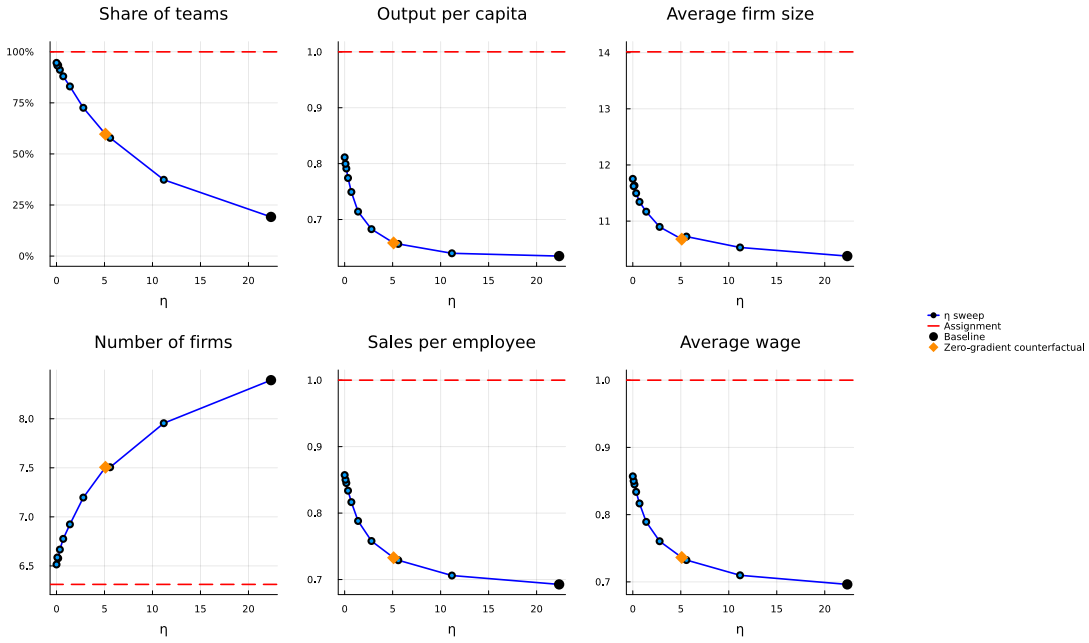
where a_i denotes the population mass of type i, and $\Gamma_{i,i'}$ is the mass of type-i agents assigned to type-i' agents. The relevant object is the *net* surplus from team formation,

$$S_{i,i'} = \pi^{T*}(i, i') - B_i - B_{i'}, \qquad B_i = \max\{R(\boldsymbol{\theta}_i), \pi^{S*}(\theta_i)\}.$$

Here, $\pi^T(i, i')$ is the joint profit of a team by types i and i', while B_i is type i's outside option, namely the best choice between paid employment and solo entrepreneurship. The surplus $S_{i,i'}$ measures the gain from matching these two agents relative to leaving them unmatched, and allowing each to pursue her best stand-alone option. From a numerical standpoint, this counterfactual is hence a general-equilibrium exercise rather than a partial-equilibrium reassignment, because the surplus matrix S depends on equilibrium wages, which shape both team profits and individual outside options. Moreover, the assignment does not force all agents into teams: the inequality constraints allow some founders to remain unmatched, since a team should form only when the joint surplus is positive. As such, the OA benchmark preserves the model's occupational logic: paid employment and solo-entrepreneurship remain relevant alternatives even in the first best. **Appendix C.5** describes in detail how we embed the assignment problem within the equilibrium solver: for any candidate wage vector, we compute outside options and pairwise team surpluses, solve for the optimal transport

plan Γ, aggregate labor demand and supply, and then update wages until labor markets clear. The OA economy is therefore the entrepreneurial-surplus maximization allocation of founders across teams within the same calibrated general-equilibrium environment.

Figure 7: Matching Bias and Optimal Assignment



Note: Computed using using the baseline calibration in **Table 8**. *Share of teams* refers to the share of firms that are run by teams; *Output per capita* is obtained by calculating total value added across all firms; *Number of firms* refers to the number of firms per 100 individuals (workers + entrepreneurs); *Average wage* is weighted by the number of workers in each occupation. *Cited on p. 37.*

Figure 7 compares the OA economy with both the calibrated baseline and the counterfactuals on reduced distance-dependent pairing bias, with the underlying values reported in **Appendix Table C.27**. The natural starting point of the sweep is $\eta = 0$, the model's uniform-pairing benchmark, which removes all distance dependence from candidate meetings while preserving random search and bilateral participation. The total cost of biased meetings is substantial. Relative to the uniform-pairing economy, baseline output is 21.7% lower and average wages are 17.9% lower. The gains along the sweep are convex in η, and aggregate outcomes move considerably as pairing approaches full uniformity. Interpreting the $\eta = 0$ gap as the cost of exposure bias requires a strong assumption: that founders end up with similar partners only because they rarely *meet* dissimilar ones. As discussed above, the co-founding gradient need not, in fact, reflect meeting opportunities alone: even upon meeting, founders may avoid dissimilar partners. Setting the distance-dependent parameter η to 0 would thus likely overstate the aggregate gains achievable through removing exposure bias alone.

As a complementary exercise, we compute an empirically interpretable intermediate

point on the path to $\eta \to 0$: the counterfactual $\eta = 5.1$, which is the unique value at which the skill-distance coefficient obtained by re-estimating **Equation 9** on simulated completed teams reaches zero. For interpretation, we report all surrounding counterfactuals, indexed by the fraction of the model-implied excess dyadic gradient that is eliminated. Moving from the baseline to $\eta = 5.1$ reduces the number of active firms by 12%, as fewer marginal solo entrepreneurs enter and activity reallocates toward productive teams, whose share rises from 20% to almost 60% of firms.[24] Since the decline in solo entrepreneurship more than offsets the creation of new team firms, the average firm becomes larger and more productive, as reflected in higher average firm size and sales per employee. Output per capita rises by about 4%, and the associated increase in labor demand raises average wages by 5.8%. The convexity of the sweep makes this benchmark informative: aggregate outcomes vary smoothly in its neighborhood, making them a reasonable guide for any scenario in which a comparable share of the matching wedge is removable.

Our second result is that the OA benchmark induces a stronger resource reallocation compared to the frictional baseline. Entrepreneurship becomes almost entirely team-based, the number of firms further decreases, and average firm size increases. The OA exercise suggest that all frictions together reduce output by more than a third. Because labor markets are competitive, these gains are transmitted to both sides of the market: average wages and output in the baseline economy are respectively 30.5% and 36.5% lower relative to OA. Unlike the move from the baseline towards lower values of η, which mostly eliminates marginal solo entrepreneurs, removing search frictions altogether impacts the firm distribution by raising the productivity of the marginal team-run firm. The OA allocation, therefore, does more than economize on fixed production costs κ: it reallocates entrepreneurial talent toward higher-surplus teams.

Importantly, our counterfactuals are statements quantified on the private, domestically controlled business sector covered by *Quadros de Pessoal*. This sector accounts for roughly two thirds of Portuguese employment and about half of GDP.[25] Scaled by these shares from the primitive results to the aggregate, the 36.5% output cost of random search corresponds to roughly 18% of GDP absent additional equilibrium effects, and the 4% model-implied gap associated with biased pairing to roughly 2%. It is also useful to highlight that common benchmarks in the firm-dynamics literature mostly emphasize wealth- or collateral-driven distortions in entry, scale, and the allocation of inputs across producers, rather than frictions to founder matching *per*

[24] Consistent with the intuition of our theoretical section, the residual solo entrepreneurs increasingly occupy the right tail of the productivity distribution when η declines.

[25] General government employs 15% of workers (OECD, 2023), state-owned enterprises outside general government a further 2% (Conselho das Finanças Públicas, 2023), and foreign-controlled affiliates account for 18% of the business-economy workforce and 28% of its value added (Eurostat, 2024), while imputed housing rents, which accrue to no firm, make up close to a tenth of GDP.

se. Our estimated distortions to production are comparable to the finance-only benchmark in Midrigan and Xu (2014), where limited external finance implies TFP losses of about 5–7%. Our misallocation estimates are also similar in magnitude to Hsieh and Klenow (2009) who compute manufacturing TFP losses of 30-60% for selected countries due to input misallocation, and below the benchmark in Buera, Kaboski and Shin (2011), where financial frictions reduce aggregate output by 52% and TFP by 36%. Our magnitudes are hence substantial, but not implausible for a friction that distorts entrepreneurial selection and the composition of firms at entry.

We stress that our counterfactual economies achieve higher aggregate gains because they improve *who matches with whom* and *who becomes an entrepreneur*: as low-productivity solo entrepreneurs exit, a larger mass of agents starts firms as members of teams rather than as solo founders. This compositional shift has two consequences. First, labor demand becomes more concentrated in high-surplus team-founded firms, which raises equilibrium wages. Second, because more individuals become entrepreneurs, fewer productive specialists remain in the labor force, further tightening labor markets and increasing competition for talent. The larger gains obtained under the OA benchmark clarify that, even under an unbiased meeting process, the inability to reallocate matches toward globally-efficient complementary pairings may leave sizable gains unrealized. Taken together, our exercises suggest that policies aimed at facilitating complementary matches between potential co-founders, rather than simply lowering barriers to firm entry, could generate substantial aggregate gains. The reason is not just that such policies would raise the number of teams, but that they would shift the composition of entrepreneurship toward more productive team-founded firms. This policy angle also connects to a growing empirical literature on the effects of promoting new business links: for instance, Cai and Szeidl (2018) show experimentally that organizing business associations among owner-managers can create new relationships and raise revenue, borrowing, and management quality, while Chatterji et al. (2019) show that peer-advice links among high-growth startups improve growth and survival.

At the same time, the magnitudes implied by our counterfactuals clearly represent an upper bound of what can be achieved by improving the market allocation via policy levers. No realistic policy could replicate the OA benchmark, or even the case of perfectly unbiased random search. In practice, the bias captured by η reflects endogenous sorting through preferences or educational, career, and location choices, which lie well beyond the scope of any policy to fully undo. Moreover, in a dynamic environment, both matching bias and search frictions could be attenuated over time through continued search for better partners. Exploring these margins is an important direction for future analyses.

7 Conclusions

We study how individuals sort into entrepreneurial teams and show that founding-team composition is a key determinant of firm performance and aggregate outcomes. Our theory emphasizes skill complementarities: individuals with unbalanced skill profiles benefit from partnering with co-founders whose strengths offset their weaknesses, while talent similarity ensures that teaming dominates outside options. Using matched employer-employee data from Portugal, we show that teams combining similar talent with diverse skill specializations create larger, more productive, and longer-lived firms; yet founders with dissimilar skills are less likely to start firms together.

Our quantitative model shows that imperfect founder matching can affect aggregate outcomes by distorting the composition of entrepreneurship. Reducing distance-dependent pairing until skill distance no longer predicts realized co-founding reallocates activity from low-productivity solo firms toward more productive teams, raising output by about 4%. An optimal-assignment benchmark reveals the broader cost of matching frictions: baseline output is about 36% below the allocation that maximizes entrepreneurial surplus. Together, these exercises show that distance-dependent pairing and random search prevent complementary founders from forming high-surplus teams. The relevant margin is therefore not simply how many individuals enter entrepreneurship, but how effectively entrepreneurial talent is matched and allocated across firms. Policies that facilitate complementary co-founder matches may improve aggregate performance by acting on this allocation margin rather than on entry alone.

Several questions remain open. Our framework is static and cannot address how teams evolve over the firm life-cycle, how or when co-founders exit or new members join, or whether the skills required at founding differ from those needed at later stages. Modeling team dynamics, including optimal team size across different stages of a firm's life, is a natural next step toward a richer understanding of the interplay between entrepreneurship and labor markets. We leave these and other questions to our future research.

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A Model Appendix

In this section we collect the analytical building blocks behind the four model predictions in Section 3.3. Two auxiliary results and one distributional condition are used throughout: **Lemma A.1** records how firm productivity responds to the balance of a skill bundle, **Lemma A.2** collects the log-differentiation of the participation cutoffs, and **Definition A.1** bounds the strength of composition effects.

We can now introduce the formal discussion of our model predictions. **Lemma A.3** characterizes how specialization affects the solo-entrepreneurship outside option, and **Lemma A.4** converts team productivity into a bilateral participation condition: more talented pairs form teams at lower levels of specialization, which is **Model Prediction I**. **Proposition A.1** isolates the technological gains from combining specialized founders, and **Proposition A.2** asks whether that direct effect survives selection into observed teams; together they deliver **Model Prediction II**. **Proposition A.3** isolates the vertical-composition channel: conditional on specialization and mean effective team skill, greater similarity in founders' talent raises productivity, corresponding to **Model Prediction III**. Finally, **Proposition A.4**, **Corollary A.1**, **Proposition A.5**, and **Corollary A.2** characterize the solo-firm comparison and the search-friction threshold under which observed teams outperform observed solo firms, delivering **Model Prediction IV**.

Assumptions and preliminaries

Since the analysis is conducted over the partial equilibrium behavior of the model, we omit the dependence of wages on any other primitive. Even more, we impose symmetric occupational wages, $w_1 = w_2 = w$. This assumption is not consequential for purely technological results, like **Proposition A.1**, and **Proposition A.3**. It does apply, however, to all results involving occupational outside options, entrepreneurial entry, and bilateral participation. In these cases, it isolates the roles of talent and skill specialization from differences in occupational skill prices, allowing us to focus on the key channels of the model. For this section, we also assume that skills are independently distributed across individuals. The quantitative analysis in **Section 5** allows occupational wages to differ and skills to have non-zero correlations across individuals. All assumptions on functional forms will be listed as follows:

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

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

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

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

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

A.VI 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.VII Schur Convexity: $(x-y)\left(\frac{\partial g}{\partial x} - \frac{\partial g}{\partial y}\right) \geq 0$, with strict inequality whenever $x \neq y$

We impose the following assumptions on matching and on the population distribution of talent and specialization.

A.VIII (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 individual has $\{\bar{\theta}, -\delta\}$.

A.IX (Talent–Specialization Independence) Let $\bar{\theta} = (\theta_1 + \theta_2)/2$ denote average talent and let $\Delta = |\theta_1 - \theta_2|/(\theta_1 + \theta_2) = |\delta|/\bar{\theta}$ denote relative specialization. The random variables $\bar{\theta}$ and Δ are independently distributed.

A.X (Ordered Increase in Specialization) The distribution of specialization belongs to a one-parameter family with density $f(\Delta; s)$ on a common support, where the index s measures how specialized the population is. The family is log-supermodular in $(\Delta; s)$: for any $s' > s$, the ratio $f(\Delta; s')/f(\Delta; s)$ is weakly increasing in Δ, and is not almost everywhere constant.

Assumption **A.X** warrants a little discussion. The index s orders populations by specialization. In the quantitative model, an individual's skill vector is drawn from a lognormal distribution with a Gaussian copula, so overall talent corresponds to the common level of log skills and specialization to their spread across dimensions. There, an ordered increase in specialization in the sense of **A.X** is a reduction in the within-person correlation across skill dimensions, which corresponds to one of the copula parameters estimated in **Section 5**. The correspondence is exact in the symmetric case considered here and approximate in the quantitative model, where skill dimensions differ in their means and in their prices.

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.I - A.IV** (we need further assumptions on the elasticity to obtain **A.V**). As we exclusively want to focus on team formation based on skills, for the proofs here we also set the fixed costs $\kappa = 0$. Firm's profit function then is:

$$\pi = \zeta(\boldsymbol{\Theta}) \cdot f(\boldsymbol{L})^{\nu} - \mathbf{w} \cdot \mathbf{L}, \quad 0 < \nu < 1$$

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

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

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

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

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:

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

Assuming symmetric wages means we can write: $\pi^I = (1-\nu)\left(D(w)^{-1}\,\zeta(\mathbf{\Theta})\right)^{\frac{1}{1-\nu}}$. 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:

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

Payoffs from team-run firms are instead given by:

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

Productivity indexes and payoffs are distinct objects. Let $Z_{ii'}^T = \zeta^T(\mathbf{\Theta}_{i,i'})$ denote the team productivity index, and let $\Pi(Z; \boldsymbol{w})$ denote optimized operating profit generated by productivity index Z. The team is formed if and only if optimized team profit covers both founders' stand-alone values:

$$\Pi(Z_{ii'}^T; \boldsymbol{w}) \geq B_i(\boldsymbol{w}) + B_{i'}(\boldsymbol{w}), \qquad B_i(\boldsymbol{w}) = \max\left\{R(\mathbf{\Theta}_i; w), \Pi(\zeta(\mathbf{\Theta}_i); \boldsymbol{w})\right\}. \tag{A.2}$$

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 first isolate the technological effect, before applying the optimized-profit map and the bilateral participation condition in (A.2). Write

$$Z^T = \zeta\Big(\theta_1^T, \theta_2^T\Big),$$

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

Two auxiliary results are used repeatedly in the rest of this Appendix. The first records how firm productivity responds to the balance of a skill bundle; the second collects the log-differentiation of the entry cutoffs, which takes the same form on the solo and the team margins.

Lemma A.1 (Balance Lemma)**.** *Suppose that ζ satisfies **A.I**, **A.IV**, and **A.VI**. For a skill bundle with mean skill $\bar{\theta} > 0$ and imbalance $\delta \in [0, 1)$, write*

$$\boldsymbol{b}(\bar{\theta}, \delta) = \left(\bar{\theta}(1+\delta), \bar{\theta}(1-\delta)\right).$$

If $\delta_1 \geq \delta_0$, then

$$\zeta\left(\boldsymbol{b}(\bar{\theta}, \delta_1)\right) \leq \zeta\left(\boldsymbol{b}(\bar{\theta}, \delta_0)\right). \tag{A.3}$$

The inequality is strict when $\delta_1 > \delta_0$ if ζ is strictly Schur-concave on fixed-sum skill bundles. Moreover, homogeneity implies that normalized productivity depends only on imbalance:

$$\frac{\zeta\left(\boldsymbol{b}(\bar{\theta},\delta)\right)}{\zeta(\bar{\theta},\bar{\theta})}=\frac{\zeta(1+\delta,1-\delta)}{\zeta(1,1)}.$$

Proof. The bundles $\boldsymbol{b}(\bar{\theta},\delta_1)$ and $\boldsymbol{b}(\bar{\theta},\delta_0)$ have the same sum, while $\boldsymbol{b}(\bar{\theta},\delta_1)$ is weakly more unequal when $\delta_1 \geq \delta_0$. A symmetric concave function is Schur-concave, so (A.3) follows from **A.IV** and **A.VI**. It is strict under strict Schur concavity. The normalization follows directly from homogeneity of degree one. □

Lemma A.2 (Cutoff elasticity)**.** *Let $r \equiv \frac{1}{1-\nu} > 1$, let $k > 0$ and $C(\boldsymbol{w}) > 0$ be constants, and let $z(\cdot)$ be positive and differentiable. For any cutoff of the form*

$$\bar{\theta}_X(\Delta)=\left[\frac{k(1+\Delta)}{C(\boldsymbol{w})\,z(\Delta)^r}\right]^{\frac{1}{r-1}},$$

we have

$$(1+\Delta)\frac{\bar{\theta}_X'(\Delta)}{\bar{\theta}_X(\Delta)}=\frac{1-r\,\varepsilon_z(\Delta)}{r-1},\qquad \varepsilon_z(\Delta)\equiv(1+\Delta)\frac{z'(\Delta)}{z(\Delta)}. \tag{A.4}$$

Proof. Taking logs, $\log\bar{\theta}_X(\Delta) = \frac{1}{r-1}\left[\log k - \log C(\boldsymbol{w}) + \log(1+\Delta) - r\log z(\Delta)\right]$. Differentiating in Δ and multiplying by $1+\Delta$ gives (A.4). □

The two entry cutoffs below are instances of (A.4) that differ only in the sign of ε_z: specialization lowers solo productivity, so the solo cutoff rises, while it raises team productivity, so the team cutoff falls whenever $r\,\varepsilon_z > 1$.

Before turning to observed productivity, it is useful to isolate the selected-mean object that appears in both the team and solo results. For any cutoff c, let

$$\mu(c)=\mathbb{E}[\bar{\theta}\mid\bar{\theta}\geq c].$$

When $\bar{\theta}$ has a continuous density and the selected mean is finite, let $h_{\bar{\theta}}(c)$ denote the hazard rate of average talent. The standard truncated-mean identity gives

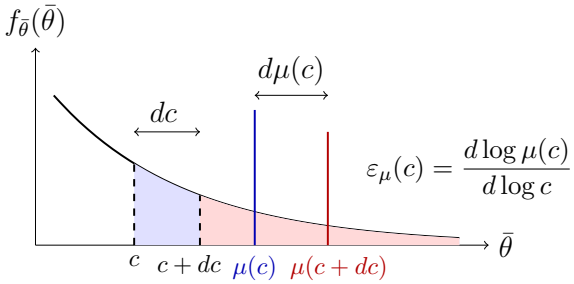
$$\mu'(c)=h_{\bar{\theta}}(c)[\mu(c)-c].$$

We define the selected-mean elasticity as

$$\varepsilon_\mu(c)\equiv\frac{d\log\mu(c)}{d\log c}=\frac{ch_{\bar{\theta}}(c)[\mu(c)-c]}{\mu(c)}.$$

This object measures how strongly the average talent of the selected population responds to a marginal increase in the cutoff. It is determined by the marginal

Figure A.1: Selected-mean elasticity.



distribution of average talent and by the cutoff at which it is evaluated. Figure $A.1$ illustrates the selected-mean elasticity. Raising the cutoff from c to $c + dc$ removes the lowest-productivity observations from the selected set and therefore increases the selected mean from $\mu(c)$ to $\mu(c + dc)$. The elasticity $\varepsilon_\mu(c)$ measures the size of this composition response in percentage terms.

Definition A.1 (Thin relevant tail)**.** *Let $\mathcal{K} \subset \mathbb{R}_+$ be a set of cutoffs such that $\overline{F}_{\bar{\theta}}(c) > 0$, $\mu(c) < \infty$, and $\varepsilon_\mu(c)$ is well defined for every $c \in \mathcal{K}$. The distribution of average talent has a* thin relevant tail *on $\mathcal{K}$ if*

$$\sup_{c\in\mathcal{K}} \varepsilon_\mu(c) < \nu.$$

The qualifier "relevant" emphasizes that this is not a global tail restriction. We only require the selected-mean elasticity to be small over the cutoff ranges generated by the participation margins used in the results below. The condition limits the strength of composition effects: small changes in the entry or participation cutoff cannot generate too large a change in the average talent of selected entrepreneurs.

A.1 Model Prediction I

Conditional on talent, individuals with more unbalanced skills are more likely to sort into entrepreneurial teams.

Lemma A.3 (Solo-entrepreneurship entry cutoff)**.** *Define normalized solo productivity as*

$$z_S(\Delta) \equiv \zeta(1 + \Delta, 1 - \Delta)$$

Suppose that ζ satisfies $A.I - A.IV$ and $A.VI$. Then, for every $\Delta \in [0, \bar{\Delta}]$, there exists a unique average-talent cutoff $\bar{\theta}_E(\Delta)$ such that solo entrepreneurship is weakly preferred to paid employment. Moreover, $\bar{\theta}_E(\Delta)$ is strictly increasing in Δ.

Proof. An individual with average talent $\bar{\theta} > 0$ and relative specialization $\Delta \in [0, \bar{\Delta}]$,

where $\bar{\Delta} < 1$, has skill vector $\left[\bar{\theta}(1+\Delta, 1-\Delta)\right]$ and earns $w\,\bar{\theta}\,(1+\Delta)$ in paid employment. Because ζ satisfies A.I, optimized profit from solo entrepreneurship is $C(w)\bar{\theta}^r z_S(\Delta)^r$.

Solo entrepreneurship is therefore weakly preferred to paid employment if and only if

$$[C(w)\bar{\theta}^r z_S(\Delta)^r \geq w\,\bar{\theta}(1+\Delta).]$$

Because $\bar{\theta} > 0$, this condition is equivalent to

$$\bar{\theta} \geq \left[\frac{w(1+\Delta)}{C(w)z_S(\Delta)^r}\right]^{\frac{1}{r-1}} \equiv \bar{\theta}_E(\Delta).$$

It remains to establish the comparative static. By **Lemma A.1**, a mean-preserving increase in specialization weakly lowers solo productivity holding mean skill fixed, so $z_S'(\Delta) \leq 0$ and hence $\varepsilon_{z_S}(\Delta) \leq 0$. Applying **Lemma A.2** with $k = w$ and $z = z_S$,

$$(1+\Delta)\frac{\bar{\theta}_E'(\Delta)}{\bar{\theta}_E(\Delta)} = \frac{1 - r\,\varepsilon_{z_S}(\Delta)}{r-1} > 0,$$

where the strict inequality follows from $r > 1$ and $\varepsilon_{z_S}(\Delta) \leq 0$. Thus $\bar{\theta}_E(\Delta)$ is strictly increasing in relative specialization. □

Team formation depends on payoffs: optimized team profit must compensate both founders for their stand-alone outside options, as in (A.2). In the symmetric mirror-matching benchmark below, the two founders have the same outside option, so bilateral participation reduces to $\Pi^T \geq 2B_i$. Under symmetric Nash bargaining, this is equivalent to each founder receiving one half of team profit and weakly preferring the team to the relevant outside option.

Let relative specialization be $\Delta \in [0, \overline{\Delta}]$, with $\overline{\Delta} < 1$. Under $A.VIII$, the two founders have skill vectors $\bar{\theta}(1+\Delta, 1-\Delta)$ and $\bar{\theta}(1-\Delta, 1+\Delta)$. Recall from **Lemma A.3** that normalized solo productivity is $z_S(\Delta) = \zeta(1+\Delta, 1-\Delta)$; we can define $a(\Delta) = \psi(1+\Delta, 1-\Delta)$ and thus normalized team productivity as $z_T(\Delta) = \zeta(a(\Delta), a(\Delta))$.

It will also be convenient to record the elasticity of effective team skill with respect to the founder's leading skill $1+\Delta$, which is also the wage outside option per unit of talent:

$$\varepsilon_\psi(\Delta) \equiv \frac{\mathrm{d}\log a(\Delta)}{\mathrm{d}\log(1+\Delta)} = (1+\Delta)\,\frac{a'(\Delta)}{a(\Delta)}. \tag{A.5}$$

By homogeneity, the corresponding productivity indexes for founders with average talent $\bar{\theta}$ are

$$Z_S(\bar{\theta}, \Delta) = \bar{\theta} z_S(\Delta), \qquad Z_T(\bar{\theta}, \Delta) = \bar{\theta} z_T(\Delta).$$

Optimized operating profit can again be written as $\Pi(Z;\boldsymbol{w}) = C(\boldsymbol{w})Z^r$, with $r = \frac{1}{1-\nu} > 1$. Notice $r > 1$ for any calibration of the span of control parameter ν that implies decreasing returns to scale - as in the case of our application.

Under symmetric wages, each founder's wage outside option is $w\,\bar{\theta}(1+\Delta)$. We want to establish the existence of a single threshold in specialization, conditional on average talent, for team formation. Define

$$\mathcal{R}_S(\Delta) \equiv \frac{1}{2}\left[\frac{z_T(\Delta)}{z_S(\Delta)}\right]^r,$$

so that a mirror-matched team compensates both founders' solo-profit outside options if and only if $\mathcal{R}_S(\Delta) \geq 1$. To guarantee that the resulting threshold is interior, so that team formation is neither impossible throughout the specialization range nor already available at zero specialization, we impose a boundary condition at each end of the range:

$$\mathcal{R}_S(0) < 1, \qquad \mathcal{R}_S(\overline{\Delta}) > 1. \tag{A.6}$$

The second condition requires that sufficient specialization eventually generates enough team surplus to compensate the two founders' solo-profit outside options.[26] The first condition is equivalent to $\psi(1,1) < 2^{1-\nu}$, and is implied by the normalization $\psi(u,u) = u$ adopted in the illustrative exposition of **Section 3**. It requires that founders with identical skills do not generate enough team surplus, so that team formation is driven by complementarity rather than by aggregation alone. The next lemma combines the two participation margins, against solo entrepreneurship and against paid employment, into a single threshold in specialization.

Lemma A.4. *This Lemma proves three, related, results:*

(*i*) *Suppose that ψ satisfies A.I − A.IV, and A.VII, while ζ satisfies A.I − A.IV and A.VI (strictly). If the boundary conditions $\mathcal{R}_S(\overline{\Delta}) > 1$ and $\mathcal{R}_S(0) < 1$ hold, then there exists a unique $\Delta_S \in (0, \overline{\Delta})$ so that a team matched under A.VIII compensates both founders' solo-entrepreneurship outside options independent of average talent if and only if $\Delta \geq \Delta_S$.*

(*ii*) *For each specialization level $\Delta \in [\Delta_S, \overline{\Delta}]$, the wage-participation constraint is equivalent to $\bar{\theta} \geq \bar{\theta}_W(\Delta)$, where*

$$\bar{\theta}_W(\Delta) = \left[\frac{2w(1+\Delta)}{C(\boldsymbol{w})z_T(\Delta)^r}\right]^{\frac{1}{r-1}}. \tag{A.7}$$

[26] This condition ensures that team formation is possible when profits are allocated using Nash bargaining, as we assume throughout. Equivalently, it would allow team formation when agents trade under transferable surplus.

If in addition $r\,\varepsilon_\psi(\Delta) > 1 \qquad$ *for all* $\Delta \in [\Delta_S, \overline{\Delta}]$ *, then* $\bar{\theta}_W(\Delta)$ *is strictly decreasing on* $[\Delta_S, \overline{\Delta}]$*. Hence the minimum average talent level for which wage participation is feasible in the relevant specialization region is* $\underline{\theta}_T = \bar{\theta}_W(\overline{\Delta})$*.*

(*iii*) *Under* $r\,\varepsilon_\psi(\Delta) > 1 \qquad$ *for all* $\Delta \in [\Delta_S, \overline{\Delta}]$*, for every average talent* $\bar{\theta} \geq \underline{\theta}_T$ *there exists a unique threshold* $\Delta^*(\bar{\theta}) \in [\Delta_S, \overline{\Delta}]$ *such that the mirror-matched pair generates non-negative bilateral surplus if and only if*

$$\Delta \geq \Delta^*(\bar{\theta}).$$

Moreover, $\Delta^*(\bar{\theta})$ *is weakly decreasing in* $\bar{\theta}$*.*

Proof. If ψ satisfies $A.IV$ and $A.VII$ then:

$$a'(\Delta) = \psi_1(1+\Delta, 1-\Delta) - \psi_2(1+\Delta, 1-\Delta) > 0$$

for $\Delta > 0$. Since ζ is increasing, $z_T'(\Delta) > 0$. By **Lemma A.1**, $z_S'(\Delta) < 0$ for $\Delta > 0$. Consequently,

$$R_S(\Delta) = \frac{1}{2}\left[\frac{z_T(\Delta)}{z_S(\Delta)}\right]^r$$

is strictly increasing and continuous. By the boundary conditions in (A.6), $\mathcal{R}_S(0) < 1 < \mathcal{R}_S(\overline{\Delta})$, so there exists a unique $\Delta_S \in (0, \overline{\Delta})$ with $\mathcal{R}_S(\Delta_S) = 1$. Since $C(\boldsymbol{w})\bar{\theta}^r z_T(\Delta)^r \geq 2\,C(\boldsymbol{w})\bar{\theta}^r z_S(\Delta)^r$ reduces to $[z_T(\Delta)/z_S(\Delta)]^r \geq 2$, average talent cancels and the threshold does not depend on $\bar{\theta}$. This is equivalent to

$$\Pi\left(\bar{\theta} z_T(\Delta); \boldsymbol{w}\right) \geq 2\Pi\left(\bar{\theta} z_S(\Delta); \boldsymbol{w}\right)$$

if and only if $\Delta \geq \Delta_S$. This proves (i).

It remains to consider paid employment. The team compensates both wage outside options if

$$C(\boldsymbol{w})\bar{\theta}^r z_T(\Delta)^r \geq 2w\bar{\theta}(1+\Delta),$$

or equivalently

$$\bar{\theta}^{r-1} H(\Delta) \geq 2w, \qquad H(\Delta) = \frac{C(\boldsymbol{w}) z_T(\Delta)^r}{1+\Delta}.$$

Solving for $\bar{\theta}$ gives $\bar{\theta}_W(\Delta)$. Homogeneity and symmetry of ζ give $z_T(\Delta) = a(\Delta)\zeta(1,1)$. Multiplying by $1+\Delta$ and using (A.5),

$$(1+\Delta)\frac{H'(\Delta)}{H(\Delta)} = r\,\varepsilon_\psi(\Delta) - 1,$$

which is strictly positive on $[\Delta_S, \overline{\Delta}]$ when $r\varepsilon_\psi(\Delta) > 1$. Hence H is strictly increasing there. Since $\bar{\theta}_W(\Delta) = [2w/H(\Delta)]^{\frac{1}{r-1}}$ with $\frac{1}{r-1} > 0$, $\bar{\theta}_W$ is strictly decreasing on $[\Delta_S, \overline{\Delta}]$ and attains its minimum at $\overline{\Delta}$. Solving for $\bar{\theta}$ gives $\bar{\theta}_W(\Delta)$. This proves (ii).

Since H is strictly increasing on the relevant region, the wage condition either already holds at Δ_S, in which case set $\Delta_W(\bar{\theta}) = \Delta_S$, or it defines a unique threshold $\Delta_W(\bar{\theta}) \in (\Delta_S, \overline{\Delta}]$. Bilateral participation therefore holds if and only if

$$\Delta \geq \Delta^*(\bar{\theta}) = \max\left\{\Delta_S, \Delta_W(\bar{\theta})\right\}.$$

Finally, because $r > 1$, an increase in $\bar{\theta}$ raises team profit faster than wage income. Hence $\Delta_W(\bar{\theta})$, and therefore $\Delta^*(\bar{\theta})$, is non-increasing (and decreasing when the wage option binds) in $\bar{\theta}$.[27] This proves (iii). □

The condition $r\,\varepsilon_\psi(\Delta) > 1$ for all $\Delta \in [\Delta_S, \overline{\Delta}]$ compares two elasticities. The condition holds automatically when effective team skill is proportional to the founder's leading skill, $a(\Delta) = a(0)(1+\Delta)$, so that $\varepsilon_\psi \equiv 1$ and $r\,\varepsilon_\psi = r > 1$ for any $\nu \in (0,1)$. Holding average talent fixed, optimized team profit is proportional to $a(\Delta)^r$ and therefore grows in the founder's leading skill with elasticity $r\,\varepsilon_\psi(\Delta)$, while the two wage outside options grow with elasticity one. The condition requires the first to dominate: specialization raises team profit faster than it raises the value of paid employment, which is why the talent cutoff falls rather than rises with specialization. Equivalently, it can be written $\varepsilon_\psi(\Delta) > 1 - \nu$, since $r(1-\nu) = 1$.

A.2 Model Prediction II

Firms run by founders with more complementary skills are more productive and, through higher optimal labor demand, larger.

Proposition A.1 (Skill complementarity and team productivity)**.** *Suppose ψ satisfies A.II − A.IV and ζ satisfies A.II − A.IV. The two statements are equivalent:*

- *$\psi(\cdot)$ satisfies A.VII, i.e. $(\theta_{i,j} - \theta_{i',j})\left(\frac{\partial\psi}{\partial\theta_{i,j}} - \frac{\partial\psi}{\partial\theta_{i',j}}\right) > 0$ whenever $\theta_{i,j} \neq \theta_{i',j}$;*
- *for every pair of skill means $(\bar{\theta}_1, \bar{\theta}_2)$, $\zeta^T(\mathbf{\Theta}_{i,i'})$ is strictly increasing in $|\delta|$.*

Proof.

[27] Notice that, when the solo outside option binds, $\Delta^*(\bar{\theta}) = \Delta_S$, which is independent of talent.

$$\Big(\Longrightarrow\Big)$$

Fix a pair of skill means $(\bar{\theta}_1, \bar{\theta}_2)$ and define, for $\delta \geq 0$,

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

so that $\zeta^T(\delta) = \zeta\left(\psi_1(\delta), \psi_2(\delta)\right)$. Differentiating and using $\psi_x(a,b) = \psi_y(b,a)$, which is **A.IV**, both components have the same derivative in δ, evaluated at their own mean:

$$\psi_1'(\delta) = D(\bar{\theta}_1, \delta), \qquad \psi_2'(\delta) = D(\bar{\theta}_2, \delta), \qquad D(m,\delta) \equiv \left[\psi_x - \psi_y\right](m+\delta, m-\delta). \quad \text{(A.8)}$$

For $\delta > 0$ the two arguments of D differ, so **A.VII** gives $D(m,\delta) > 0$ for every m. Since ζ is strictly increasing by **A.III**,

$$\frac{\partial \zeta^T(\cdot)}{\partial \delta} = \frac{\partial \zeta}{\partial \psi_1} D(\bar{\theta}_1, \delta) + \frac{\partial \zeta}{\partial \psi_2} D(\bar{\theta}_2, \delta) > 0$$

for every $(\bar{\theta}_1, \bar{\theta}_2)$, which is the second statement.

$$\Big(\Longleftarrow\Big)$$

Suppose $\partial \zeta^T / \partial \delta > 0$ for every pair of skill means and every $\delta > 0$. A positive sum does not by itself sign each term in the display above, so we evaluate the condition at equal means, $\bar{\theta}_1 = \bar{\theta}_2 = m$. By **A.IV** for ψ, $\psi_1(\delta) = \psi(m+\delta, m-\delta) = \psi(m-\delta, m+\delta) = \psi_2(\delta)$, so the two arguments of ζ coincide; by **A.IV** for ζ, its two partial derivatives coincide there, with common value $\zeta' > 0$ by **A.III**. Using (A.8),

$$0 < \left.\frac{\partial \zeta^T(\cdot)}{\partial \delta}\right|_{\bar{\theta}_1 = \bar{\theta}_2 = m} = 2\,\zeta'\, D(m,\delta) \qquad \Longrightarrow \qquad D(m,\delta) > 0.$$

Every pair (x,y) with $x > y$ can be written as $(m+\delta, m-\delta)$ with $m = (x+y)/2$ and $\delta = (x-y)/2 > 0$, so $\psi_x - \psi_y > 0$ whenever $x > y$; the case $x < y$ follows from **A.IV**. Hence $(x-y)\left(\psi_x - \psi_y\right) > 0$ for all $x \neq y$, which is **A.VII**. QED. □

We can now make some claims about relative performance. 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 $p_E = \mathbb{P}(E = 0)$. 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 $F = \mathbb{1}(\zeta^I < R)$.

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**.

The thin relevant tail condition of **Definition A.1** restricts the selected-mean elasticity $\varepsilon_\mu(c)$, the distributional object that controls composition. A useful benchmark is a Pareto tail: there the selected mean is proportional to the cutoff, so $\varepsilon_\mu(c) = 1$. Since $\nu < 1$, such a tail would make composition effects too strong for the results below. The condition we impose is local: we only require $\varepsilon_\mu(c) < \nu$ over the cutoff ranges generated by team and solo participation margins.

This formulation is well suited to the quantitative model. There, skills have lognormal marginals connected through a Gaussian copula, so average talent $\bar{\theta}$ is not exactly lognormal and the selected-mean elasticity has no simple closed-form expression. We therefore treat the thin relevant tail condition as a finite-range restriction and verify it directly on the calibrated distribution of $\bar{\theta}$: we simulate the model's skill distribution, compute average talent, evaluate $\mu(c)$ over the relevant team and solo cutoff ranges, and check that $d \log \mu(c) / d \log c$ remains below ν throughout those ranges.

The next result asks whether the direct productivity effect from **Proposition A.1** survives selection into observed teams.

Proposition A.2 (Selection effect into founding teams)**.** *Suppose $\psi(\cdot)$ satisfies **A.I**–**A.IV**, and $\zeta(\cdot)$ satisfies **A.I**–**A.IV**, plus **A.VI** strictly. Also assume **A.IX**–**A.X**. If $\varepsilon_\mu(c) < \nu$, as in **Definition A.1**, and **Lemma A.4** hold, then the economy with the more specialized population has weakly higher observed average team productivity. This holds strictly if **A.X** is strict on a set of positive probability.*

Proof.

Step 1. By **Proposition A.1**, $z_T(\Delta)$ is strictly increasing in relative specialization, and because of **A.I** we can write $z_T(\bar{\theta}, \Delta) = \bar{\theta}\, z_T(\Delta) = \bar{\theta}\, a(\Delta)\, \zeta(1,1)$, where $a(\Delta) = \psi(1+\Delta, 1-\Delta)$. By **Lemma A.4**, observed teams in the relevant region satisfy $\Delta \geq \Delta_S$,

and $\bar{\theta} \geq \bar{\theta}_W(\Delta)$, where $\bar{\theta}_W$ is defined in **Equation A.7**. Conditional on Δ, expected observed team productivity is

$$M(\Delta) = \mathbb{E}\left[Z_T(\bar{\theta}, \Delta) \mid \bar{\theta} \geq \bar{\theta}_W(\Delta)\right] = z_T(\Delta)\mu\left(\bar{\theta}_W(\Delta)\right).$$

Step 2. We log-differentiate M. To do so, consider each element:

- $z_T(\Delta) \Longrightarrow (1+\Delta)\frac{z_T'(\Delta)}{z_T(\Delta)} = \varepsilon_\psi(\Delta)$
- $\mu(c) \Longrightarrow c\frac{\mu'(c)}{\mu(c)} = \varepsilon_\mu(c)$
- $\bar{\theta}_W \Longrightarrow (1+\Delta)\frac{\bar{\theta}_W'}{\bar{\theta}_W} \underbrace{=}_{A.7} \frac{1+\Delta}{r-1}\left[\frac{1}{1+\Delta} - r\frac{z_T'(\Delta)}{z_T(\Delta)}\right] = \frac{1-r\,\varepsilon_\psi}{r-1}$.

Combining them:

$$(1+\Delta)\frac{M'}{M} = \varepsilon_\psi + \varepsilon_\mu(c)\frac{1-r\varepsilon_\psi}{r-1}$$

Step 3. Collecting terms in ε_ψ:

$$(1+\Delta)\frac{M'}{M} = \frac{\big(r-1-r\,\varepsilon_\mu(c)\big)\varepsilon_\psi + \varepsilon_\mu(c)}{r-1}$$

By **Definition A.1**, $\varepsilon_\mu(c) < \nu$ for $c \in \mathcal{K}$, so $r-1-r\,\varepsilon_\mu(c) > \underbrace{r-1-\nu\,r}_{=0 \text{ as } r(1-\nu)=1} = 0$. Since $\varepsilon_\psi \geq 0$ and $\varepsilon_\mu(c) > 0$, both terms in the numerator are non-negative and the second is strictly positive. Hence $M'(\Delta) > 0$ for any $\varepsilon_\psi \geq 0$.

Step 4. Under **A.IX**, $\bar{\theta}$ and Δ are independent, so the density of relative specialization among observed teams in an economy with index s is:

$$g(\Delta, s) = \frac{f(\Delta, s)\overline{F}_{\bar{\theta}}\left(\bar{\theta}_W(\Delta)\right)\mathbb{1}\{\Delta \geq \Delta_S\}}{\int_{\Delta_S}^{\overline{\Delta}} f(u, s)\overline{F}_{\bar{\theta}}\left(\bar{\theta}_W(u)\right)du}.$$

The selection factor $\overline{F}_{\bar{\theta}}\left(\bar{\theta}_W(\Delta)\right)$ depends on Δ but not on s, since the economies share the marginal distribution of $\bar{\theta}$ and hence the same cutoff function. Therefore, for any $s' > s$:

$$\frac{g(\Delta, s')}{g(\Delta, s)} \propto \frac{f(\Delta, s')}{f(\Delta, s)}$$

which is weakly increasing in Δ by **A.X**. So $g(\cdot, s')$ dominates $g(\cdot, s)$ in the likelihood-ratio order, hence in first-order stochastic dominance.

Step 5. Let $s_0 < s_1$ index the two economies and write $A^{(k)} \equiv \int M(\Delta)\, g(\Delta, s_k)\, d\Delta$.

By **Step 4**, $g(\cdot, s_1)$ dominates $g(\cdot, s_0)$ in the monotone-likelihood-ratio order, hence in first-order stochastic dominance. Since $M(\Delta)$ is weakly increasing,

$$A^{(1)} = \int M(\Delta) g(\Delta, s_1) d\Delta \geq \int M(\Delta) g(\Delta, s_0) d\Delta = A^{(0)}.$$

The stated strictness condition gives a strict inequality.

□

A.3 Model Prediction III

Among cross-specialized teams with the same average founder talent and fixed opposite specialization profiles, greater talent dissimilarity makes the effective team skill bundle more imbalanced. Consequently, conditional on mean effective team skill, teams whose founders are more similar in talent are more productive and demand more labor.

This prediction concerns a different margin of team composition. Holding the degree of specialization fixed, how does team productivity vary with the gap between the founders' overall talent? The effect on raw team productivity cannot be signed directly, because vertical dissimilarity may also change the scale of the effective team skill bundle through ψ. We therefore isolate the composition effect by normalizing team productivity by mean effective team skill. Consider two founders with opposite specializations of fixed magnitude $\delta > 0$, average team talent $\bar{\theta}$, and vertical dissimilarity d:

$$\boldsymbol{\theta}_i(d) = \left(\bar{\theta} + \frac{d}{2} + \delta, \bar{\theta} + \frac{d}{2} - \delta\right), \qquad \boldsymbol{\theta}_{i'}(d) = \left(\bar{\theta} - \frac{d}{2} - \delta, \bar{\theta} - \frac{d}{2} + \delta\right),$$

The subset $0 \leq d < 2\delta$ consists of cross-specialized teams, as defined in Section 3.1: the first founder has an advantage in skill 1 and the second has an advantage in skill 2. We focus on this subset to isolate the effect of vertical dissimilarity while both founders continue to contribute a distinct comparative strength. Define the two effective team skills as

$$\theta_1^T(d) = \psi\left(\bar{\theta} + \delta + \frac{d}{2}, \bar{\theta} - \delta - \frac{d}{2}\right), \quad \theta_2^T(d) = \psi\left(\bar{\theta} - \delta + \frac{d}{2}, \bar{\theta} + \delta - \frac{d}{2}\right),$$

their mean as $M(d) = \left[\theta_1^T(d) + \theta_2^T(d)\right]/2$, and scale-normalized team productivity as

$$\widetilde{\zeta}(d) = \frac{\zeta\left(\theta_1^T(d), \theta_2^T(d)\right)}{\zeta\left(M(d), M(d)\right)}.$$

In this example, $\theta_1^T(d) \geq \theta_2^T(d)$ because δ and d are added with the same sign in $\theta_1^T(d)$

and in the opposite sign in $\theta_2^T(d)$. The following result uses this convention but applies without loss of generality since we assume symmetry throughout.

Proposition A.3 (Vertical composition channel)**.** *Fix average team talent $\bar{\theta}$ and the magnitude of opposite specialization $\delta > 0$. Assume that ψ satisfies $A.II - A.IV$ and $A.VII$, while ζ satisfies $A.I$, $A.IV$, and $A.VI$. Then $\widetilde{\zeta}(d)$ is weakly decreasing in vertical dissimilarity d. The decrease is strict if ζ is strictly Schur-concave over fixed-sum skill bundles. Among cross-specialized teams with the same average talent and conditional on their horizontal dissimilarity, greater vertical dissimilarity lowers productivity conditional on mean effective team skill.*

Proof. Define

$$F(\delta) = \psi(\bar{\theta} + \delta, \bar{\theta} - \delta), \qquad \delta \geq 0.$$

By symmetry and strict Schur convexity of ψ,

$$F'(\delta) = \psi_1(\bar{\theta} + \delta, \bar{\theta} - \delta) - \psi_2(\bar{\theta} + \delta, \bar{\theta} - \delta) > 0, \text{ for } \delta > 0$$

Symmetry of ψ therefore implies

$$\theta_1^T(d) = F\left(\delta + \frac{d}{2}\right), \qquad \theta_2^T(d) = F\left(\delta - \frac{d}{2}\right).$$

The ratio $\theta_1^T(d)/\theta_2^T(d)$ is strictly increasing in d, since

$$\frac{\mathrm{d}}{\mathrm{d}d} \log\left(\frac{\theta_1^T(d)}{\theta_2^T(d)}\right) = \frac{1}{2}\frac{F'\left(\delta + d/2\right)}{F\left(\delta + d/2\right)} + \frac{1}{2}\frac{F'\left(\delta - d/2\right)}{F\left(\delta - d/2\right)} > 0.$$

Define the imbalance of the effective team skill bundle as

$$q(d) = \frac{\theta_1^T(d) - \theta_2^T(d)}{\theta_1^T(d) + \theta_2^T(d)}.$$

Since $\theta_1^T(d) \geq \theta_2^T(d)$ and $\theta_1^T(d)/\theta_2^T(d)$ is strictly increasing, $q(d)$ is strictly increasing. The normalized effective skill vector is

$$\left(\frac{\theta_1^T(d)}{M(d)}, \frac{\theta_2^T(d)}{M(d)}\right) = \left(1 + q(d), 1 - q(d)\right).$$

The Balance Lemma **A.1** therefore implies that $\widetilde{\zeta}(d)$ is weakly decreasing in d, and strictly decreasing when ζ is strictly Schur-concave over fixed-sum skill bundles. □

The proposition isolates the productivity loss generated by a less balanced effective

team skill bundle. It does not impose a sign on raw team productivity $\zeta(\theta_1^T(d), \theta_2^T(d))$, because the mean effective skill $M(d)$ may itself change with vertical dissimilarity. Empirically, we can test this prediction by relating firm sales to founders' talent dissimilarity while controlling for their average talent and skill dissimilarity, as is done in **Equation 10**. These controls provide reduced-form counterparts to holding fixed the scale and specialization of the team's effective skill bundle. The corresponding regression in the calibrated model therefore evaluates whether the vertical-balance effect is sufficiently strong to generate a negative relationship between talent dissimilarity and raw firm performance

A.4 Model Prediction IV

In the presence of search frictions, entrepreneurial teams are on average more productive than solo entrepreneurs.

We now turn to the observed productivity of solo firms run by generalists. Recall from **Lemma A.3** that $Z_S(\bar{\theta}, \Delta) = \bar{\theta} z_S(\Delta)$ and that optimized solo profit is $C(w)\bar{\theta}^r z_S(\Delta)^r$. The key difference relative to the team-productivity result is that specialization works in two opposite directions for observed solo firms. Holding average talent fixed, specialization lowers solo productivity because it makes the founder's skill bundle less balanced. At the same time, specialization raises the talent cutoff for solo entrepreneurship, because the more specialized founder must compensate both the productivity loss from imbalance and the larger wage outside option. The proposition below gives a sufficient condition under which the direct productivity loss dominates this favorable selection effect.

Proposition A.4 (Aggregate Effect of Specialization on Solo Entrepreneurs)**.** *Suppose that ζ satisfies **A.I–A.IV** and **A. VI**, and suppose that the conditions of **Lemma A.4** hold, so that the solo-profit threshold $\Delta_S \in (0, \overline{\Delta})$ is well defined. Define the solo-productivity imbalance elasticity*

$$\varepsilon_S(\Delta) \equiv -\frac{d \log z_S(\Delta)}{d \log(1+\Delta)} = -(1+\Delta)\frac{z_S'(\Delta)}{z_S(\Delta)}.$$

Then:

1. *Holding average talent $\bar{\theta}$ fixed, solo productivity $Z_S(\bar{\theta}, \Delta) = \bar{\theta} z_S(\Delta)$ is weakly decreasing in relative specialization Δ. It is strictly decreasing for $\Delta > 0$ if ζ is strictly Schur-concave on fixed-sum skill bundles.*

2. *By **Lemma A.3**, solo entrepreneurship is preferred to paid employment iff $\bar{\theta} \geq \bar{\theta}_E(\Delta)$, where*

$$\bar{\theta}_E(\Delta) = \left[\frac{w(1+\Delta)}{C(\boldsymbol{w}) z_S(\Delta)^r}\right]^{\frac{1}{r-1}}, \tag{A.9}$$

and this cutoff is strictly increasing in Δ.

Now impose ***A.IX-A.X****. Let the portion of the common support associated with potential generalist solos be* $\mathcal{D}_C = [\underline{\Delta}, \Delta_S)$*, with* $0 < \underline{\Delta} < \Delta_S$.

Let $\mathcal{K}_S = \{\bar{\theta}_E(\Delta) : \Delta \in \mathcal{D}_C\}$*. Suppose* $\bar{\theta}$ *has a continuous density, the survival probability and* $\mu(c)$ *are positive and finite for every* $c \in \mathcal{K}_S$*, and the distribution of average talent has a thin relevant tail on* $\mathcal{K}_S$ *in the sense of* ***Definition A.1****. If, throughout* $\mathcal{D}_C$*,*

$$\varepsilon_S(\Delta) \geq \frac{(1-\nu)\varepsilon_\mu(\bar{\theta}_E(\Delta))}{\nu - \varepsilon_\mu(\bar{\theta}_E(\Delta))}, \tag{A.10}$$

then the economy with the more specialized population has weakly lower observed average productivity among solo firms run by generalists:

$$C^{(1)} = \mathbb{E}_1[Z_S(\bar{\theta}, \Delta) \mid S = 0, E = 0] \leq \mathbb{E}_0[Z_S(\bar{\theta}, \Delta) \mid S = 0, E = 0] = C^{(0)}.$$

The inequality is strict if the likelihood ratio in ***A.X*** *is strictly increasing on a set of positive measure and* (A.10) *is strict on a set of positive probability.*

Proof. By homogeneity of ζ,

$$\zeta(\bar{\theta}(1+\Delta), \bar{\theta}(1-\Delta)) = \bar{\theta}\zeta(1+\Delta, 1-\Delta) = \bar{\theta} z_S(\Delta).$$

The normalized bundle $(1+\Delta, 1-\Delta)$ has mean one and imbalance Δ. The Balance Lemma therefore implies that $z_S(\Delta)$ is weakly decreasing in Δ. Since ζ is differentiable, this gives $z_S'(\Delta) \leq 0$, or equivalently $\varepsilon_S(\Delta) \geq 0$. The inequality is strict for $\Delta > 0$ when ζ is strictly Schur-concave on fixed-sum skill bundles. This proves the first claim.

Now compare solo entrepreneurship with paid employment. Under symmetric wages, the founder's employment option is $w\bar{\theta}(1+\Delta)$. Solo entrepreneurship is preferred to paid employment if and only if

$$C(\boldsymbol{w})\bar{\theta}^r z_S(\Delta)^r \geq w\bar{\theta}(1+\Delta) \quad \Longrightarrow \quad \bar{\theta} \geq \left[\frac{w(1+\Delta)}{C(\boldsymbol{w}) z_S(\Delta)^r}\right]^{\frac{1}{r-1}} = \bar{\theta}_E(\Delta).$$

Because $r > 1$. Applying **Lemma A.2** to (A.9) with $k = w$ and $z = z_S$,

$$(1+\Delta)\frac{\bar{\theta}_E'(\Delta)}{\bar{\theta}_E(\Delta)} = \frac{1}{r-1}\left[1 - r(1+\Delta)\frac{z_S'(\Delta)}{z_S(\Delta)}\right] = \frac{1 + r\varepsilon_S(\Delta)}{r-1} > 0.$$

Thus, greater relative specialization lowers solo productivity at a fixed level of average talent, but raises the average-talent cutoff for solo entrepreneurship. For

$\Delta < \Delta_S$, a mirror-matched team cannot compensate both founders' solo-profit outside options. Hence, on the generalist-solo region $\mathcal{D}_C$, observed solo entrepreneurs are characterized by

$$\mathcal{G} = \left\{(\bar{\theta}, \Delta) : \Delta \in \mathcal{D}_C, \quad \bar{\theta} \geq \bar{\theta}_E(\Delta)\right\}.$$

Conditional on relative specialization Δ, mean observed productivity among these solo firms is

$$N(\Delta) = \mathbb{E}[Z_S(\bar{\theta}, \Delta) \mid \bar{\theta} \geq \bar{\theta}_E(\Delta)] = z_S(\Delta)\mu(\bar{\theta}_E(\Delta)).$$

We next show that **Definition A.1**, applied to $\mathcal{K}_S$, and (A.10) are sufficient for $N(\Delta)$ to be weakly decreasing.

Differentiating $N(\Delta) = z_S(\Delta)\mu(\bar{\theta}_E(\Delta))$ in logs yields

$$\begin{aligned}(1+\Delta)\frac{N'(\Delta)}{N(\Delta)} &= (1+\Delta)\frac{z_S'(\Delta)}{z_S(\Delta)} + (1+\Delta)\frac{\mu'(\bar{\theta}_E(\Delta))}{\mu(\bar{\theta}_E(\Delta))}\bar{\theta}_E'(\Delta) \\ &= -\varepsilon_S(\Delta) + \varepsilon_\mu(\bar{\theta}_E(\Delta))(1+\Delta)\frac{\bar{\theta}_E'(\Delta)}{\bar{\theta}_E(\Delta)}.\end{aligned}$$

where the last equality follows from $\frac{c\mu'(c)}{\mu(c)} = \varepsilon_\mu(c)$. Using the cutoff derivative derived above,

$$(1+\Delta)\frac{N'(\Delta)}{N(\Delta)} = -\varepsilon_S(\Delta) + \frac{\varepsilon_\mu(\bar{\theta}_E(\Delta))}{r-1}\left[1 + r\varepsilon_S(\Delta)\right].$$

Therefore, $N'(\Delta) \leq 0$ whenever

$$\varepsilon_S(\Delta) \geq \frac{\varepsilon_\mu(\bar{\theta}_E(\Delta))}{r-1}\left[1 + r\varepsilon_S(\Delta)\right].$$

Rearranging,

$$\left[r - 1 - r\varepsilon_\mu(\bar{\theta}_E(\Delta))\right]\varepsilon_S(\Delta) \geq \varepsilon_\mu(\bar{\theta}_E(\Delta)).$$

Since $r = 1/(1-\nu)$,

$$r - 1 - r\varepsilon_\mu(\bar{\theta}_E(\Delta)) = \frac{\nu - \varepsilon_\mu(\bar{\theta}_E(\Delta))}{1-\nu}.$$

By **Definition A.1**, applied to $\mathcal{K}_S$, $\varepsilon_\mu(\bar{\theta}_E(\Delta)) < \nu$, so the denominator in (A.10) is positive. Therefore, (A.10) is exactly the condition ensuring $N'(\Delta) \leq 0$. Hence $N(\Delta)$ is

weakly decreasing on $\mathcal{D}_C$.

It remains to compare the two economies. By **A.IX**, average talent $\bar{\theta}$ and relative specialization Δ are independent. Therefore, the density of relative specialization among observed generalist solos in an economy with index s is

$$g^C(\Delta, s) = \frac{f(\Delta, s)\overline{F}_{\bar{\theta}}(\bar{\theta}_E(\Delta))\mathbb{1}\{\Delta \in \mathcal{D}_C\}}{\int_{\mathcal{D}_C} f(u, s)\overline{F}_{\bar{\theta}}(\bar{\theta}_E(u))du}.$$

The talent-selection term is common across economies, because the marginal distribution of $\bar{\theta}$ is the same. Hence, for any $s' > s$,

$$\frac{g^C(\Delta, s')}{g^C(\Delta, s)} = K_C \frac{f(\Delta, s')}{f(\Delta, s)}$$

for some constant $K_C > 0$, which is weakly increasing in Δ by **A.X**. Thus, relative specialization among observed generalist solos is higher in the more specialized economy in the monotone-likelihood-ratio order. Let $s_0 < s_1$ index the two economies and write $C^{(k)} \equiv \int_{\mathcal{D}_C} N(\Delta)\, g^C(\Delta, s_k)\, d\Delta$. Since $N(\Delta)$ is weakly decreasing,

$$C^{(1)} = \int_{\mathcal{D}_C} N(\Delta) g^C(\Delta, s_1) d\Delta \leq \int_{\mathcal{D}_C} N(\Delta) g^C(\Delta, s_0) d\Delta = C^{(0)}.$$

The stated strictness conditions give a strict inequality. □

The condition in (A.10) uses the same decomposition as the observed team-productivity result in **Proposition A.2**. The term $\varepsilon_S(\Delta)$ is technological: it is the elasticity of the solo-productivity loss from making a fixed-mean skill bundle more imbalanced, and is pinned down by the primitive productivity aggregator ζ. The shared selected-mean elasticity $\varepsilon_\mu(\cdot)$ is evaluated here at the solo-entry cutoff $\bar{\theta}_E(\Delta)$, where it captures how strongly the selected mean of average talent responds to the cutoff induced by specialization. In **Proposition A.2**, specialization raises direct team productivity but lowers the team-entry talent cutoff, creating an adverse composition effect. Here the signs are reversed. Specialization lowers direct solo productivity but raises the solo-entry talent cutoff, creating a favorable composition effect. The proposition requires the former force to dominate the latter on the relevant generalist-solo region.

By symmetry, $z_S'(0) = 0$, and therefore $\varepsilon_S(0) = 0$. At the same time, the solo-entry cutoff is increasing at zero because the wage outside option rises with the founder's strongest skill. If the average-talent density is positive at $\bar{\theta}_E(0)$ and the upper tail above that cutoff is non-degenerate, the favorable selection effect dominates in a neighborhood of zero. Hence the model does not imply that observed generalist-solo productivity falls

for arbitrary shifts in specialization that place substantial mass arbitrarily close to perfect balance. The result applies on the empirically relevant generalist-solo region where specialization is positive enough for the imbalance penalty in solo production to be active.

This formulation also connects naturally to the quantitative model. The production side determines $\varepsilon_S(\Delta)$ through the same skill aggregator ζ used to compute solo productivity. The distributional side determines $\varepsilon_\mu(c)$ through the tail behavior of average talent. The thin relevant tail condition bounds this distributional force at both the team and solo cutoffs. The two sides are disciplined differently. On the team side, the only technological condition is $r\,\varepsilon_\psi(\Delta) > 1$ in **Lemma A.4**, which makes the team-formation cutoff fall with specialization; given it, the direct productivity gain dominates the adverse composition effect whenever $\varepsilon_\mu < \nu$, with no further restriction on the aggregator. On the solo side, (A.10) additionally requires the technological imbalance penalty $\varepsilon_S(\Delta)$ to dominate the favorable selection effect among solo firms.

Corollary A.1 (Higher Specialization Lowers Productivity of Solos in the Economy)**.** *Under the conditions of* ***Proposition A.4****, let* $\mathcal{D}_B = [\Delta_S, \overline{\Delta}]$ *denote the relative-specialization region associated with potential team founders, and define*

$$\bar{\theta}_B(\Delta) = \max\{\bar{\theta}_W(\Delta), \bar{\theta}_E(\Delta)\}, \qquad \mathcal{K}_B = \{\bar{\theta}_B(\Delta) : \Delta \in \mathcal{D}_B\}.$$

Suppose the distribution of average talent has a thin relevant tail on $\mathcal{K}_B$ *in the sense of* ***Definition A.1****, and suppose* (A.10) *holds whenever* $\bar{\theta}_E(\Delta) \geq \bar{\theta}_W(\Delta)$*. Then the economy with the more specialized population has weakly lower observed productivity among specialist solos:*

$$B^{(1)} \leq B^{(0)}.$$

Proof. A specialist who does not form a team operates a solo firm only if two conditions hold. First, the founder must satisfy the team-participation condition characterized in **Lemma A.4**. Second, conditional on not forming a team, the founder must prefer solo entrepreneurship to paid employment.

Observed specialist solos are therefore characterized by

$$\Delta \in \mathcal{D}_B, \qquad \bar{\theta} \geq \bar{\theta}_B(\Delta).$$

Conditional on relative specialization Δ, their mean observed solo productivity is

$$P_B(\Delta) = \mathbb{E}\left[Z_S(\bar{\theta}, \Delta) \mid \bar{\theta} \geq \bar{\theta}_B(\Delta)\right] = z_S(\Delta)\mu(\bar{\theta}_B(\Delta)).$$

We first show that $P_B(\Delta)$ is weakly decreasing. There are two cases. If $\bar{\theta}_B(\Delta) = \bar{\theta}_W(\Delta)$, then the team-participation cutoff binds. By **Lemma A.4**, $\bar{\theta}_W(\Delta)$ is weakly decreasing on $[\Delta_S, \overline{\Delta}]$. By the Balance Lemma, $z_S(\Delta)$ is weakly decreasing. Since $\mu(c)$ is weakly increasing in c, the composition term $\mu(\bar{\theta}_W(\Delta))$ is also weakly decreasing. Hence $P_B(\Delta)$ is weakly decreasing on this region.

If $\bar{\theta}_B(\Delta) = \bar{\theta}_E(\Delta)$, then the solo-entry cutoff binds. The same calculation as in **Proposition A.4** applies. The thin relevant tail condition on $\mathcal{K}_B$ and (A.10) imply that the direct solo-productivity loss from specialization dominates the favorable selection effect, so $P_B'(\Delta) \leq 0$ on the region where the solo-entry cutoff binds. Therefore $P_B(\Delta)$ is weakly decreasing on $\mathcal{D}_B$.

It remains to compare the two economies. By **A.IX**, average talent $\bar{\theta}$ and relative specialization Δ are independent. Therefore, the density of relative specialization among observed specialist solos in an economy with index s is

$$g^B(\Delta, s) = \frac{f(\Delta, s)\overline{F}_{\bar{\theta}}(\bar{\theta}_B(\Delta))\mathbb{1}\{\Delta \in \mathcal{D}_B\}}{\int_{\mathcal{D}_B} f(u, s)\overline{F}_{\bar{\theta}}(\bar{\theta}_B(u))du}.$$

The talent-selection term is common across economies, because the marginal distribution of $\bar{\theta}$ is the same. Hence, for any $s' > s$,

$$\frac{g^B(\Delta, s')}{g^B(\Delta, s)} = K_B \frac{f(\Delta, s')}{f(\Delta, s)}$$

for some constant $K_B > 0$, which is weakly increasing in Δ by **A.X**. Thus, relative specialization among observed specialist solos is higher in the more specialized economy in the monotone-likelihood-ratio order. Let $s_0 < s_1$ index the two economies and write $B^{(k)} \equiv \int_{\mathcal{D}_B} P_B(\Delta)\, g^B(\Delta, s_k)\, d\Delta$. Since $P_B(\Delta)$ is weakly decreasing,

$$B^{(1)} = \int_{\mathcal{D}_B} P_B(\Delta) g^B(\Delta, s_1) d\Delta \leq \int_{\mathcal{D}_B} P_B(\Delta) g^B(\Delta, s_0) d\Delta = B^{(0)}.$$

The inequality is strict if the likelihood-ratio shift is strict on a set of positive probability and $P_B(\Delta)$ is strictly decreasing on that set. □

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

$$D = \quad p_E \left(1 - \underbrace{p \cdot q}_{\text{teams}} - \underbrace{p \cdot (1-q) \cdot \pi}_{\text{specialists who prefer paid work}} \right) =$$

$$= \underbrace{p_E \cdot (1-p)}_{\text{non-specialists who prefer solo firms to employment}} + \underbrace{p_E \cdot p \cdot (1-q) \cdot (1-\pi)}_{\text{specialists who prefer solo firms to employment}}$$

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 accounting result:

Proposition A.5 (Team vs solo founders productivity and Search Frictions)**.** *Suppose $A > B$. Then observed average team productivity exceeds observed average solo productivity if and only if*

$$\mu_T > \mu_I \iff q < q^*,$$

where

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

Proof. Observed team productivity is

$$\mu_T = A.$$

Observed solo firms are a mixture of two groups. Generalist solos have mass $p_E(1-p)$ and average productivity C. Specialist solos have mass $p_E p(1-q)(1-\pi)$ and average productivity B. Therefore, total observed solo mass is

$$D = p_E(1-p) + p_E p(1-q)(1-\pi),$$

and observed average solo productivity is

$$\mu_I = \frac{p_E(1-p)C + p_E p(1-q)(1-\pi)B}{p_E(1-p) + p_E p(1-q)(1-\pi)}.$$

Since $p_E > 0$, it cancels. Hence $\mu_T > \mu_I$ if and only if

$$A > \frac{(1-p)C + p(1-q)(1-\pi)B}{(1-p) + p(1-q)(1-\pi)}.$$

Multiplying by the positive denominator gives

$$A(1-p) + Ap(1-q)(1-\pi) > (1-p)C + p(1-q)(1-\pi)B.$$

Rearranging,

$$p(1-q)(1-\pi)(A-B) > (1-p)(C-A).$$

Since $A > B$, this is equivalent to

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

or

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

□

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.

For the comparative static below, let $p_k = \Pr_k(S = 1 \mid E = 0)$ denote the share of non-workers who are specialists in economy k, and let $\pi_k = \Pr_k(F = 1 \mid S = 1, E = 0)$ denote the share of specialists who, after not forming a team, choose paid employment rather than solo entrepreneurship. Define

$$R_k = \frac{1-p_k}{p_k(1-\pi_k)}, \qquad G_k = \frac{C_k - A_k}{A_k - B_k}.$$

The term R_k is the mass of generalist solos relative to specialist solos among non-workers. The term G_k is the productivity-gap term in the search threshold.

Corollary A.2 (Search threshold)**.** *Consider two economies, $k = 0, 1$, that differ only in the distribution of relative specialization Δ. Suppose economy 1 has more dispersed relative skill profiles than economy 0, in the sense of **A.X**. Let q_k^* denote the search threshold characterized above.*

*Suppose the conditions of **Proposition A.2**, **Proposition A.4**, and **Corollary A.1** hold, so that*

$$A_1 \geq A_0, \qquad B_1 \leq B_0, \qquad C_1 \leq C_0.$$

Assume also that $A_k > B_k$ and $C_k \geq A_k$. Then:

1. *If $R_1 G_1 \leq R_0 G_0$, then $q_1^* \geq q_0^*$. Hence the observed team-productivity advantage can arise under weakly less severe search frictions.*

2. *If $R_1 G_1 > R_0 G_0$, then $q_1^* < q_0^*$. Hence the observed team-productivity advantage requires more severe search frictions.*

In particular, because the productivity-gap term falls under the propositions above, $R_1 \leq R_0$ is sufficient for $q_1^* \geq q_0^*$. If instead $R_1 > R_0$, the sign is ambiguous: search frictions become more important only when the increase in the relative mass of generalist solos is large enough to dominate the fall in the productivity-gap term.

Proof. From the definition of q_k^*,

$$q_k^* = 1 - R_k G_k.$$

We first show that $G_1 \leq G_0$. From **Proposition A.2** and **Corollary A.1**,

$$A_1 - B_1 \geq A_0 - B_0.$$

From **Proposition A.4** and **Proposition A.2**,

$$C_1 - A_1 \leq C_0 - A_0.$$

Since $A_k > B_k$ and $C_k \geq A_k$, both denominators are positive and both numerators are nonnegative. Therefore,

$$G_1 = \frac{C_1 - A_1}{A_1 - B_1} \leq \frac{C_0 - A_0}{A_0 - B_0} = G_0.$$

Finally, since $q_k^* = 1 - R_k G_k$, we have $q_1^* \geq q_0^*$ if and only if $R_1 G_1 \leq R_0 G_0$, and $q_1^* < q_0^*$ if and only if $R_1 G_1 > R_0 G_0$. The stated interpretation follows from the previous proposition, because teams are more productive than solos if and only if $q < q^*$. □

B Data Appendix

B.1 Quadros de Pessoal

The main data source is the *Quadros de Pessoal* (hereafter QP) for the 1985-2018 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[28]. 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 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 (2025) 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

[28]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.

in **Table C.3** descriptive statistics for workers in the sample, covering all years from 1991 to 2018.

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 2018. 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 exclusion of the public sector, finance and insurance businesses).[29]

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. In order to separate firm owner from plausibly self-employed people, we label the former as individuals running a firm with more than 1 employee.

Entrepreneurs can be further characterized as *serial* when they own multiple enterprises 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.[30] We calculate quantiles of several characteristics for their work careers upon becoming entrepreneurs: size of the firm, sales,

[29] 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.

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

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.

Skills. We construct individual skill exposure by combining occupation-level skill requirements from O*NET 30.3 Skill Levels with individuals' work histories. We exploit both "Essential Skills" (e.g. Speaking, Writing, Mathematics, Reading Comprehension, Critical Thinking etc.) and "Transferable Skills" (e.g. Complex Problem Solving, Social Perceptiveness, Negotiation, System Analysis, Equipment Maintenance, Repairing etc.) for a total of 35 skills.[31] For each individual, we weight the skill bundle of every occupation held over their career by tenure. For founders, we consider their careers up to their first entrepreneurial spell.

For the estimation of the model, we collapse the 35-dimensional skill vector into the first three factors, obtained with a restriction of non-negativity on their weights. **Figure B.1** reports the individual loadings for each of them.

O*NET Level ratings are elicited on behaviorally anchored scales: each level is pinned to concrete task exemplars, and the same anchored scale applies to every occupation, so that a given skill is measured comparably across occupations and level differences carry an interval interpretation — in contrast to importance indexes, which are ordinal by construction. Comparability across *different* skills is not anchored by the instrument; in our construction it is supplied by the data, through the non-negative factor loadings of **Figure B.1** and the market prices of skill bundles in **Table 2**.

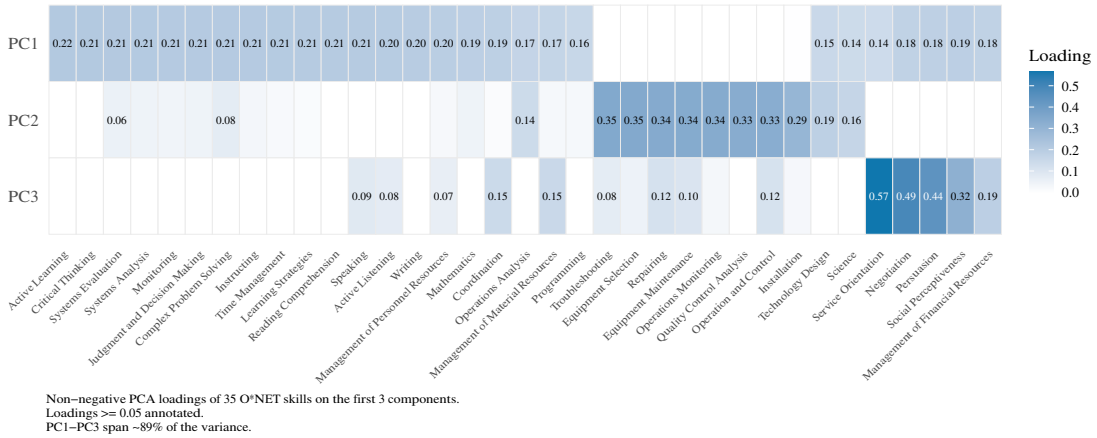
Similarity measures. To characterize the composition of founding teams, we construct measures of within-team dissimilarity along two dimensions. Let f be a founding team of size N_f and $\mathbf{x}_i$ a K-dimensional vector of characteristics for founder $i \in f$. For each pair (i, i'), we compute the Euclidean distance $d(\mathbf{x}_{ii'}) = \|\mathbf{x}_i - \mathbf{x}_{i'}\|$ and define team-level dissimilarity as the average pairwise distance:

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

We apply this separately to two vectors: (i) founders' AKM worker fixed effects, yielding *Vertical Dissimilarity (VD)*, and (ii) founders' O*NET skill specialization vectors, yielding *Horizontal Dissimilarity (HD)*.

[31] We map O*NET occupation into ISCO using the ESCO-O*NET Crosswalk.

Figure B.1: O*NET Loadings



Note: The figure reports the non-negative loadings on each of the 35 O*NET skills. *Cited on p. 19, 27.*

Two properties of this construction deserve note. First, the three non-negative factors preserve the contrast the analysis is built on: projecting each founding pair's 35-skill difference vector onto the space spanned by the factor loadings retains 84% of its squared magnitude, and teams pairing an engineering or ICT professional with a business or sales professional — the sharpest case of cross-functional complementarity — rank in the top quartile of skill dissimilarity whether distances are computed on the 35 skills or on the three factors. Second, no result rides on the metric of the O*NET scale: recomputing Δ_f after replacing each skill with its population percentile rank, or on two to four principal components instead of three, leaves the association between skill dissimilarity and firm performance in **Table 5** positive, significant, and of similar magnitude.

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.

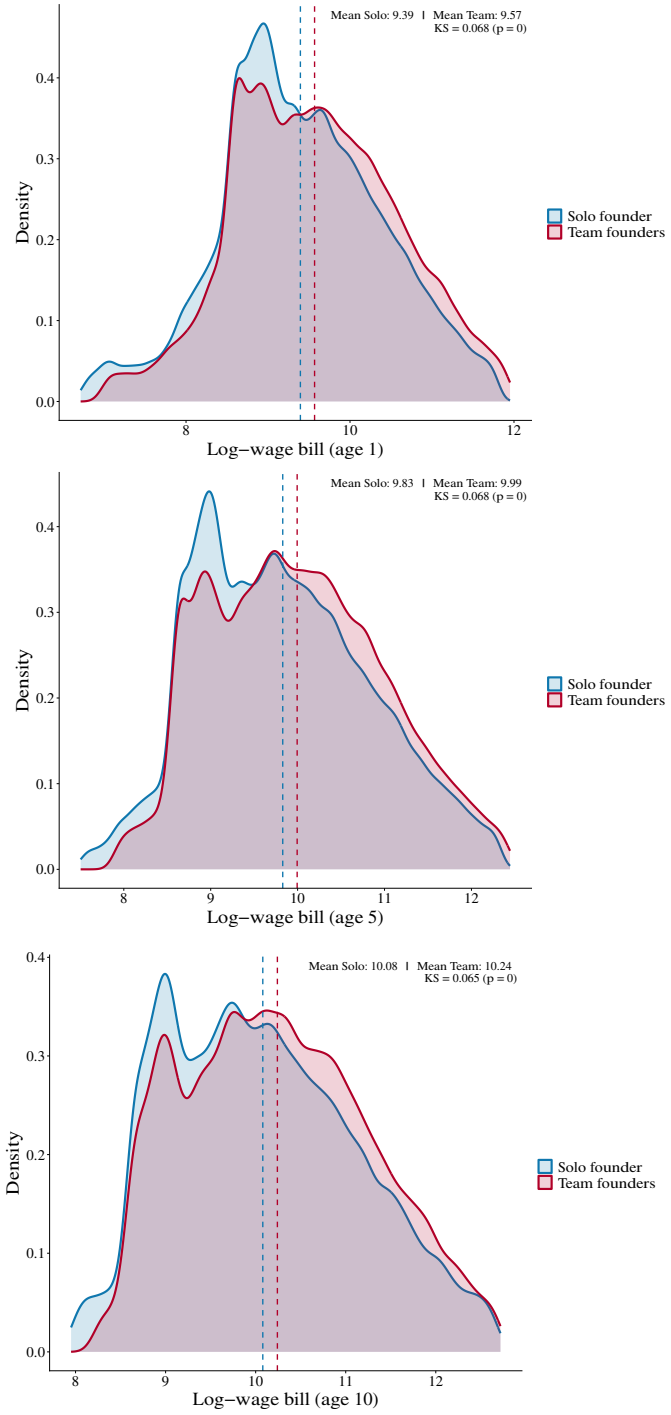
One way to overcome this limitation is to give up the estimation of workplace effects, and aim at estimating effects corresponding to more broadly defined categories that can expand the connected set. That is the approach in Bonhomme, Lamadon and Manresa (2019), who employ a K-means clustering algorithm (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.[32]

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.

[32]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.

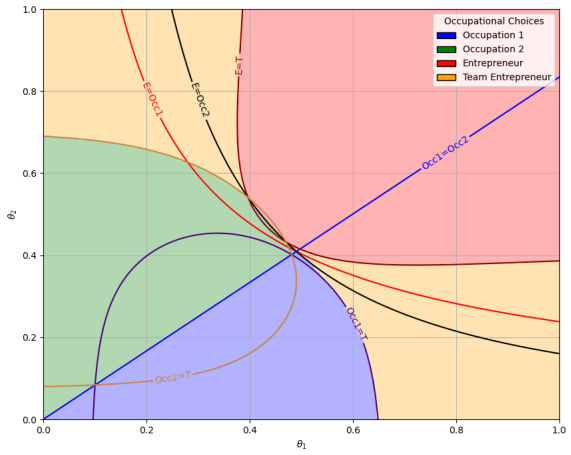
C Appendix Tables and Figures

Figure C.1: Distribution of Residualized log-Wage Bill: Solo vs Team-Founded Firms



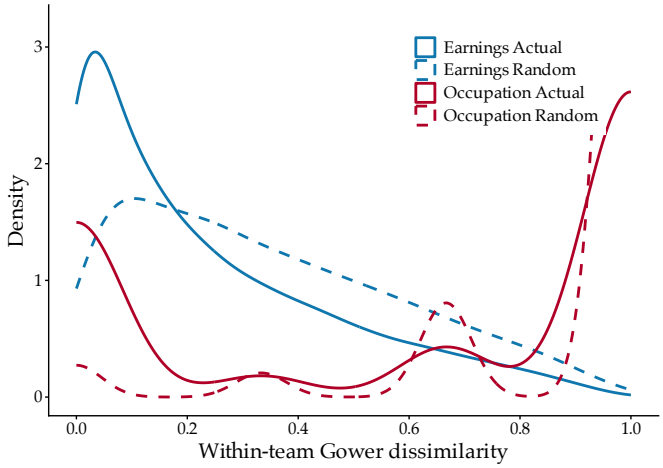
Note: Kernel density estimates of log-wage bill for solo-founded (blue) and team-founded (red) firms at firm age 1 (top left), firm age 5 (top right), and firm age 10 (bottom). Data is from *Quadros de Pessoal*, 1991–2018. *Cited on p. 8.*

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



Note: The figure shows the choices of agent i, in partial equilibrium, upon meeting a potential partner i' with skill bundle $(\theta_1, \theta_2) = (0.45, 0.45)$, represented by the star in the figure. Contrary to **Figure 4a**, in which the skills are unbalanced, this potential partner is equally specialized in skill 1 and 2. The areas report the choice of individual i of occupation, solo entrepreneurship and team formation as a function of their skill mix. *Cited on p. 15.*

Figure C.3: Within-team dissimilarity: actual vs. random matching benchmark



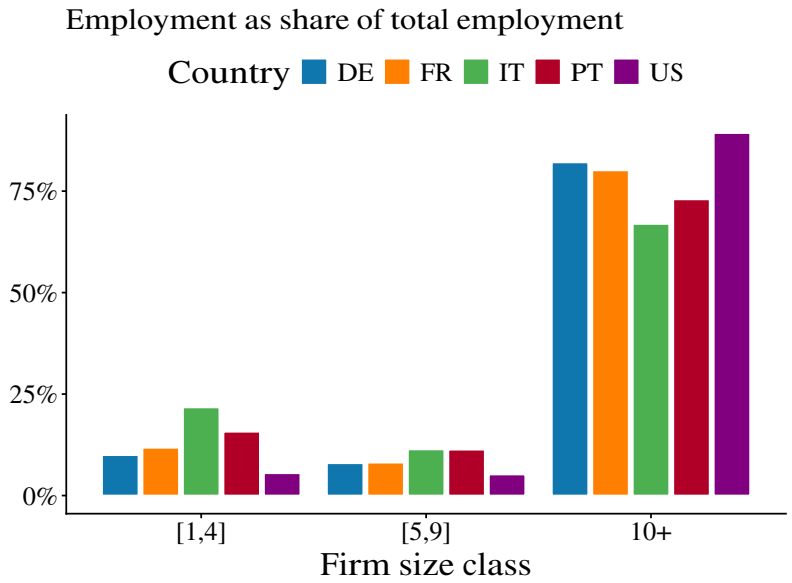
Note: Density estimates of within-team Gower dissimilarity for two-founder teams (solid lines) compared to randomly matched pairs drawn from the same founder pool (dashed lines). Earnings index (blue): absolute difference in within-year earnings percentile ranks, normalized to $[0, 1]$. Occupation index (red): hierarchical distance on three-digit occupation codes (0 = same 3-digit, 1/3 = same 2-digit only, 2/3 = same 1-digit only, 1 = different 1-digit). Random benchmark: 10,000 pairs drawn with replacement from all founders with non-missing earnings and occupation. Both actual distributions are shifted left relative to their random benchmarks, confirming positive sorting on both dimensions. Sample: 19,888 two-founder teams with pre-entry earnings and three-digit occupation observed for both co-founders (out of 60,634 two-founder teams in the universe). Data from *Quadros de Pessoal*, 1991–2018. *Cited on p. 9.*

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

	Mean	SD	Median	P25	P75	N
Age	44.49	10.26	44.00	37.00	52.00	3,700,724
Age at Founding	41.50	9.93	41.00	34.00	49.00	3,251,597
College %	0.17	0.38	0.00	0.00	0.00	3,580,478
Firm Age	12.31	12.54	8.00	4.00	16.00	3,700,724
# Employees	2.18	0.97	2.00	1.00	3.00	3,536,527
Firms Owned	1.06	0.39	1.00	1.00	1.00	3,700,724
# Founders	1.50	1.14	1.00	1.00	2.00	3,700,724
# Owners	1.63	0.95	1.00	1.00	2.00	3,700,724
Log Sales	12.39	1.46	12.25	11.39	13.28	3,397,313
Female %	0.29	0.45	0.00	0.00	1.00	3,700,724

Note: The table reports descriptive statistics for entrepreneurs in the matched employer-employee sample from *Quadros de Pessoal*, covering all years from 1991 to 2018. Sales are deflated by using the 2010 CPI. *Cited on p. 6, 44.*

Figure C.4: Employment Shares by Firm Size Class: International Comparison



Note: The figure reports the share of total employment accounted for by firms in each of three size classes ($[1, 4]$, $[5, 9]$, 10+ workers) across Germany (DE), France (FR), Italy (IT), Portugal (PT), and the United States (US). *Sources:* EU: Eurostat, Employer business demography by size class and NACE Rev. 2, 2021; US: Business Dynamics Statistics, 2021. *Cited on p. 6.*

Table C.2: Characteristics of Solo and Team Founders

	Solo Founders		Team Founders		Difference	
	Mean	SD	Mean	SD	Diff	SE
Panel A: Demographics						
Age at founding	40.3	10.2	44.5	10.2	4.2***	(0.0)
Sh. female	0.309	0.462	0.296	0.456	-0.013***	(0.001)
Sh. college	0.170	0.376	0.135	0.341	-0.036***	(0.001)
Sh. prev. entrep. exp.	0.187	0.390	0.147	0.354	-0.040***	(0.001)
Panel B: Pre-entry labor market						
Sh. previously manager	0.146	0.353	0.129	0.335	-0.017***	(0.001)
Prev. 5y avg. earnings	11,489	10,285	11,091	9,574	-398***	(35)
Cumul. earnings	63,118	88,593	57,995	79,151	-5,124***	(292)
Prev. employee jobs	5.10	4.21	4.97	4.11	-0.13***	(0.01)
Prev. job tenure (quintile)	2.35	1.29	2.40	1.29	0.05***	(0.00)
Prev. empl. size (quintile)	2.05	1.23	2.03	1.20	-0.02***	(0.00)
Prev. sect.: manufacturing	0.237	0.425	0.263	0.440	0.026***	(0.002)
Prev. sect.: trade/retail	0.366	0.482	0.360	0.480	-0.006***	(0.002)
Prev. sect.: construction	0.124	0.329	0.130	0.336	0.006***	(0.001)
Obs. (Panel A)	391,898		299,822			
Obs. (Panel B)	198,926		136,887			

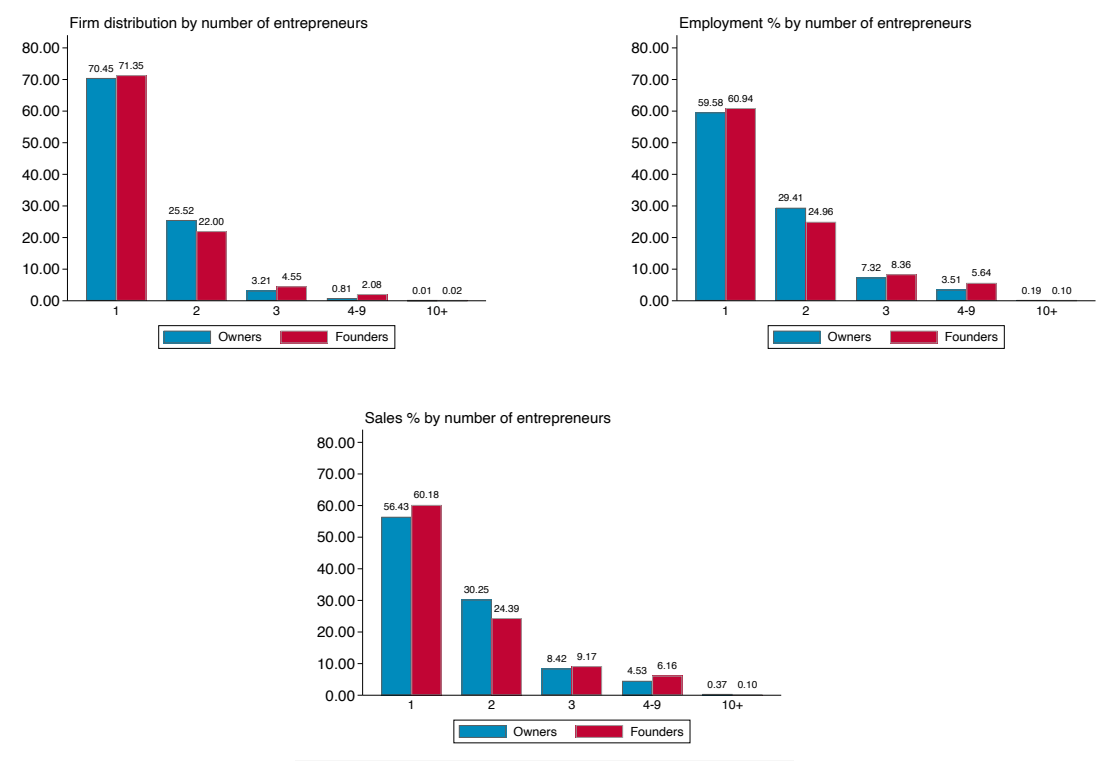
Note: The table compares characteristics of solo founders (one founder) and team founders (two or more founders). Panel A reports demographics measured at the time of firm founding. Panel B reports pre-entry labor market characteristics, conditional on the founder having previous employment history in the data. Tenure and employer size are within-year quintiles (1–5). Sector shares are computed among founders with a recorded prior sector. The Difference column reports the team–solo difference in means; standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from *Quadros de Pessoal*, 1991–2018. All nominal values deflated by the 2010 CPI. *Cited on p. 8.*

Table C.3: Descriptive Statistics from *Quadros de Pessoal*, workers

	Mean	SD	Median	P25	P75	N
Age	37.2	11.2	36	28	45	55,436,136
Sh. Female	.413	.492	0	0	1	55,436,136
Sh. High educated	.105	.307	0	0	0	54,197,020
Sh. Managers	.0562	.23	0	0	0	49,044,731
Sh. Temp. contracts	.283	.451	0	0	1	36,586,965
Sh. Part-time	.129	.335	0	0	0	55,427,884
Tenure	7.83	8.66	5	1	12	55,436,136
Yearly wage	11,985	10,046	9,100	6,356.49	14,440.5	55,436,136
Firm size	1,164	3,533	59	12	417	55,436,136
Num. jobs	1.02	.404	1	1	1	55,436,045

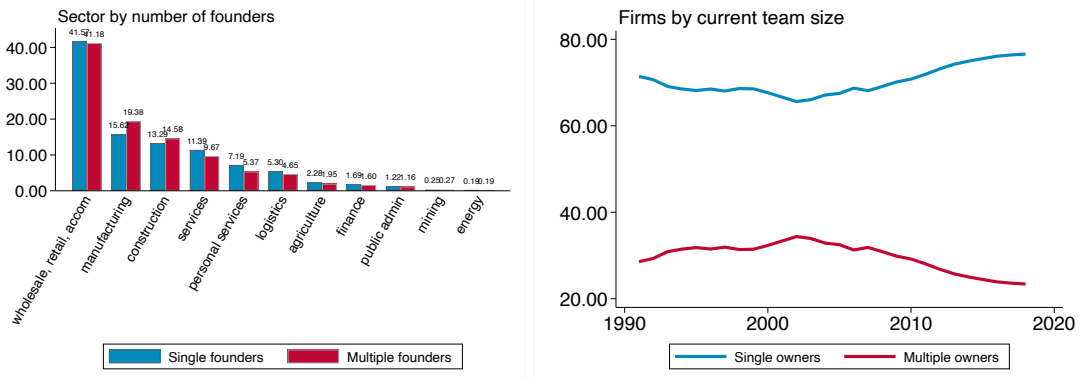
Note: The table reports descriptive statistics for workers in the sample, covering all years from 1991 to 2018. Wages are deflated by the 2010 CPI. The detail on temporary vs. permanent contract is only available from 2000 onwards. *Cited on p. 6, 26.*

Figure C.5: Distributions of Firms, Employment and Sales by Number of Entrepreneurs



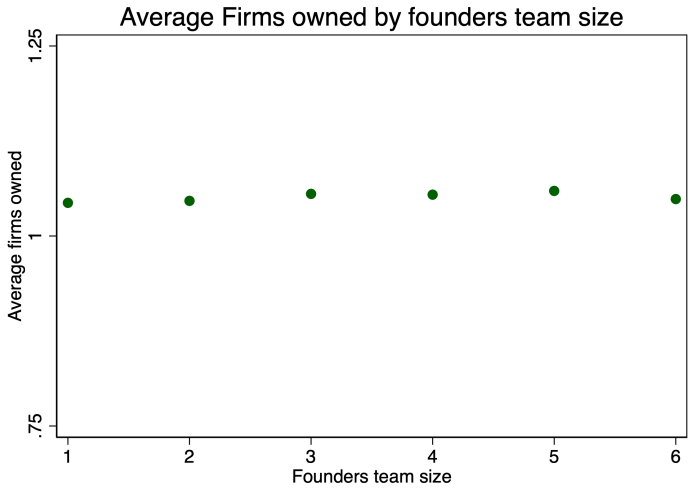
The figure shows the distribution of privately-held firms (left), employment by these firms (center), and sales of these firms (right), by number of owners (in blue) and number of founders (in red). Data is from the matched employer-employee sample of *Quadros de Pessoal*, covering all years from 1991 to 2018. *Cited on p. 6.*

Figure C.6: Industry and Time Trends of Firms by Team Ownership



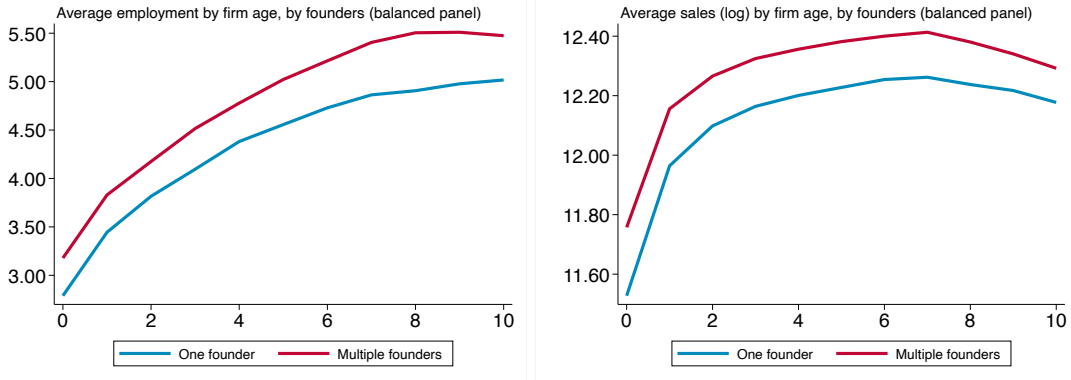
Note: The left panel presents the distribution of privately owned firms in each sector of the economy, using 1-digit NACE codes to define sectors. The blue bars cover exclusively the subset of firms founded by one entrepreneur, while the red bars cover the subset of firms founded by more than one entrepreneur. The right panel shows the percentage of privately owned firms by single or multiple owner status. The data are from the Portuguese *Quadros de Pessoal*, and range from 1991 to 2018. *Cited on p. 6.*

Figure C.7



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 2018. *Cited on p. 6.*

Figure C.8: Average Life-Cycle Employment and Sales for a Balanced Panel of Firms



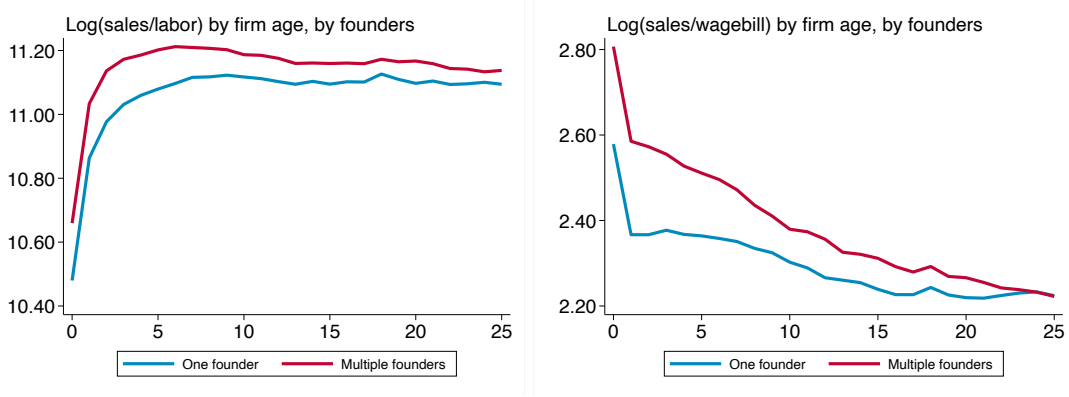
Note: The figure shows the average number of workers per firm (left) and average logged sales (right) of firms by firm age, measured in years. In both cases, the blue line represents firms founded by only one entrepreneur, while the red line represents firms founded by more than one entrepreneur. The data are from the Portuguese *Quadros de Pessoal*, and range from 1991 to 2018. *Cited on p. 7.*

Table C.4: Founding Team Characteristics and Firm Performance

Dependent Variable:	Log Sales				
	(1)	(2)	(3)	(4)	(5)
Variables					
Avg. Work FE	0.181***	0.128***	0.111***	0.111***	0.056***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Worker FE dissimilarity (std.)	−0.021***	−0.015***	−0.008***	−0.008***	−0.007**
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
O*NET skill dissimilarity (std.)	0.036***	0.037***	0.039***	0.039***	0.010*
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
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
Serial Entrepreneur	Yes	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes	Yes
Size, Employment quintiles		Yes	Yes	Yes	Yes
Log Total Earnings, quintiles			Yes	Yes	Yes
Initial size, Employment quintiles				Yes	Yes
Log Initial Total Assets, quintiles					Yes
Fit statistics					
Observations	83,915	83,915	83,915	83,915	43,199
R^2	0.285	0.538	0.543	0.548	0.633
Within R^2	0.018	0.015	0.011	0.011	0.004
No. Firms	25,397	25,397	25,397	25,397	13,183

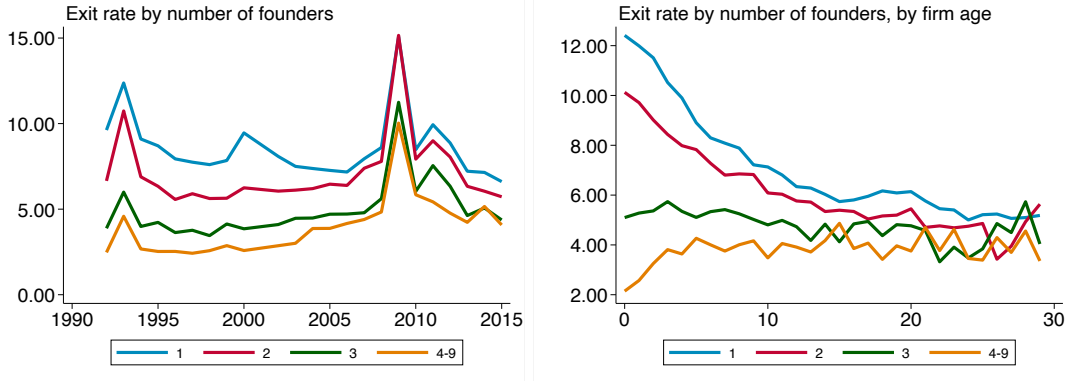
Note: The table reports the relationship between founding team characteristics and firm performances based on **Equation 10**. *Avg. Work FE* is the average AKM worker FEs of founders, *Worker FE dissimilarity* is the average of pairwise Euclidean distances of founders' AKM worker FEs, and *Skill dissimilarity* 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. This table extends the specification of **Table 5** with all five progressive control sets. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 54, 55, 60.*

Figure C.9: Average Life-Cycle Labor Productivity by Number of Entrepreneurs



Note: The figure presents two measures of average log labor productivity by firm age. The left-hand-side panel plots log(sales/number of workers); the right-hand-side panel plots log(sales/wage bill), a measure of revenue productivity that nets out variation in hours and worker composition. In both panels, the blue line is the average for firms founded by a single entrepreneur, and the red line is for firms founded by more than one entrepreneur. The data are from the Portuguese *Quadros de Pessoal*, and cover all years from 1991 to 2018. *Cited on p. 7.*

Figure C.10: Exit Rates by Number of Entrepreneurs



Note: The figure shows the exit rate, defined, separately for each founder-team-size group, as the number of firms of that group exiting over the total number of firms of that group, multiplied by 100. The left-hand-side chart presents yearly exit rates, while the right-hand-side chart 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 2018. *Cited on p. 7.*

C.1 Robustness: Teams Outside the Skill-Measurement Sample

Our measure of founders' horizontal dissimilarity requires a pre-founding O*NET skill vector for each team member. We cannot build one for every founder: first-time founders with no prior employment spell in *Quadros de Pessoal*, founders who enter from prior ownership or self-employment, and founders whose recorded occupation does not map to O*NET all lack a skill vector. Firms with at least one such founder are dropped from the skill-dissimilarity regressions, or enter them with fewer founders. The restriction concerns the skill vector alone; it does not itself condition on AKM fixed effects or on the presence of an employment history. It raises the concern that the descriptive gap between team- and solo-founded firms is an artifact of selecting on measurable skills. It is not. **Table C.5** restricts attention to exactly these firms: team founders are older at founding (45.3 against 41.3 years) and less likely to hold a college degree (0.125 against 0.159), the same pattern as in the full sample, and team-founded firms start out with 0.28 log points higher sales (12.181 against 11.903) and a lower exit share (0.071 against 0.103). The life-cycle gaps in **Table C.6** match the full-sample ones almost exactly. Finally, **Table C.7** shows that the firms the skill analysis cannot cover are not negatively selected: at age 1 they are slightly larger and more productive, and by age 10 they are indistinguishable from firms with full coverage. The team premium holds in the firms the skill-dissimilarity analysis leaves out.

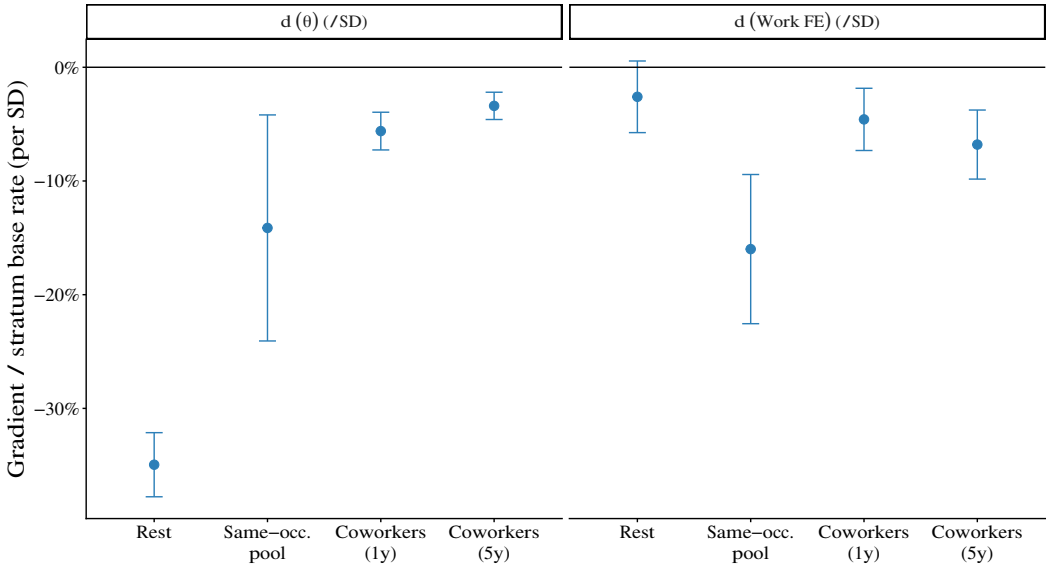
C.2 Dyadic Gradients by Exposure Stratum

This section decomposes the dyadic distance gradients of **Equation 9** by founders' pre-entry exposure. We assign every dyad in the worker-sample design of **Table 4** to one of three mutually exclusive strata: confirmed former *coworkers*, who were employed at the same firm in at least one common calendar year strictly before entrepreneurial entry;[33] pairs in the same region–occupation pool (same NUTS II region and occupation code, never coworkers); and a residual stratum of unconnected pairs. We then interact all three distance regressors with the stratum indicators, and additionally allow the coworker gradients to vary with the length of overlapping tenure. Because the co-founding base rates of the three strata differ by orders of magnitude in our case-control sample, **Figure C.11** reports each gradient divided by its stratum-year base rate: the proportional change in the co-founding rate per standard deviation of distance, a scale on which the strata are directly comparable and which is invariant, to first order, to the counterfactual-pair sampling rates.

[33] Coworker status is measured at the firm level; firm-years with more than 1,000 employees are excluded, since very large plants are uninformative about targeted co-founder search. Employment spells are censored at the founding-cohort year, so no post-founding contact enters the exposure measure.

The two skill dimensions respond to exposure very differently. The HD gradient declines monotonically with proximity – roughly −35% of the base rate per standard deviation among unconnected pairs, −14% within region–occupation pools, and −5.6% and −3.4% among coworkers with one and five years of overlapping tenure – indicating that skill distance deters team formation mainly by limiting encounters, with familiarity progressively attenuating the residual penalty. The VD gradient instead peaks where potential partners can best observe one another's quality: it is small and imprecise among unconnected pairs, strongest within occupation pools (−16%), and, among coworkers, steepens with overlapping tenure (from −4.6% at one year to −6.8% at five). Horizontal sorting thus behaves like an exposure friction, which the matching technology in our model can in principle undo, whereas vertical sorting operates through information about partner quality that accumulates with contact. The residual distance penalty among long-acquainted coworkers is the component that removing meeting bias cannot eliminate; it motivates the intermediate counterfactuals of **Section 6**, which remove only a fraction of the estimated wedge.

Figure C.11: Co-founding distance gradients by exposure stratum

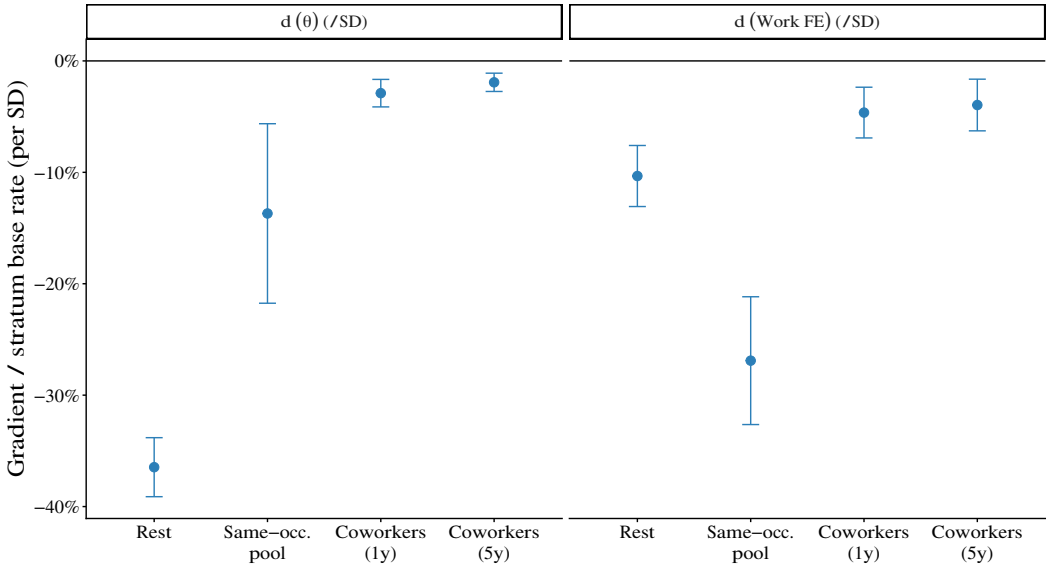


Note: Average coefficients from **Equation 9** augmented with exposure-stratum interactions, estimated year by year (1995–2015, excluding 2001 for lack of worker-level data) and divided by each stratum's co-founding base rate, with 95% confidence intervals. Left panel: skill distance $d(\boldsymbol{\theta})$ (HD); right panel: distance in AKM worker effects (VD); both per 1 SD of the random-founder-pair distributions, as in **Table 4**. Coworker gradients are evaluated at one and five years of pre-entry overlapping tenure via the interaction with log overlap length. Standard errors are two-way clustered by dyad members and treat base rates as known. *Cited on p. 38, 39, 40.*

Founders-only candidate pool. The stratified design of **Figure C.11** draws counterfactual partners from the worker population, so its gradients combine selection

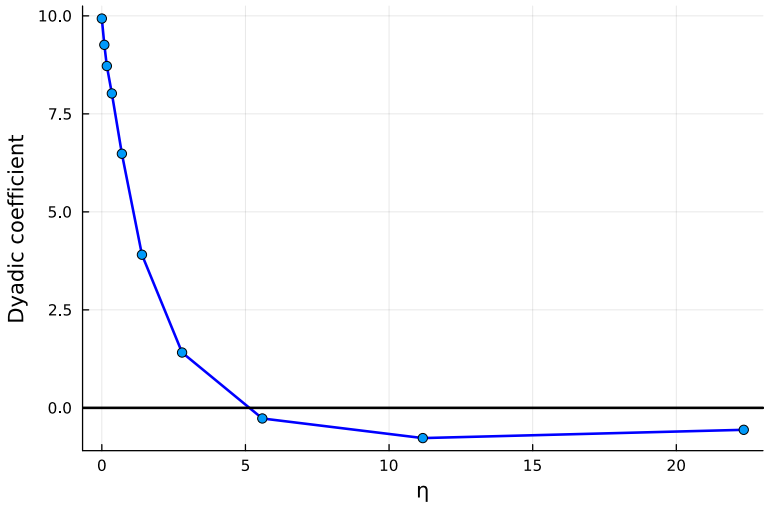
into entrepreneurship with the choice of partner. **Figure C.12** re-estimates the same specification restricting the candidate pool to other founders of the same cohort, all of whom did enter entrepreneurship that year, so that only partner choice remains. The HD pattern is unchanged: the skill-distance gradient still falls monotonically with exposure, from −36% of the base rate per standard deviation among unconnected founders to −14% within occupation pools and −2 to −3% among former coworkers. The VD gradient, by contrast, is considerably stronger than in the baseline – −10% among unconnected founders, against a precise zero in the worker pool, and −27% within occupation pools. Sorting on talent is thus a founder-to-founder phenomenon that the worker-population comparison masks, since there most candidate pairs oppose a founder to someone who never became one, and the entry margin dominates.

Figure C.12: Distance gradients by exposure stratum: founders-only candidate pool



Note: As **Figure C.11**, except that counterfactual dyads pair each founder only with other founders of the same cohort and region rather than with the worker population. Estimated year by year, 1995–2015 (21 cohorts, including 2001). Gradients are divided by each stratum's co-founding base rate; coworker gradients are evaluated at one and five years of pre-entry overlapping tenure. Standard errors are two-way clustered by dyad members and treat base rates as known. *Cited on p. 40.*

Figure C.13: Dyadic Regression: Coefficient for Horizontal Dissimilarity



Note: Results from regression in **Equation 9** on simulated data, for different values of η. The reported coefficient is associated with the horizontal dissimilarity term, or $d(\boldsymbol{\theta}_{i,i'})$

Table C.5: Solo vs. Team Founders Outside the Skill-Measurement Sample

	Solo Founders		Team Founders		Difference	
	Mean	SD	Mean	SD	Diff	SE
Panel A: Demographics						
Age at founding	41.3	11.2	45.3	10.5	4.0***	(0.0)
Sh. female	0.309	0.462	0.296	0.456	-0.013***	(0.001)
Sh. college	0.159	0.366	0.125	0.330	-0.034***	(0.001)
Sh. prev. entrep. exp.	0.209	0.407	0.149	0.356	-0.060***	(0.001)
Panel B: Pre-entry labor market						
Sh. previously manager	0.127	0.333	0.115	0.319	-0.012***	(0.002)
Prev. 5y avg. earnings	11,125	10,236	10,632	9,179	-492***	(70)
Cumul. earnings	49,159	75,382	47,495	67,656	-1,664***	(513)
Prev. employee jobs	4.05	3.91	4.21	3.66	0.16***	(0.03)
Prev. job tenure (quintile)	2.31	1.29	2.37	1.29	0.06***	(0.01)
Prev. empl. size (quintile)	1.96	1.19	1.99	1.21	0.03***	(0.01)
Prev. sect.: manufacturing	0.283	0.450	0.279	0.449	-0.003	(0.003)
Prev. sect.: trade/retail	0.345	0.475	0.355	0.479	0.010***	(0.003)
Prev. sect.: construction	0.118	0.322	0.134	0.340	0.016***	(0.002)
Panel C: Firm performance (first year observed)						
Log sales	11.903	1.441	12.181	1.400	0.277***	(0.005)
# Employees	1.9	0.9	2.0	0.9	0.2***	(0.0)
Firm age	4.7	7.2	4.5	6.5	-0.2***	(0.0)
Sh. exit	0.103	0.304	0.071	0.258	-0.032***	(0.001)
Obs. (Panel A)	174,137		217,053			
Obs. (Panel B)	29,004		67,589			

Note: The table compares solo and team founders among firms with at least one founder for whom no pre-founding O*NET skill vector can be constructed, so that the firm is excluded from, or under-represented in, the skill-dissimilarity analysis. Panel A reports demographics at founding; Panel B pre-entry labor market characteristics, conditional on prior employment history; Panel C firm performance measured in the first year the founder-firm pair is observed. The Difference column reports the team−solo difference in means, with standard errors from a two-sample t-test in parentheses. Data from *Quadros de Pessoal*, 1991–2018. All nominal values deflated by the 2010 CPI. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 38.*

Table C.6: Team vs. Solo-founded Firms at Different Horizons, Outside the Skill-Measurement Sample

	Firm Age = 1			Firm Age = 5			Firm Age = 10		
	Solo	Team	Δ	Solo	Team	Δ	Solo	Team	Δ
Log Employment	0.81	0.93	0.12***	0.97	1.12	0.15***	1.09	1.25	0.16***
Log Wage Bill	9.35	9.53	0.18***	9.74	9.94	0.21***	9.99	10.19	0.20***
Log Sales	11.69	11.96	0.28***	12.04	12.33	0.29***	12.18	12.43	0.25***
Log Productivity	10.90	11.05	0.15***	11.10	11.21	0.12***	11.11	11.19	0.08***
Survival Rate	0.89	0.93	0.04***	0.92	0.94	0.02***	0.93	0.95	0.01***

Note: The table compares mean outcomes for solo- and team-founded firms at firm ages 1, 5, and 10, restricted to firms outside the skill-measurement sample (at least one founder without a constructible pre-founding O*NET skill vector). Δ is the team−solo difference; stars denote significance from a two-sample t-test. The log-sales gaps of 0.28, 0.29, and 0.25 across horizons compare to 0.29, 0.28, and 0.22 in the full-sample counterpart, **Table 1**. Data from *Quadros de Pessoal*, 1991–2018. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 38.*

Table C.7: Firms With and Without Full Skill Coverage

	Firm Age = 1			Firm Age = 5			Firm Age = 10		
	Rest	No info	Δ	Rest	No info	Δ	Rest	No info	Δ
Log Employment	0.85	0.87	0.02***	1.04	1.04	0.00	1.19	1.17	-0.02**
Log Sales	11.68	11.81	0.13***	12.10	12.17	0.08***	12.29	12.30	0.01
Log Productivity	10.87	10.97	0.10***	11.09	11.15	0.06***	11.14	11.15	0.02**
Survival Rate	0.90	0.90	0.00***	0.92	0.93	0.01***	0.94	0.94	0.00
Share Team	0.20	0.43	0.23***	0.19	0.46	0.27***	0.19	0.50	0.31***

Note: The table compares firms with full founder-team skill coverage (*Rest*) to firms with at least one founder lacking a pre-founding O*NET skill vector (*No info*), at firm ages 1, 5, and 10. Δ is the difference (No info − Rest); stars denote significance from a two-sample t-test. No-coverage firms are slightly larger and more productive at age 1 (log-sales difference +0.13) and converge by age 10 (+0.01, not significant); they are more often team-founded (a team share of 0.43 against 0.20 at age 1). *Share Team* is the fraction of team-founded firms in each group. Data from *Quadros de Pessoal*, 1991–2018. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 38.*

C.3 Robustness: A Stricter Definition of Entrepreneurs

We also check that the descriptive patterns survive a stricter definition of who counts as an entrepreneur. A founder qualifies only if the firm is incorporated as a limited-liability or joint-stock company when it first appears in the data; the firm reports positive sales in at least one of its first two reported-sales years; the firm shows positive equity and total assets at its first balance-sheet observation, with firms predating the balance-sheet data retained; and the founder holds a top-management position in the first role we observe for them in the firm. About 44.6% of founders (227,000 of 509,000) meet all four conditions. For the team regressions we further require every founding-team member to pass the active-role screen, so that dissimilarity measures computed on the original team stay valid. Under this definition entrepreneurs are younger (mean age 43.4 against 44.5 in the full sample), better educated (a college share of 21% against 17%), and run younger firms (7.5 against 12.3 years); **Table C.8**. The solo-team contrast keeps its shape, with a first-year log-sales gap of 0.19 (**Table C.9**). The performance regression barely moves: the O*NET skill-dissimilarity coefficient is 0.036, 0.042, and 0.010 across the three columns, against 0.036, 0.039, and 0.010 in the baseline **Table 5**, while the sample roughly halves (**Table C.10**). Re-matching the founder-separation sample within the strict-definition population leaves a pooled effect of −6.4% at the age-≤60 baseline, between −4.7% and −7.2% across every restriction (**Table C.11**).

Table C.8: Descriptive Statistics, Strict Entrepreneur Definition

	Mean	SD	Median	P25	P75	N
Age	43.39	9.81	43.00	36.00	51.00	1,235,215
Age at Founding	40.65	9.46	40.00	33.00	47.00	1,235,215
College %	0.21	0.40	0.00	0.00	0.00	1,207,375
Firm Age	7.51	6.35	6.00	3.00	11.00	1,235,215
# Employees	2.07	0.89	2.00	1.00	3.00	1,158,908
Firms Owned	1.05	0.35	1.00	1.00	1.00	1,235,215
# Founders	1.62	0.87	1.00	1.00	2.00	1,235,215
# Owners	1.55	0.72	1.00	1.00	2.00	1,235,215
Log Sales	12.26	1.31	12.15	11.37	13.06	1,166,782
Female %	0.28	0.45	0.00	0.00	1.00	1,235,215

Note: Descriptive statistics for entrepreneurs who satisfy the strict definition: incorporation as a limited-liability or joint-stock company, positive sales in one of the first two reported-sales years, positive equity and total assets at the first balance-sheet observation, and a top-management role at the first observed position. The full-sample counterpart is **Table C.1**. Sales are deflated by the 2010 CPI. Data from *Quadros de Pessoal*, 1991–2018. *Cited on p. 44.*

Table C.9: Solo vs. Team Founders, Strict Entrepreneur Definition

	Solo Founders		Team Founders		Difference	
	Mean	SD	Mean	SD	Diff	SE
Panel A: Demographics						
Age at founding	40.1	10.0	43.4	9.9	3.4***	(0.0)
Sh. female	0.282	0.450	0.285	0.452	0.004*	(0.002)
Sh. college	0.229	0.420	0.168	0.374	-0.061***	(0.002)
Sh. prev. entrep. exp.	0.227	0.419	0.169	0.375	-0.058***	(0.002)
Panel B: Pre-entry labor market						
Sh. previously manager	0.179	0.384	0.151	0.358	-0.028***	(0.002)
Prev. 5y avg. earnings	12,363	10,970	11,660	10,128	-704***	(60)
Cumul. earnings	71,692	96,940	63,457	85,421	-8,235***	(518)
Prev. employee jobs	5.42	4.28	5.16	4.06	-0.25***	(0.02)
Prev. job tenure (quintile)	2.33	1.28	2.39	1.28	0.06***	(0.01)
Prev. empl. size (quintile)	2.08	1.23	2.06	1.20	-0.02***	(0.01)
Prev. sect.: manufacturing	0.231	0.422	0.262	0.440	0.031***	(0.002)
Prev. sect.: trade/retail	0.344	0.475	0.345	0.476	0.002	(0.003)
Prev. sect.: construction	0.140	0.347	0.144	0.351	0.004**	(0.002)
Panel C: Firm performance (first year observed)						
Log sales	11.849	1.353	12.038	1.319	0.188***	(0.006)
# Employees	1.9	0.9	1.9	0.8	0.1***	(0.0)
Firm age	2.7	4.5	2.6	4.0	-0.1***	(0.0)
Sh. exit	0.019	0.138	0.020	0.140	0.001	(0.001)
Obs. (Panel A)	124,142		103,084			
Obs. (Panel B)	71,891		52,996			

Note: The table compares solo and team founders under the strict entrepreneur definition. Panel A reports demographics at founding; Panel B pre-entry labor market characteristics, conditional on prior employment history; Panel C firm performance in the first year the founder-firm pair is observed. The Difference column reports the team−solo difference in means, with two-sample t-test standard errors in parentheses. Data from *Quadros de Pessoal*, 1991–2018. All nominal values deflated by the 2010 CPI. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 44.*

Table C.10: Founding Team Characteristics and Firm Performance, Strict Entrepreneur Definition

Dependent Variable:	Log Sales		
	(1)	(2)	(3)
Main variables			
Avg. Work FE	0.207***	0.126***	0.065***
	(0.009)	(0.007)	(0.006)
Worker FE dissimilarity (std.)	−0.024***	−0.006	−0.002
	(0.006)	(0.005)	(0.005)
O*NET skill dissimilarity (std.)	0.036***	0.042***	0.010
	(0.009)	(0.008)	(0.006)
Controls			
Baseline FE	Yes	Yes	Yes
Size / employment	No	Yes	Yes
Total earnings	No	Yes	Yes
Initial size	No	No	Yes
Initial assets	No	No	Yes
Fit statistics			
Observations	43,372	43,372	25,242
R^2	0.276	0.539	0.653
Within R^2	0.023	0.014	0.005
No. Firms	13,149	13,149	7,936

Note: Same specification as **Table 5**, restricting the sample to founding teams whose members all satisfy the strict entrepreneur definition. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 26, 44.*

Table C.11: Founder Separations, Strict Entrepreneur Definition

Dependent Variable:	Log Sales					
	All ages	Age ≤ 60	Age ≤ 55	Age ≤ 50	Excl. 2010–2012	Portuguese-born
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Treated	-0.072***	-0.064***	-0.070***	-0.070***	-0.047*	-0.071***
	(0.019)	(0.022)	(0.024)	(0.027)	(0.027)	(0.022)
Observations	6,502	5,379	4,798	4,162	3,576	5,282
No. firms	773	640	575	498	442	630
Sector × year and firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Difference-in-differences estimates of the effect of a founder's permanent separation on firm log sales, with the matched founder-separation sample re-matched within the strict-definition population. Same specification as **Table 6**; columns report alternative sample restrictions: all ages; founder age at separation ≤ 60 (baseline), ≤ 55, ≤ 50; excluding the 2010–2012 cohorts; and Portuguese-born founders only. Firm and sector × year FE. Clustered (sector-year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 27, 44.*

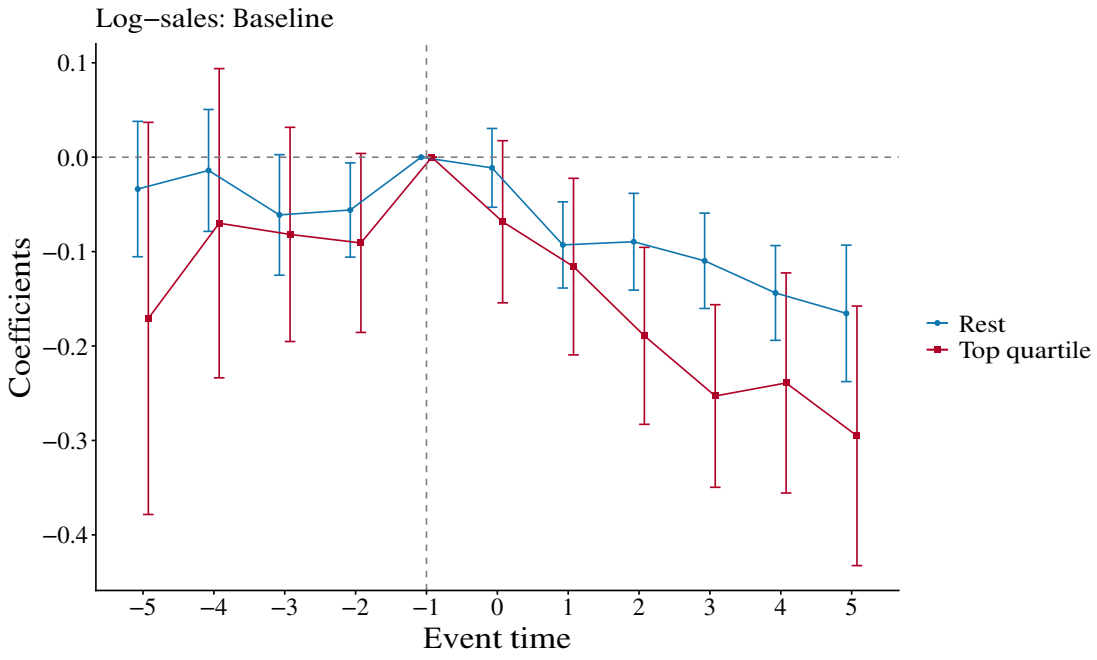
C.4 Event Study: Founder Separations

This section reports the full dynamic event-study specification corresponding to the difference-in-differences estimate in **Section 4**. Replacing the pooled post-treatment indicator in **Equation 11** with event-time interactions, we estimate:

$$Y_{i,j,t} = \sum_{k=-5}^{5} \lambda_k \, \mathbf{1}\{t - \tau_i = k\} + \delta_k \, \mathbf{1}\{t - \tau_i = k\} \times \text{Treat}_i + \alpha_i + \tau_{j,t} + \varepsilon_{i,t} \tag{C.1}$$

where τ_i is the year of separation for treated firm i (and the matched event year for controls), and all other variables are defined as in **Equation 11**. The coefficients δ_k trace the treatment effect at each event time k, with $k = -1$ as the reference period. **Figure C.14** plots the estimated δ_k separately for firms in the top quartile of pre-event skill dissimilarity and the rest, while **Table C.12** reports selected coefficients.

Figure C.14: Event study: founders early separations



Note: The regression reports the coefficient from the event study in **Equation** C.1. 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 by founders' skill dissimilarity: top quartile vs. the rest, computed in the year before the separation event. Errors clustered at the sector by year level. *Cited on p. 27, 47.*

Table C.13 reports covariate balance between the matched treated and control firms.

Table C.12: Event Study: Founder Separation and Firm Sales

Dependent Variable:	Log Sales		
	All	Top Q4 dissim.	Rest
	(1)	(2)	(3)
Event time			
Treated × Event time = −5	-0.056	-0.171	-0.034
	(0.035)	(0.105)	(0.036)
Treated × Event time = −2	-0.070***	-0.091*	-0.056**
	(0.021)	(0.048)	(0.025)
Treated × Event time = 0	-0.018	-0.068	-0.011
	(0.020)	(0.044)	(0.021)
Treated × Event time = 1	-0.097***	-0.116**	-0.093***
	(0.020)	(0.047)	(0.023)
Treated × Event time = 3	-0.130***	-0.253***	-0.110***
	(0.023)	(0.049)	(0.026)
Treated × Event time = 5	-0.175***	-0.295***	-0.165***
	(0.030)	(0.070)	(0.037)
Observations	10,777	2,510	8,043
No. firms	1,317	316	976

Note: The table reports selected event-time coefficients from **Equation C.1**. Treated firms are matched to control firms via nearest-neighbor propensity score matching on founder demographics, firm characteristics, and pre-event measures of talent and skill dissimilarity. *Top quartile dissim.* refers to firms in the top quartile of pre-event skill dissimilarity among founders. All specifications include firm and year fixed effects. Clustered (sector-year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 27, 47.*

The two sides track each other closely, with the largest normalized difference at 0.27, on the average age of the firm's owners. **Table C.14** describes the exiting founders themselves. They separate at a mean age of 44.8, women make up 28% of the group, and more than four in five held a managerial occupation in the year before leaving—the profile of active founders in their working prime rather than of owners retiring out of the firm.

C.4.1 Robustness of the Founder-Separation Effect

A potential concern with our identification of permanent separations is that some exits—particularly of older founders—reflect voluntary retirement rather than the plausibly exogenous departures we want to isolate, and that the estimate could be sensitive to the financial-crisis years or to emigration. **Table C.15** re-estimates **Equation 11** under a battery of sample restrictions: progressively tighter age cutoffs at separation (all ages; ≤ 60, our baseline; ≤ 55; ≤ 50), which address the retirement concern; exclusion of the 2010–2012 financial-crisis cohorts; and restriction to Portuguese-born founders, which rules out emigration. The pooled effect stays between -4.5% and -5.9% and significant under every restriction: -4.7% at the ≤ 55 cutoff, -5.9% at ≤ 50, -4.6% once the crisis

Table C.13: Founder Separations: Matching Balance

	Treated (N=728)	Control (N=728)	Norm. diff.
Age	43.77	45.46	-0.194
Female	0.28	0.27	+0.022
College	0.11	0.10	+0.049
Log sales (avg t-2,t-3)	12.34	12.50	-0.122
Log employment (avg t-2,t-3)	1.71	1.78	-0.083
Firm age	6.77	7.38	-0.126
No. owners	2.22	2.20	+0.025
Avg. owner age	42.89	44.90	-0.265
Log cumul. earnings	10.42	10.43	-0.007
Work-FE dissim.	0.70	0.71	-0.011
Avg. work FE	-0.47	-0.44	-0.031
O*NET skill dissim.	2.66	2.78	-0.057

Note: Covariate balance between treated (separating) founders' firms and their nearest-neighbor propensity-score-matched controls, on the full matched estimation sample (728 pairs; founder age at separation ≤ 60, the baseline restriction). Founder demographics and firm characteristics are measured before the separation event; sales and employment are averaged over $t-2$ and $t-3$. *Norm. diff.* is the normalized difference in means, $(\bar{x}_T - \bar{x}_C)/\sqrt{(s_T^2 + s_C^2)/2}$. *Cited on p. 26, 47.*

Table C.14: Descriptives: Exiting Founders

	Exiting founders
N (treated founders)	728
Mean age at separation	44.8
Median age at separation	44
SD age at separation	8.7
p25–p75 age	39–52
% female	28.5
% foreign-born	2.1
% college	9.6
% managerial occupation	82.6
% top mgmt level	80.0
% both	74.6
% neither (passive)	12.0

Note: Descriptive statistics for the treated (exiting) founders in the matched separation sample (728 founders; age at separation ≤ 60, the baseline restriction). *Managerial occupation* is an ISCO-08 major-group-1 role and *top mgmt level* the top establishment-hierarchy (qualification) category; *both* and *neither (passive)* indicate founders holding both or neither at $t-1$. Ages in years. *Cited on p. 26, 48.*

cohorts are dropped, and -5.2% for Portuguese-born founders. The result is thus not driven by retirement-aged exits, the financial crisis, or emigration.

A separate concern is that a separation could matter through the change in ownership rather than through the loss of the founder's own human capital. **Table C.16** splits treated separations by the founder's operational role in the year before the event. The loss concentrates among founders who held a top-management position at $t-1$: their

Table C.15: Robustness of the Founder-Separation Effect on Firm Sales

Dependent Variable:	Log Sales					
	All ages	Age ≤ 60	Age ≤ 55	Age ≤ 50	Excl. 2010–2012	Portuguese-born
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Treated	-0.057***	-0.045***	-0.047***	-0.059***	-0.046**	-0.052***
	(0.013)	(0.014)	(0.017)	(0.019)	(0.020)	(0.015)
Observations	13,606	10,777	9,248	7,748	7,445	10,567
No. firms	1,660	1,317	1,138	961	954	1,292
Sector × year and firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Difference-in-differences estimates of the effect of a founder's permanent separation on firm log sales, pooled Post×Treated coefficient under alternative sample restrictions (columns): all ages; founder age at separation $\leq$ 60 (baseline), $\leq$ 55, $\leq$ 50; excluding the 2010–2012 cohorts; and Portuguese-born founders only. Treated firms matched via nearest-neighbor PSM on founder demographics, firm characteristics, and pre-event measures of talent and skill dissimilarity. Firm and sector × year FE. Clustered (sector-year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 48.*

departure lowers sales by 5.1% (1,042 firms), against a baseline of 4.5%. For founders below top management the estimate is -2.4% and not significant (244 firms). The null for passive owners fits an effect that runs through the founder's human capital rather than ownership alone, though the passive cell is small and we read it as suggestive.

Table C.16: Founder Separations by Operational Role

Dependent Variable:	Log Sales		
	Baseline ($\leq$60)	Active (top mgmt)	Passive (below top)
	(1)	(2)	(3)
Post × Treated	-0.045***	-0.051***	-0.024
	(0.014)	(0.016)	(0.039)
Observations	10,777	8,512	2,006
No. firms	1,317	1,042	244
Sector × year and firm FE	Yes	Yes	Yes

Note: Difference-in-differences estimates of the effect of a founder's permanent separation on firm log sales, splitting treated separations by the founder's operational role in the year before the event. Column (1) reproduces the baseline (age at separation $\leq$ 60); column (2) restricts to founders holding a top-management position at $t-1$; column (3) to founders below top management. Same specification and matching as **Table 6**. Firm and sector × year FE. Clustered (sector-year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 27, 49.*

The split by skill dissimilarity in **Table 6** relies on the O*NET measure. **Table C.17** repeats it with skills measured on the 74-dimension ESCO taxonomy: separations in top-quartile teams are followed by a sales decline of 8.5%, against 3% for the remaining teams, the same pattern as in the baseline. The pooled coefficient is identical by construction, since the skill measure enters only through the split.

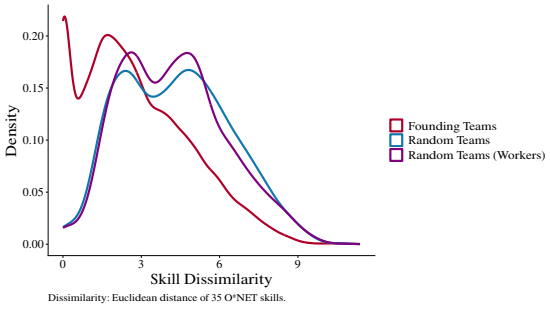
Table C.17: Founder Separations by Skill Dissimilarity: ESCO Measure

Dependent Variable:	Log Sales		
	All	Top Q4	Rest
	(1)	(2)	(3)
Post × Treated	-0.045***	-0.085***	-0.030*
	(0.014)	(0.029)	(0.018)
Observations	10,777	2,676	7,875
No. firms	1,317	329	958
Sector × year and firm FE	Yes	Yes	Yes

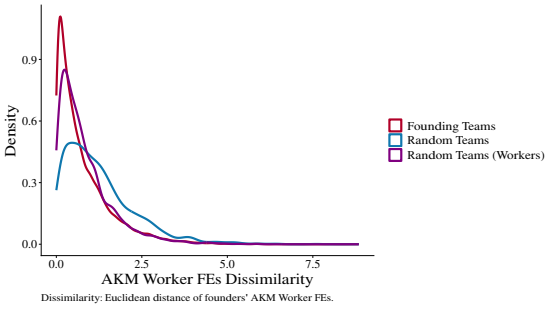
Note: Same specification, sample, and matching as **Table 6**, with the top-quartile split defined on the ESCO skill-dissimilarity measure instead of O*NET. The skill measure does not enter the matching, so column (1) coincides with the baseline. Firm and sector × year FE. Clustered (sector-year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 27, 50.*

Figure C.15: Similarities in two-entrepreneurs founding teams and random pairs of entrepreneurs

(a) O*NET Skills

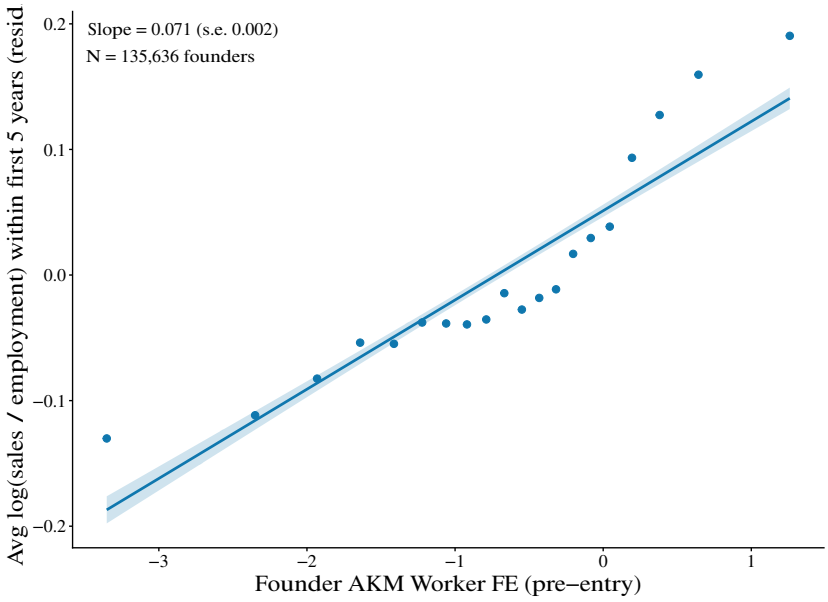


(b) AKM Worker Fixed Effects



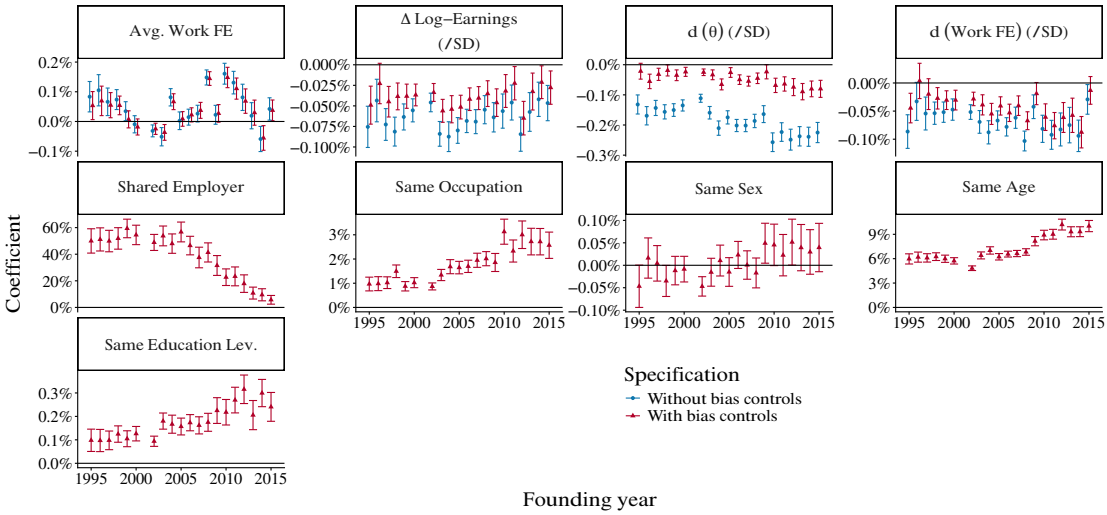
Note: The figure plots the densities of the Skill dissimilarities between founders and a sample of random pairs of entrepreneurs and workers. *Cited on p. 20.*

Figure C.16: Founders' pre-entry AKM Worker FE and firm labor productivity



Note: Binscatter (20 bins) of founders' pre-entry AKM worker fixed effects against the average log labor productivity of the firm they found, measured as log(sales/employment) averaged within the firm's first five years of activity. Employment includes owners, matching the definition used in the main performance regressions. Labor productivity is residualized on sector-of-activity × founding-year fixed effects. Each observation is an individual founder: founders of the same firm are assigned the productivity of their firm. The solid line is an OLS linear fit and the shaded band its 95% confidence interval. *Cited on p. 18.*

Figure C.17: Dyadic regressions



Note: The figure reports the dyadic regression coefficients from **Equation 9**, for pairs of workers or entrepreneurs having the same age or sex, ever being colleagues, having worked in the same occupation or having the same educational level. *Cited on p. 23, 24.*

The performance premium of skill-dissimilar teams is also not a by-product of unfamiliarity between founders. From the pre-founding employment histories we flag teams whose members were employed at the same firm in the same year before founding together — former colleagues, for whom acquaintance is given. Almost a quarter of the teams in the skill analysis pass this screen, and their composition leans heavily toward similarity: their average skill dissimilarity is 2.07, against 3.31 for the remaining teams — the pool of trusted contacts is occupationally homogeneous. **Table C.23** shows that the dissimilarity premium survives, and in fact doubles, where familiarity is held fixed: the coefficient is 0.095 among former-colleague teams against 0.038 elsewhere, with an interaction of 0.075 (s.e. 0.008). Former-colleague teams also carry a sizable level premium of 0.24 log points. Part of the larger within-colleague coefficient may reflect screening — founders who have worked together form dissimilar teams knowing the complementarity is real — but under either reading, the premium is not an artifact of differential trust between similar and dissimilar founders.

Table C.18: Founding team characteristics and firm performance, firm age ≤ 1

Dependent Variable:	Log Sales				
	(1)	(2)	(3)	(4)	(5)
Variables					
Avg. Work FE	0.179***	0.134***	0.116***	0.116***	0.062***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
Worker FE dissimilarity (std.)	−0.022***	−0.017***	−0.010*	−0.010*	−0.005
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
O*NET skill dissimilarity (std.)	0.025***	0.026***	0.027***	0.026***	−0.001
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
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
Serial Entrepreneur	Yes	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes	Yes
Size, Employment quintiles		Yes	Yes	Yes	Yes
Log Total Earnings, quintiles			Yes	Yes	Yes
Initial size, Employment quintiles				Yes	Yes
Log Initial Total Assets, quintiles					Yes
Fit statistics					
Observations	27,048	27,048	27,048	27,048	13,247
R^2	0.297	0.508	0.513	0.517	0.620
Within R^2	0.017	0.014	0.010	0.010	0.004
No. Firms	18,851	18,851	18,851	18,851	8,951

Note: Same specification as **Table C.4**, restricted to firms in their first year of activity. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table C.19: Founding team characteristics and firm performance, firm age ≤ 10

Dependent Variable:	Log Sales				
	(1)	(2)	(3)	(4)	(5)
Variables					
Avg. Work FE	0.176^{***}	0.118^{***}	0.104^{***}	0.103^{***}	0.056^{***}
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Worker FE dissimilarity (std.)	-0.022^{***}	-0.014^{***}	-0.008^{***}	-0.008^{***}	-0.009^{***}
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
O*NET skill dissimilarity (std.)	0.042^{***}	0.041^{***}	0.042^{***}	0.042^{***}	0.016^{***}
	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)
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
Serial Entrepreneur	Yes	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes	Yes
Size, Employment quintiles		Yes	Yes	Yes	Yes
Log Total Earnings, quintiles			Yes	Yes	Yes
Initial size, Employment quintiles				Yes	Yes
Log Initial Total Assets, quintiles					Yes
Fit statistics					
Observations	130,383	130,383	130,383	130,383	67,763
R^2	0.281	0.561	0.565	0.571	0.641
Within R^2	0.017	0.014	0.011	0.011	0.004
No. Firms	26,495	26,495	26,495	26,495	14,688

Note: Same specification as **Table C.4**, restricted to firms surviving up to 10 years. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table C.20: Founding team characteristics and firm performance, control for initial employees skills

Dependent Variable:	Log Sales				
	(1)	(2)	(3)	(4)	(5)
Variables					
Avg. Work FE	0.181***	0.131***	0.124***	0.179***	0.091***
	(0.006)	(0.005)	(0.008)	(0.006)	(0.008)
Worker FE dissimilarity (std.)	−0.021***	−0.015***	−0.019***	−0.033***	−0.013***
	(0.004)	(0.003)	(0.005)	(0.005)	(0.005)
O*NET skill dissimilarity (std.)	0.036***	0.038***	0.015*	0.084***	0.029***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)
Fixed-effects					
Team Characteristics	Yes	Yes	Yes	Yes	Yes
Serial Entrepreneur	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	83,915	83,915	26,107	83,898	26,107
R^2	0.285	0.529	0.327	0.287	0.536
Within R^2	0.018	0.015	0.011	0.020	0.009
No. Firms	25,397	25,397	8,059	25,391	8,059

Note: Same specification as **Table 5**. Columns (4) and (5) additionally control for the worker FE dissimilarity and skill dissimilarity of employees present in the firm during the initial three years from foundation. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 26.*

Table C.21: Founding team characteristics and labor productivity

Dependent Variable:	Log Productivity			
	(1)	(2)	(3)	(4)
Variables				
Avg. Work FE	0.114***	0.112***	0.076***	0.077***
	(0.005)	(0.005)	(0.008)	(0.008)
Worker FE dissimilarity (std.)	−0.012***	−0.012***	−0.007*	−0.007**
	(0.003)	(0.003)	(0.004)	(0.004)
O*NET skill dissimilarity (std.)	0.032***	0.031***	0.016**	0.017**
	(0.006)	(0.006)	(0.007)	(0.007)
Fixed-effects				
Incorporation type	Yes	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes	Yes
Serial Entrepreneur	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes
Initial size, Employment quintiles		Yes		Yes
Log Total Earnings, quintiles			Yes	Yes
Log Fixed Assets, quintiles			Yes	Yes
Fit statistics				
Observations	83,915	83,915	26,107	26,107
R^2	0.324	0.325	0.306	0.307
Within R^2	0.014	0.013	0.007	0.007
No. Firms	25,397	25,397	8,059	8,059

Note: Same specification as **Table 5**, with log labor productivity (log sales per employee) as the dependent variable. The estimation sample is based on firms surviving up to 5 years. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table C.22: Alternative Measures of Founder Talent and Vertical Diversity

Dependent Variable:	Log Sales			
	(1)	(2)	(3)	(4)
Variables				
Avg. Work FE	0.181***	0.274***	0.181***	
	(0.006)	(0.009)	(0.006)	
Avg. Firm FE		0.166***		
		(0.008)		
Avg. talent rank				0.959***
				(0.027)
Worker FE dissim. (Euclidean)	−0.028***			
	(0.006)			
Worker+Firm FE dissim.		−0.025***		
		(0.004)		
Worker FE dissim. (Gower)			−0.411***	
			(0.083)	
Talent-rank dissim.				−0.052**
				(0.021)
O*NET skill dissimilarity (std.)	0.036***	0.036***	0.036***	0.029***
	(0.007)	(0.007)	(0.007)	(0.007)
Fixed-effects				
Incorporation type	Yes	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes	Yes
Serial Entrepreneur	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes
Standardized magnitude				
Δ log sales (SD) per +1 SD of dissim.	−0.017	−0.019	−0.017	−0.008
Fit statistics				
Observations	83,915	83,915	83,915	83,915
R^2	0.285	0.291	0.285	0.297
Within R^2	0.018	0.026	0.018	0.035
No. Firms	25,397	25,397	25,397	25,397

Note: Alternative measures of founders' vertical (talent) dimension, all in the baseline specification of **Table 5**, column (1), with no progressive controls. Column (1) uses the Euclidean dissimilarity of founders' AKM worker fixed effects; column (2) the dissimilarity of combined worker and firm fixed effects; column (3) the Gower index; column (4) an earnings-rank measure. The earnings-rank measure is the percentile rank of a founder's average real earnings over the six years before founding, computed against the full workforce, and requires no AKM connected set. The fixed-effect set matches the baseline column of **Table 5**. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 26.*

Table C.23: Founding Team Performance and Former-Colleague Status

Dependent Variable:	Log Sales			
			Former colleagues	Other teams
	(1)	(2)	(3)	(4)
Avg. Work FE	0.182***	0.182***	0.180***	0.188***
	(0.006)	(0.006)	(0.008)	(0.008)
Worker FE dissimilarity (std.)	0.009**	0.008*	0.015*	0.006
	(0.004)	(0.004)	(0.008)	(0.005)
O*NET skill dissimilarity (std.)	0.065***	0.031***	0.095***	0.038***
	(0.007)	(0.007)	(0.010)	(0.007)
Former colleagues	0.240***	0.239***		
	(0.009)	(0.009)		
O*NET dissim. × Former colleagues		0.075***		
		(0.008)		
Observations	83,915	83,915	40,692	43,127
No. firms	25,397	25,397	12,155	13,212
Baseline fixed effects	Yes	Yes	Yes	Yes

Note: Baseline specification of **Table 5**, column (1). *Former colleagues* indicates founding teams in which at least two founders were employed at the same firm in the same year before founding, constructed from pre-founding employment spells. Columns (1)–(2) add the indicator and its interaction with skill dissimilarity; columns (3)–(4) split the sample by it. Former-colleague teams concentrate at low skill dissimilarity, so the split coefficients are partly identified on different ranges of the measure; the estimation sample requires complete team employment histories, which raises the former-colleague share relative to the full population of teams. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 26, 53.*

Table C.24: Founding Team Characteristics and Firm Performance: ESCO Skill Measure

Dependent Variable:	Log Sales				
	(1)	(2)	(3)	(4)	(5)
Variables					
Avg. Work FE	0.183***	0.129***	0.113***	0.112***	0.056***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Worker FE dissimilarity (std.)	−0.019***	−0.014***	−0.007**	−0.007**	−0.007**
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
ESCO skill dissimilarity (std.)	0.022***	0.024***	0.027***	0.028***	0.009*
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
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
Serial Entrepreneur	Yes	Yes	Yes	Yes	Yes
Sector × Year	Yes	Yes	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes	Yes	Yes
Size, Employment quintiles		Yes	Yes	Yes	Yes
Log Total Earnings, quintiles			Yes	Yes	Yes
Initial size, Employment quintiles				Yes	Yes
Log Initial Total Assets, quintiles					Yes
Fit statistics					
Observations	83,908	83,908	83,908	83,908	43,193
R^2	0.285	0.538	0.542	0.548	0.633
Within R^2	0.018	0.014	0.011	0.011	0.004
No. Firms	25,395	25,395	25,395	25,395	13,181

Note: Same specification as **Table C.4**, with founders' horizontal dissimilarity measured on the 74-dimension ESCO skill taxonomy instead of O*NET. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 26.*

Table C.25: Founding team characteristics and firm performance, additional financial controls

Dependent Variable:	Log Sales		
	(1)	(2)	(3)
Variables			
Avg. Work FE	0.091^{***}	0.056^{***}	0.057^{***}
	(0.008)	(0.006)	(0.005)
Worker FE dissimilarity (std.)	-0.013^{***}	-0.007^{*}	-0.008^{**}
	(0.004)	(0.004)	(0.003)
O*NET skill dissimilarity (std.)	0.015^{**}	0.007	0.010^{*}
	(0.008)	(0.007)	(0.006)
Fixed-effects			
Incorporation type	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes
Serial Entrepreneur	Yes	Yes	Yes
Log Total Earnings, quintiles	Yes	Yes	Yes
Initial size, Employment quintiles	Yes	Yes	Yes
Log Initial Tang. Assets, quintiles	Yes		
Sector × Year	Yes	Yes	Yes
Sector × Founding Year	Yes	Yes	Yes
Whited-Wu Index, quintiles		Yes	
Log Initial Total Assets, quintiles			Yes
Fit statistics			
Observations	25,929	21,074	43,199
R^2	0.539	0.680	0.623
Within R^2	0.009	0.005	0.004
No. Firms	7,992	7,708	13,183

Note: Same specification as **Table 5**, column (3), with alternative financial controls. Column (1): log initial tangible assets. Column (2): Whited-Wu index. Column (3): log initial total assets. The estimation sample is based on firms surviving up to 5 years. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table C.26: Founding team characteristics and firm performance, "sequentials" sample

Dependent Variable:	Log Sales			
	(1)	(2)	(3)	(4)
Variables				
Avg. Work FE	0.181***	0.091***	0.214***	0.125***
	(0.006)	(0.008)	(0.010)	(0.016)
Worker FE dissimilarity (std.)	−0.021***	−0.013***	−0.034***	−0.010
	(0.004)	(0.005)	(0.006)	(0.008)
O*NET skill dissimilarity (std.)	0.036***	0.029***	0.044***	0.050***
	(0.007)	(0.009)	(0.009)	(0.014)
Fixed-effects				
Incorporation type	Yes	Yes	Yes	Yes
At least one College Founder	Yes	Yes	Yes	Yes
Mixed Gender Team	Yes	Yes	Yes	Yes
Serial Entrepreneur	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 Dissimilarities		Yes		Yes
Sample	Full	Full	Only Seq.	Only Seq.
Fit statistics				
Observations	83,915	26,107	33,710	9,642
R^2	0.285	0.536	0.304	0.552
Within R^2	0.018	0.009	0.022	0.015
No. Firms	25,397	8,059	10,207	2,996

Note: Same specification as **Table 5**. Columns (1)–(2): full sample. Columns (3)–(4): restricted to firms with at least one sequential entrepreneur (individuals who will own more than one business throughout their career). Even columns add controls for initial size, initial assets, and initial employees' dissimilarity. The estimation sample is based on firms surviving up to 5 years. Clustered (sector × year) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. *Cited on p. 28.*

C.5 Computation of the Optimal-Assignment Benchmark

This appendix describes how we compute the optimal-assignment (OA) benchmark studied in Section 6. The purpose of this exercise is to remove not only the meeting bias embedded in the decentralized meeting technology, but also the residual randomness of search. The OA therefore assigns potential founders to partners so as to maximize aggregate entrepreneurial surplus, while preserving the same occupational-choice and labor-market structure as in the calibrated general-equilibrium (GE) environment.

Discretized founder distribution. We approximate the continuous distribution of founder characteristics with a finite set of founder types $i = 1, \ldots, 9000$. Each type i is represented by a centroid skill vector θ_i and has population mass a_i, with $\sum_i a_i = 1$. In

Table C.27: Matching Bias, Search Frictions, and Aggregate Outcomes

η	Share of teams (%)	Output per capita	Average firm size	Number of firms	Sales per employee	Average wage
0.00	94.1	0.811	11.88	6.51	0.847	0.847
0.09	93.1	0.799	11.75	6.58	0.840	0.840
0.17	92.7	0.791	11.75	6.58	0.835	0.835
0.35	90.8	0.774	11.61	6.66	0.825	0.825
0.70	87.6	0.749	11.46	6.78	0.808	0.808
1.40	82.6	0.714	11.26	6.92	0.781	0.782
2.79	72.6	0.683	10.99	7.20	0.752	0.755
5.1	59.7	0.657	10.70	7.51	0.730	0.735
5.59	57.9	0.656	10.80	7.51	0.725	0.728
11.17	37.7	0.639	10.59	7.95	0.703	0.707
22.35	19.5	0.635	10.40	8.39	0.691	0.695
Assignment benchmark	99.9	1.000	14.02	6.31	1.000	1.000

Note: All outcomes are normalized to the assignment benchmark economy. The baseline corresponds to the estimated meeting-bias parameter $\eta = 22.35$. The "No Bias" economy sets $\eta = 0$, removing assortative bias in meetings while preserving random search. The "Optimal Assignment" economy solves the planner's assignment problem over founder types, allowing agents to remain unmatched and recomputing equilibrium wages. *Cited on p. 37.*

the quantitative implementation types are bins of the simulated founder distribution. We construct these bins adaptively. Starting from a single cell containing all Monte Carlo draws, we repeatedly split the cell where additional resolution is most useful for approximating team formation. Each split is made at the median of the skill dimension with the largest within-cell variance. Cells containing highly productive and relatively unbalanced agents receive higher priority, since these are the types most likely to sort into entrepreneurial teams. The discretization therefore becomes progressively finer precisely in the regions of the type space that matter most for surplus and matching.

Outside options and bilateral surplus. Fix a candidate wage vector $\mathbf{w} = (w_1, w_2, w_3)$. For a founder of type i, the value of remaining unmatched is

$$B_i(\mathbf{w}) = \max\{R(\theta_i; \mathbf{w}), \pi_I^S(\theta_i; \mathbf{w})\},$$

that is, the better of paid employment and solo entrepreneurship. If two founders of types i and i' form a team, their joint profit is $\pi^T(i, i'; \mathbf{w})$. The gain from assigning these two founders to one another is then the net team surplus given by:

$$s_{i,i'}(\mathbf{w}) = \pi^T(i, i'; \mathbf{w}) - B_i(\mathbf{w}) - B_{i'}(\mathbf{w}).$$

As in the main text, we suppress the dependence on $\mathbf{w}$ whenever no confusion arises. By construction, $s_{i,i'}$ measures the value created by team formation relative to leaving both founders unmatched and letting each choose her best stand-alone option.

Assignment problem. Given the surplus matrix $\mathcal{S} = (s_{i,i'})$, the OA benchmark solves

$$\max_{\Gamma \geq 0} \sum_{i,i'} \Gamma_{i,i'} \, S_{i,i'}$$

subject to

$$\sum_{i'} \Gamma_{i,i'} \leq a_i \qquad \text{for all } i, \qquad \sum_{i} \Gamma_{i,i'} \leq a_{i'} \qquad \text{for all } i'.$$

Here $\Gamma_{i,i'}$ is the mass of type-i founders assigned to type-i' founders. The row and column inequalities allow some founders to remain unmatched, so the planner does not force all founders into teams. Instead, team formation occurs when the associated surplus is sufficiently high relative to outside options. Since founders are drawn from the same population on both sides of the market, the matrix Γ is converted into team-firm masses without double counting. We define the mass of teams formed by types i and i' as:

$$\mu_{i,i'} = \begin{cases} \frac{1}{2}\big(\Gamma_{i,i'} + \Gamma_{i',i}\big) & \text{if } i \neq i', \\ \frac{1}{2}\,\Gamma_{i,i} & \text{if } i = i'. \end{cases}$$

For $i \neq i'$, $\Gamma_{i,i'} = \Gamma_{i',i}$ by symmetry of the pairing, so $\mu_{i,i'} = \Gamma_{i,i'}$ equals the mass of (i, i') teams. For $i = i'$, the halving reflects the fact that a mass $\Gamma_{i,i}$ of assigned type-i founders corresponds to $\Gamma_{i,i}/2$ team firms, since each (i, i) team contains two type-i founders. The mass of unmatched type-i founders is instead given by:

$$u_i = a_i - \sum_{i'} \Gamma_{i,i'}.$$

Hence, the assignment outcome partitions each type into a matched mass, which becomes part of a team-founded firm, and an unmatched mass, which chooses between paid employment and solo entrepreneurship.

Optimal transport implementation. This linear assignment problem is a discrete optimal-transport (OT) one as in Galichon (2016), with surplus matrix $\mathcal{S}$, or equivalently cost matrix $C = -\mathcal{S}$. Numerically, we solve an entropically regularized version,

$$\max_{\Gamma \geq 0} \sum_{i,i'} \Gamma_{i,i'} s_{i,i'} - \varepsilon \sum_{i,i'} \Gamma_{i,i'} \big(\log \Gamma_{i,i'} - 1\big),$$

subject to the same feasibility constraints, where $\varepsilon > 0$ is a regularization parameter. The entropy term smooths the transport plan and allows the problem to be solved with Sinkhorn-type iterations. Smaller values of ε yield a sparser and more concentrated transport plan, at the cost of slower convergence. To accommodate the fact that some founders optimally remain unmatched, we use the standard unmatched option in the

transport problem. This is implemented by augmenting the surplus matrix with a dummy "non-team" row and column with zero surplus, and then solving the balanced Sinkhorn problem.

Iterative refinement of the discretization. The founder grid is refined jointly with the transport solution. After each OT solve, we use the resulting transport plan to update the refinement score of each founder type. In particular, founder types with a high team-participation rate

$$r_i = \frac{1}{a_i} \sum_{i'} \Gamma_{i,i'}$$

receive higher priority, since they account for a large share of matched founders. We also give higher priority to founder types whose matches are spread across many distinct partner types. To measure this, define the normalized row of the transport plan,

$$p_{i,i'} = \frac{\Gamma_{i,i'}}{\sum_j \Gamma_{i,j}},$$

so that $p_{i,i'}$ is the share of type-i founders matched to type i'. We then compute

$$H_i = -\sum_{i'} p_{i,i'} \log p_{i,i'},$$

which is the Shannon entropy of this distribution, i.e. a standard measure of how dispersed the matches of type i are across partners. Entropy is low when almost all type-i founders are matched to a single partner type, and high when they are matched more evenly across many partner types. The associated effective number of partners is then given by:

$$N_{\text{eff}}(i) = \exp(H_i).$$

This object is close to 1 when type i is matched almost entirely to a single partner type, and larger when type i is matched more evenly across many partner types. Intuitively, the grid is refined more aggressively in regions where founder types both participate heavily in teams and interact with a broad set of potential complements. We track the active set of founder types accounting for at least 99% of matched mass and stop refining when both that active set and the total team share stabilize across iterations.

Aggregation and occupational choice. Given Γ, the unmatched mass u_i of each founder type follows the same occupational-choice logic as in the decentralized model. In particular, unmatched type-i founders choose the option embedded in B_i: if $B_i = R(\theta_i)$, they become workers; if $B_i = \pi^S(\theta_i)$, they become solo entrepreneurs.

Let $LS_k(\mathbf{w}, \Gamma)$ denote aggregate labor supply in market $k \in \{1, 2, 3\}$, and let

$$LD_{k,\text{solo}}(\mathbf{w}, \Gamma), \qquad LD_{k,\text{team}}(\mathbf{w}, \Gamma)$$

denote labor demand from solo-founded and team-founded firms, respectively. Labor supply is generated by the unmatched founders who choose paid employment. Labor demand comes from two sources: unmatched founders who choose solo entrepreneurship, and matched founders assigned into team firms according to the team masses $\mu_{i,i'}$.

For team-founded firms, labor demand is computed from the team production problem that determines $\pi^T(i, i')$ in the main model. To aggregate this object efficiently, we restrict attention to an active set $\mathcal{A}$ of founder-pair bins (i, i') that accounts for at least 99% of total team-firm mass. For each bin $(i, i') \in \mathcal{A}$, we draw $N_{i,i'}$ within-bin founder pairs $\{(\boldsymbol{\theta}_i^{(n)}, \boldsymbol{\theta}_{i'}^{(n)})\}_{n=1}^{N_{i,i'}}$ and compute, for each draw, the optimal labor demands $l_k\big(\boldsymbol{\theta}_i^{(n)}, \boldsymbol{\theta}_{i'}^{(n)}; \mathbf{w}\big)$ for $k \in \{1, 2, 3\}$. Aggregate team-firm labor demand is then given by the Monte Carlo average of within-bin labor demands, summed across bins and weighted by team masses $\mu_{i,i'}$:

$$LD_{k,\text{team}}(\mathbf{w}, \Gamma) = \sum_{(i,i') \in \mathcal{A}} \mu_{i,i'} \cdot \frac{1}{N_{i,i'}} \sum_{n=1}^{N_{i,i'}} l_k\big(\boldsymbol{\theta}_i^{(n)}, \boldsymbol{\theta}_{i'}^{(n)}; \mathbf{w}\big), \qquad k \in \{1, 2, 3\}.$$

Aggregate labor demand from solo entrepreneurs is obtained analogously by integrating the labor demand of solo-founded firms over the unmatched founders who choose solo entrepreneurship.

General-equilibrium fixed point. The OA benchmark is a general-equilibrium object, not a partial-equilibrium reassignment. The reason is that the surplus matrix $\mathcal{S}$ depends on equilibrium wages through both outside options and team profits. We therefore nest the assignment problem inside the labor-market equilibrium solver.

For any candidate wage vector $\mathbf{w}$, we:

1. compute outside options $B_i(\mathbf{w})$ for all founder types i;
2. compute pairwise team profits $\pi^T(i, i'; \mathbf{w})$ and surpluses $s_{i,i'}(\mathbf{w})$;
3. solve the regularized assignment problem for $\Gamma(\mathbf{w})$;
4. aggregate labor supply $LS_k(\mathbf{w}, \Gamma)$ and labor demand

$$LD_k(\mathbf{w}, \Gamma) = LD_{k,\text{solo}}(\mathbf{w}, \Gamma) + LD_{k,\text{team}}(\mathbf{w}, \Gamma)$$

in each labor market $k \in \{1, 2, 3\}$.

The excess-demand system is therefore

$$F_k(\mathbf{w}) = LD_k(\mathbf{w}, \Gamma(\mathbf{w})) - LS_k(\mathbf{w}, \Gamma(\mathbf{w})), \qquad k \in \{1, 2, 3\}.$$

An OA equilibrium is a wage vector $\mathbf{w}^*$ such that

$$F_k(\mathbf{w}^*) = 0 \qquad \text{for all } k.$$

Numerical solution. We solve for the equilibrium wage vector $\mathbf{w}^*$ with the same iterative procedure used elsewhere in the paper. Starting from an initial guess $\mathbf{w}^{(0)}$, we compute excess demand in each labor market and update wages in the direction that would reduce these imbalances. To do so, we first construct a local linear approximation of the excess-demand system using finite differences. This delivers a Newton step. We then use a dampened Newton method, with the dampening parameter $\lambda_n \in (0, 1]$ selected by Armijo backtracking line search, which ensures global convergence of the damped Newton iteration. At each trial wage vector, the inner loop resolves the assignment problem and recomputes aggregate labor demand and supply. Iteration continues until excess demand is sufficiently close to zero in all labor markets.