The Two Faces of Worker Specialization

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Discussion Paper

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The Two Faces of Worker Specialization*

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Abstract

We study how worker specialization—the distance between a worker's skill set and those prevalent in the labor market—shapes employment outcomes. Using US and French data, we first document that specialized jobs are characterized by asymmetric skill profiles and a scarcity of nearby employment opportunities. We incorporate these features into a random search model with multidimensional skills, mismatch penalties and skill complementarity. We show that specialization lowers job-finding rates due to a lack of suitable jobs, but raises re-employment wages via improved productivity. Empirical evidence from displaced workers in both countries confirms these predictions. Our findings reconcile competing views in the literature by showing that specialization entails trade-offs and is neither uniformly beneficial nor harmful.

JEL Classification: J24, J41, J63, J64
Keywords: Specialization, Skills, Displacement

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1 Introduction

The benefits of specialization in the organization of work have been recognized since the seminal contribution of Adam Smith (1776). More recently, however, a growing literature has highlighted the potential negative effects of worker specialization for labor market outcomes (Macaluso, 2025; Hernandez Martinez et al., 2022).This paper seeks to reconcile these seemingly conflicting perspectives. Combining empirical evidence and theoretical analysis, we show that specialization entails a fundamental trade-off: while it raises match productivity conditional on employment, it also reduces the probability of job finding due to the limited availability of specialized job opportunities. Using data from France and the US, we provide empirical evidence consistent with this trade-off. In particular, we find that—conditional on skill—specialization tends to reduce the value of unemployment, suggesting a negative net effect. These findings help reconcile prior empirical results and offer a broader perspective on the conditions under which specialization is beneficial in the labor market.

We define specialization as the average deviation of a worker's skill set from the distribution of skill profiles observed in the economy. Using data from France and the United States, we document two key empirical features of specialized skill portfolios. First, such skill sets tend to exhibit greater asymmetry—featuring high proficiency in some dimensions and low proficiency in others. Second, employment opportunities are less dense in the vicinity of specialized skill profiles, reflecting the relative scarcity of nearby job matches. To illustrate our notion of specialization, consider an analogy from athletics. A sprinter competing in the 100-meter race exemplifies a specialist, with training narrowly focused on a specific performance domain. In contrast, a decathlete—who competes across ten distinct events—represents a more generalist skill profile, spreading effort and ability across a broader skill set. According to our definition, the decathlete is less specialized, as their overall skill vector aligns more closely with the average profile across disciplines. The sprinter's skills are more asymmetrical, with fewer events in athletics closely aligned with their specific strengths.[1]

Building on the empirical characterization of specialized skill portfolios, we examine the implications of specialization for labor market outcomes, both theoretically and empirically. First, we develop a parsimonious random search model, drawing on Lise and Postel-Vinay

[1]Similarly, not all skill profiles are equally far apart. In fact, some disciplines have such overlap that athletes at times perform in a number of a priori distinct disciplines. For example, there have been repeated instances of athletes competing both in water polo and in swimming at the Olympic Games. For example, this happened for: John Arthur Jarvis (UK, 1900), Paul Radmilovic (UK, 1908) Louis Handley, Joe Ruddy, Leo Goodwin (USA, 1904), Gunnar Wennerström, Pontus Hanson and Torsten Kumfeldt (Sweden, 1908), Harald Julin (Sweden, 1908 and 1912), Robert Andersson (Sweden, 1908, 1912 and 1920), Gérard Blitz (Belgium, 1920, 1924 and 1928), Erich Rademacher (Germany, 1928).

(2020) and Mortensen and Pissarides (1994), to analytically characterize the effects of specialization conditional on average skill. To do so, we consider the two characteristics of specialized skill portfolios in turn. First, we consider the impact of skill asymmetry. In the model, more specialized workers—with more asymmetric skill profiles—enjoy higher productivity in well-matched jobs and optimally accept a broader set of offers. These gains arise whenever production features mismatch penalties and complementarity gains between worker skills and job requirements. Under the assumption of a uniform job offer distribution, more specialized workers—so long as their acceptance sets are fully contained within the interior of the distribution—benefit from larger acceptance sets, which in turn lead to higher job-finding rates, higher expected wages, and a greater value of unemployment. These predictions are consistent with Adam Smith's insight into the gains from specialization. However, once the second characteristic of specialized skill portfolios—namely, the sparsity of opportunities—is introduced, these predictions no longer carry through. In fact, when job offers are unevenly distributed—as in the data, where specialized jobs are less densely surrounded by nearby opportunities—the productivity advantage of specialized jobs may be offset by lower job arrival rates. In this case, while expected wages for specialized workers remain higher, their exit rate from unemployment may decline. As a result, the net impact of specialization depends on the interaction between mismatch penalties, complementarity gains, and the distribution of job offers. Whether specialization increases or reduces the labor market value of skills is therefore, in general, ambiguous and must ultimately be resolved empirically.

Second, we bring these theoretical insights to the data. To empirically assess the dual effects of specialization, we examine worker-level data on mobility and wages from two countries: the United States and France. Specifically, we study labor market outcomes following displacement, focusing on variation in both average skill levels and the degree of specialization in workers' skill portfolios. To address endogeneity concerns in mobility decisions, we restrict attention to workers displaced due to firm closures, thereby isolating exogenous separation events. Our analysis yields two main findings. First, higher pre-displacement specialization is associated with longer non-employment durations. Second, conditional on re-employment, more specialized workers tend to receive higher entry wages. A heterogeneity analysis further reveals that the adverse effects of specialization are particularly pronounced among lower-skilled workers. We conjecture that this results from the limited productivity gains they derive from specialization, combined with an equally constrained set of nearby job matches compared to higher-skilled individuals. Intuitively, the net effect of specialization depends on the relative strength of these opposing forces—reduced job-finding prospects versus higher match productivity. Finally, we discipline the theoretical model using our empirical estimates and calibrate it to assess the overall impact of specialization in the French labor market. The results suggest that, on average, specialization weakly reduces the value of unemployment, indicating that the negative effects outweigh the positive effects overall in France.

Our paper contributes primarily to the literature on the negative labor market consequences of worker specialization, as highlighted by Macaluso (2025) and Hernandez Martinez et al. (2022). Macaluso (2025) shows that workers with more locally specialized skill sets experience larger earnings losses following displacement. Her approach compares individuals with identical skill vectors but different job opportunity distributions, thereby isolating the negative effects of specialization arising from limited local job availability. In contrast, our analysis compares workers with different skill portfolios while holding average skill levels constant, allowing both the positive and negative aspects of specialization to manifest. In a contemporaneous study, Hernandez Martinez et al. (2022) also find that specialization negatively affects earnings after displacement, though their measure of specialization differs substantially from ours.

Our paper also relates to the growing literature on multidimensional skill sets, which emphasizes that different skills may either enhance or diminish match productivity depending on the specific job context (Lise and Postel-Vinay, 2020; Alon and Fershtman, 2019; Gibbons and Waldman, 2004; Lindenlaub and Postel-Vinay, 2020, 2023; Lindenlaub, 2017; Gathmann and Schönberg, 2010; Guvenen et al., 2020). In line with this perspective, several empirical studies document that workers who transition into occupations requiring substantially different skill sets face larger post-displacement earnings losses (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010; Ormiston, 2014; Nawakitphaitoon and Ormiston, 2015; Braxton and Taska, 2023). Relative to Gathmann and Schönberg (2010), we explicitly model both the costs and benefits of specialization in a frictional search framework and link them to observable labor market outcomes of displaced workers. The model generates new insights into the distributional consequences of specialization and its role in shaping unemployment risk and wage inequality—predictions that are supported by the data.

Our theoretical framework also helps reconcile seemingly contradictory findings in the literature, such as the specialization premium associated with education (Silos and Smith, 2015; Leighton and Speer, 2020) and the specialization penalty observed for displaced workers (Lamo et al., 2011). We show that both can coexist for different types of workers and across different labor market outcomes. In this sense, our analysis offers a unified interpretation of these contrasting results. To the best of our knowledge, the only other paper that documents both positive and negative aspects of specialization for workers is Silos and Smith (2015).

Yet, Silos and Smith (2015) conceptualize the source of specialization risk differently. The source of risk in their study is uncertainty about personal fit to a given occupation, which makes the acquisition of specialized skills risky. In our framework, the source of specialization risk arises from the structure of job opportunities in random labor search, as in Lise and Postel-Vinay (2020). Contrary to Silos and Smith (2015), where specialization risk vanishes over a worker's career, in our framework labor market risk is persistent throughout the career and becomes particularly salient upon job displacement.

The paper proceeds as follows. First, we define our measure of specialization and show the two key empirical characteristics of specialized skill sets in Section 2. Next, we develop a framework to articulate the mechanisms in Section 3, and derive analytical results, which we complement with a quantitative illustration. We then describe our data sets and the sample we use for our empirical data exercise. Finally, we describe our empirical results in Section 5 and use our model to assess the overall impact of specialization in France, before concluding in Section 6.

2 Specialization: Definition and Characteristics

We define worker specialization as the distance between a worker's skill set and the skill requirement vector of jobs observed in the economy. Formally, let worker i possess a skill vector x_i over K distinct skill dimensions. We define the worker's specialization at time t as

$$\text{Spec}_{i,t} \equiv \sum_{o=1}^{O} n_{o,t} \sum_{k=1}^{K} (x_{i,k} - y_{o,k})^2,$$

where $y_{o,k}$ denotes the skill requirement vector associated with occupation o in skill dimension $k \in \{1, \ldots, K\}$, and $n_{o,t}$ represents the share of employment in occupation o at time t, with $\sum_{o=1}^{O} n_{o,t} = 1$. To facilitate interpretation, we normalize the specialization measure on the unit interval.

2.1 Measurement

To construct an empirical measure of specialization, we require data on the distribution of employment across occupations, as well as information on both occupational skill requirements and individual worker skills.

Employment data We measure employment shares across occupations from large and representative cross-sectional data sets. For the US, we leverage the *Annual Social and Economic Supplement* (ASEC) of the *Current Population Survey* (CPS) for the years 1996-2020; and for France we use the cross-sectional version of the administrative matched employer-employee data set *Déclarations annuelles des données sociales* (DADS) for the years 2007-2019.

Skill requirements and worker skills In order to measure skills in the data, we leverage the Occupational Information Network (ONET) database to construct skill requirements by fine occupational categories. The ONET 19.0 release contains standardized descriptors on tasks needed to perform a job for each of the 954 occupational categories of the Standard Occupational Classification (SOC). We keep the importance value of all descriptors in Abilities, Knowledge, Skills and Work Activities, and the value of all the descriptors in the Work Context section, altogether 199 descriptors.

We use a principal component analysis (PCA) with exclusion restrictions to extract cognitive, manual and interpersonal skills for all SOC occupation codes (as in e.g., Lise and Postel-Vinay (2020) and Bárány et al. (2020)). Specifically, we extract the first three principal components and rotate them in order to satisfy the following exclusion restrictions: 'Mathematical Knowledge' only affects the first component, 'Multilimb Coordination' only affects the second component, and 'Social Perceptiveness Skill' only affects the third component. This allows us to conceptualize the first component as cognitive, the second as manual and the third as interpersonal skill requirement. A central advantage of our approach is that it yields broad measures of occupational skill requirements while retaining most of the underlying variation in detailed descriptors. For instance, key contributors to manual skills include 'Multilimb Coordination', 'Gross Body Equilibrium', and 'Speed of Limb Movement', while cognitive skills are primarily captured by descriptors such as 'Complex Problem Solving', 'Mathematics', and 'Perceptual Speed'.[2] Aggregating descriptors into broad skill categories mitigates two measurement concerns. First, occupations that rely on the same underlying skill type may appear artificially distant from each other if they have different values across the various descriptors that measure the given skill type. This can lead to incorrect distance measures relative to occupations that are indeed far in terms of skill types used. Second, if a given skill type is represented by more descriptors than other skill types, then distance measures will overemphasize differences in the given skill type. Therefore, occupations that use the overrepresented skill type more heavily will artificially appear further from other

[2]See Table 3 in the Appendix for the 25 most important descriptors contributing to each skill category.

occupations.[3] Collapsing similar descriptors into a common one ensures that occupations are compared on conceptually meaningful skill distances.

To integrate the skill and labor market data, we map SOC occupation codes to the 479 occupation codes of the French DADS (similarly to Laffineur and Mouhoud (2015) and Laffineur (2019)) and to the 352 harmonized occupation codes of the US CPS (similarly to Acemoglu and Autor (2011) and Lise and Postel-Vinay (2020)), and collapse the extracted skill measures to the level of these occupation codes.[4]

Because worker skills are not directly observed in the data, we impute a worker's skill vector using the skill requirements of their previous occupation, as in Macaluso (2025) and Hernandez Martinez et al. (2022). Formally, we set $x_{i,k} = y_{o,k}$ if the worker's last job was in occupation o. This approach effectively measures the specialization of the worker's most recent occupation.

2.2 Characteristics of Specialized Jobs

In the following we illustrate two key characteristics of specialized jobs. First, we show that skill asymmetry, commonly associated with specialized skills, is strongly positively correlated with our measure of specialization. Second, we show that employment opportunities in skill-close occupations are scarcer for more specialized jobs. These two aspects reflect the two distinct dimensions of specialization: lopsided skill profiles and limited availability of jobs in their proximity.

Skill asymmetry Let us define the asymmetry of a skill set as $\text{asym}(x) = \max_k x_k - \min_k x_k$. Higher values signify greater disparities in skills. It captures the conventional concept of specialized skills, where a worker possesses exceptionally strong skills in one area while potentially lacking skills in another. To illustrate the link between specialization and skill asymmetry, it is helpful to factorize specialization as follows:

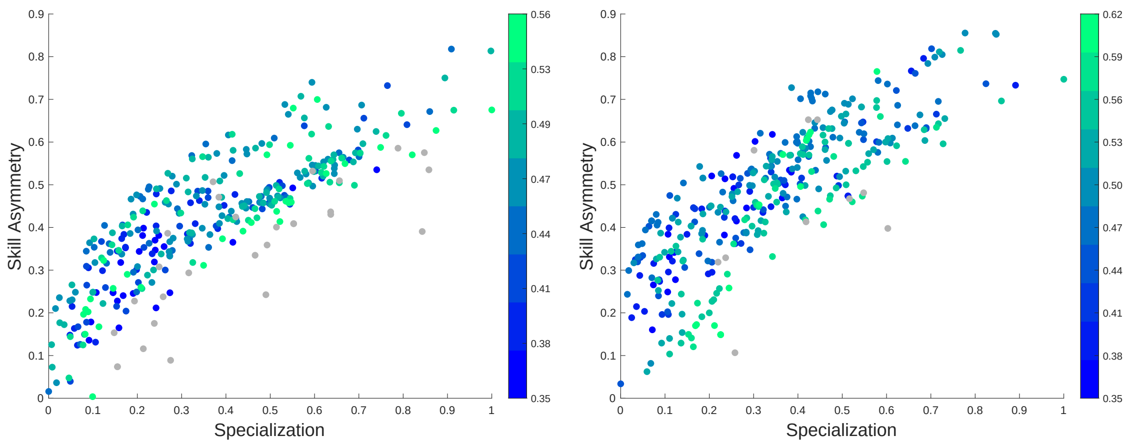
$$\text{Spec}_i = \sum_k E[y_k^2] + \sum_k x_{i,k}^2 - 2\sum_k x_{i,k} E[y_k], \tag{1}$$

where E denotes the expectation across occupations weighted by employment shares. This decomposition shows that if economy-wide average skills are similar across skill dimensions,

[3] In Appendix A.2 we provide more details on this important point.

[4] See Appendix A.3 for a description of correlations between skills, and Appendix A.4 for a demonstration that our measure of skill requirements has economic meaning.

i.e., $E[y_k] \approx E[y_l]$ for all $k, l \in K$, then among individuals with similar average skills, i.e. $\sum_k x_{ik}/K \approx \overline{x}$, those with a higher specialization measure will also have a more asymmetric skill set.[5] Thus, our definition of specialization reflects the intuitive idea that, conditional on average skill, a worker with a more asymmetrical or more concentrated skill profile–for example, a sprinter–is more specialized. It is important to note that skill asymmetry implies specialization only relative to $E[y_k]$, which depends on the entire distribution of jobs. This can be illustrated by the observation that in an economy composed entirely of sprinters, a sprinter would not have asymmetric skills, and would not be considered specialized. Therefore, our measure of specialization depends fundamentally on the distribution of jobs in the economy.



(a) US

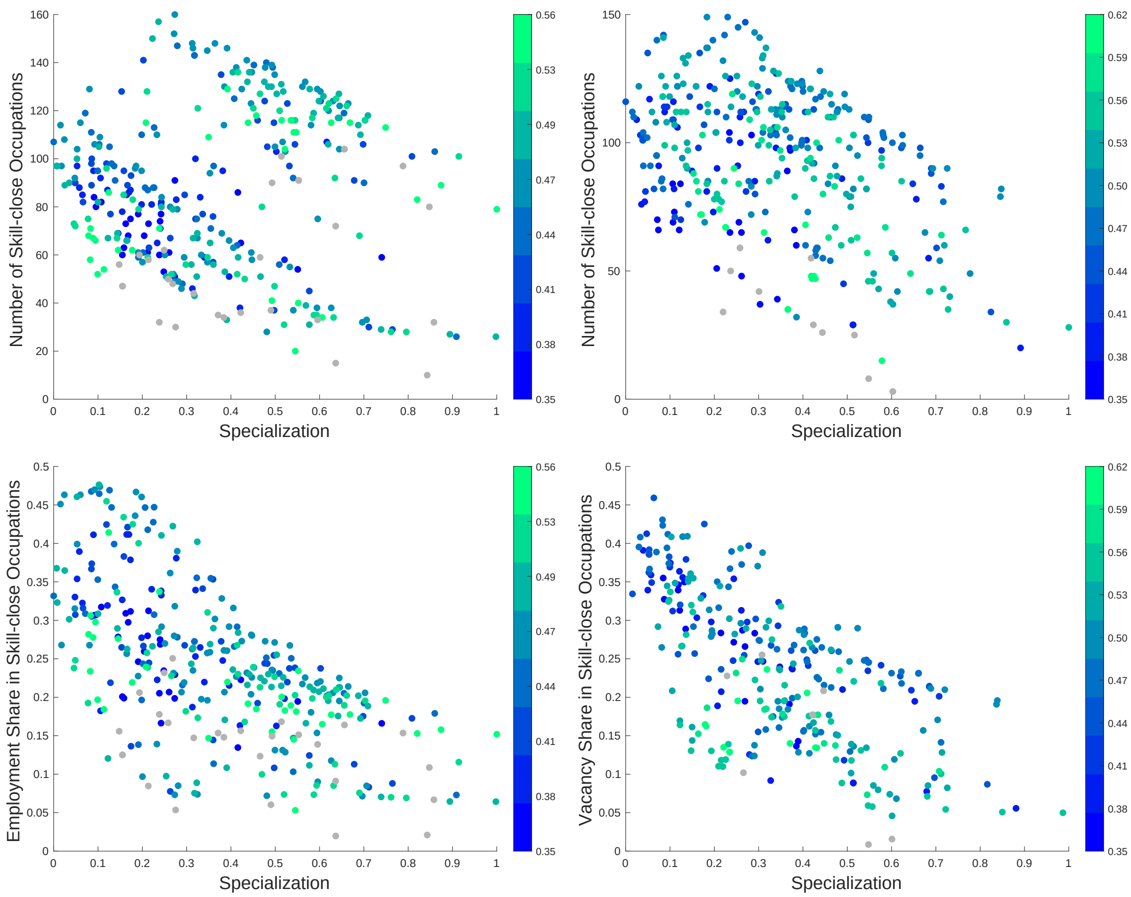
(b) France

Figure 1: Specialization and Skill Asymmetry

Notes: The figures show scatter plots of the asymmetry of skills against the specialization of skills across all occupations for the US (left panel) and France (right panel). In both the US and the French data, specialization and employment shares are measured in the year 2010. Occupations are binned by average skill level, with colors indicating different skill levels according to the colormap. Average skills are calculated as the simple average across the $K = 3$ skill dimensions.

Figure 1 plots skill asymmetry against specialization by occupation for the US (left panel) and France (right panel). Occupations are binned by average skill level, with colors indicating different skill levels. The figure shows that more specialized occupations exhibit greater skill asymmetry, both overall and within narrow skill bands.

[5] To see this, note that the first term in the specialization decomposition is the same for all workers. If $E[y_k]$ is similar across all skill dimensions k, then the last term is similar for workers whose average skills are similar. However, the middle term, $\sum_k x_k^2$, is larger for workers with the more asymmetric skill set, due to Jensen's inequality.



(a) US

(b) France

Figure 2: Specialization and Employment Opportunities

Notes: The top panels show the number of occupations closer to the given occupation than the 25th percentile of pair-wise skill distances against the specialization of a given occupation. The bottom panels show the share of employment (for the US) and the share of vacancies (for France) in occupations closer to the given occupation than the 25th percentile of pair-wise skill distances against the specialization of a given occupation. The left panels show this for the US, while the right panel depicts it for France. In both the US and the French data, specialization and employment and vacancy shares are measured in the year 2010. Occupations are binned by average skill level, with colors indicating different skill levels according to the colorbar. The dots in gray show occupations outside the range of the colorbar. Average skills are calculated as the simple average across the $K = 3$ skill dimensions.

Employment opportunities in skill-close occupations Our specialization measure captures the extent to which a worker's skill set differs from those of other jobs in the economy. Highly specialized occupations are characterized by skill requirements that are far from most others, while less specialized ones are close to many. As a result, we expect specialized jobs to have fewer nearby occupations in the skill space and fewer employment opportunities in those occupations.

Empirically, employment opportunities near specialized jobs depend on both the number of nearby jobs and the mass of open vacancies in them. While both are equilibrium outcomes, they likely reflect different economic forces: the selection of skill requirement vectors may reflect an extensive margin response—driven, for instance, by production technologies and broader economic conditions—whereas the number of open vacancies in each of these jobs may reflect an intensive margin response, such as to business cycle fluctuations. Figure 2 investigates these two aspects for both the US and France. Using the 25th percentile of pairwise skill distances as a cutoff,[6] we compute, for each occupation, (i) the number of occupations within the cutoff and (ii) the share of total open vacancies in those nearby occupations. To operationalize the distribution of vacancies across occupations, for France we use administrative data on occupation-level vacancy postings from the French public employment agency, *Pôle Emploi*.[7] For the US, unfortunately, data on open vacancies by occupation is not available publicly. We therefore use occupational employment shares, n_o, as a proxy, as we conjecture that the distribution of employment and vacancies, which are both endogenous objects, are likely to be positively correlated.[8] The top panels show that the number of skill-close occupations weakly declines in specialization; the bottom panels reveal a stronger negative relationship between specialization and the density of employment opportunities in nearby occupations. These patterns hold both in the aggregate and by average skill level, as indicated by the different colors in the figure. These patterns imply that specialized workers face not only fewer nearby occupations in terms of skill similarity, but also that in those occupations there are fewer employment opportunities.

3 Theoretical Framework

This section develops a framework to assess how specialization affects a worker's expected labor market outcomes. Section 3.1 introduces a simplified model, adapted from Lise and Postel-Vinay (2020), that incorporates both mismatch penalties and complementarities in a multidimensional production function. For tractability, we abstract from on-the-job mobility and learning, and wages are set via Nash bargaining, as in Mortensen and Pissarides (1994). We then examine the effect of the two defining characteristics of specialized skill sets within our model. In Section 3.2, we first focus on the role of skill set asymmetry and show that specialization improves labor market outcomes under knife-edge conditions. We then introduce the second characteristic—job scarcity in skill-close occupations—in Section 3.3,

[6] Skill distance is calculated as the Euclidean distance between occupational skill requirement vectors.

[7] This data covers the years 2010-2019. Occupations are classified according to the ROME occupational scheme, which we map to the DADS PCS-ESE occupation codes using standard crosswalks.

[8] Figure 11 in the Appendix confirms that the distribution of employment is a good proxy for the distribution of vacancies in France.

and illustrate how specialization can lead to both positive and negative consequences for labor market outcomes.

3.1 Setting and Labor Market Outcomes

Environment The economy is set in continuous time. Workers have a set of skills $x = \{x_1, ..., x_K\}$, $x_k \in \mathbb{R}_+$ in K distinct skill dimensions. Firms have skill requirement vectors $y = \{y_1, ..., y_K\}$, $y_k \in \mathbb{R}_+$ in the same K skill dimensions. Both workers and firms are risk neutral and discount the future at rate r. The worker's output, $f(x, y)$, and their disutility from working, $c(x, y)$, depend on their skills, x, and on the technology, y, of the firm with which the worker is matched. Employed workers receive wages $w(x, y)$. Workers enter the labor market as unemployed and sample jobs from the exogenously given distribution $F(y)$ at rate λ. Matches are destroyed exogenously at rate $\delta \geq 0$.

Match output and worker disutility We assume that the match-specific output of worker x with firm y is given by

$$f(x, y) = \sum_k \left(\gamma_k y_k + \alpha_k x_k y_k - \kappa_k^u (\min(0, x_k - y_k))^2\right),$$

where γ_k, α_k, κ_k^u are assumed to be positive for all K dimensions. Also, assume that the flow disutility of worker x from working at firm y is

$$c(x, y) = \sum_k \left(\kappa_k^o (\max(0, x_k - y_k))^2\right),$$

where κ_k^o are also assumed to be positive for all K dimensions, indicating a disutility whenever a worker's skills exceed job skill requirements in any dimension. Let us denote the net flow value of the match by $\tilde{f}(x, y)$

$$\begin{aligned} \tilde{f}(x, y) &= f(x, y) - c(x, y) \\ &= \sum_k \left(\gamma_k y_k + \alpha_k x_k y_k - \kappa_k^u (\min(0, x_k - y_k))^2 - \kappa_k^o (\max(0, x_k - y_k))^2\right), \end{aligned}$$

The term $\gamma_k y_k$ allows for jobs with higher skill requirements, y_k, to be more productive regardless of a worker's skill set. Instead, the terms $\kappa_k^u (\min 0, x_k - y_k)^2$ and $\kappa_k^o (\max 0, x_k - y_k)^2$ represent mismatch penalties arising from discrepancies between worker skills and job requirements. The complementarity between worker skills and job requirements is captured by the terms $\alpha_k x_k y_k$.

Value functions. Let $U(x)$ denote the value of an unemployed worker with skill x, $W(x,y)$ the value of an employed worker x at job y, and $J(x,y)$ the value of a filled job y employing worker x. Let us denote the joint surplus of the match by $S(x,y) = J(x,y)+W(x,y)-U(x)$. Under linear preferences over income, $S(x,y)$ is invariant to the wage, as surplus division between worker and firm does not affect total surplus. We assume that firms and workers engage in Nash bargaining over the firm-worker surplus with a relative worker bargaining weight β such that

$$W(x,y) - U(x) = \beta S(x,y).$$

The Bellman equation for the value of unemployment satisfies

$$rU(x) = \lambda \int_y \max\{0, (W(x,y) - U(x))\}dF(y) = \beta\lambda \int_y \max\{0, S(x,y)\}dF(y).$$

The value of an unemployed worker is equal to the expected capital gain from becoming employed $\lambda \int_y \max\{0, (W(x,y) - U(x))\}dF(y)$. The last equality is obtained from the sharing rule, $W(x,y) - U(x) = \beta S(x,y)$. Matching occurs only in mutual agreement between the worker and the firm when the surplus is positive.

The value function of employed workers is

$$rW(x,y) \quad = \quad w(x,y) - c(x,y) - \delta\left(W(x,y) - U(x)\right).$$

Employed workers earn wage $w(x,y)$ and incur disutility $c(x,y)$; if exogenously displaced, they transition to unemployment and incur an expected loss of $\delta\left(W(x,y) - U(x)\right)$.

The firm's value of a filled job satisfies

$$rJ(x,y) = f(x,y) - w(x,y) - \delta J(x),$$

reflecting flow profit and the loss in value if the match is destroyed. Combining these last two value functions, we can express the surplus as $(r+\delta)S(x,y) = f(x,y) - c(x,y) - rU(x) = \tilde{f}(x,y) - rU(x)$. Substituting this into the worker's unemployment value and rearranging yields:

$$rU(x) = \quad \beta\lambda \int_{S^+(x)} \frac{\tilde{f}(x,y) - rU(x)}{r+\delta} dF(y) = \frac{\beta\lambda \int_{S^+(x)} \tilde{f}(x,y)dF(y)}{r+\delta+\beta\lambda \int_{S^+(x)} dF(y)}. \tag{2}$$

where $S^+(x)$ denotes the set of acceptable matches for worker x, that is, $\forall y \in S^+(x)$: $rS(x, y) > 0$, or equivalently $\tilde{f}(x, y) > rU(x)$, and $\forall y \notin S^+(x) : rS(x, y) \leq 0$. Equation (2) implicitly pins down $rU(x)$ as the unique fixed point of the equation, as it appears on both sides and enters the right-hand side through the acceptance set $S^+(x)$.

Labor market outcomes. The probability that an unemployed worker with skill vector x forms a match with a random draw from distribution $F(y)$ is

$$P(x) \equiv P(S(x, y) > 0) = \int_{S^+(x)} dF(y).$$

Given Nash bargaining over the surplus, it follows that the wage is

$$w(x, y) = \beta \tilde{f}(x, y) + c(x, y) + (1 - \beta) rU(x).$$

The expected wage of an unemployed worker is given by

$$\begin{aligned} E\left[w(x, y)\right] &= \frac{\int_{S^+(x)} \beta \tilde{f}(x, y) + c(x, y) + (1 - \beta) rU(x) dF(y)}{P(x)} \\ &= rU(x) \frac{r + \delta + \lambda P(x)}{\lambda P(x)} + E\left[c(x, y) \mid y \in S^+(x)\right]. \end{aligned}$$

We aim to analyze how these outcomes depend on workers' specialization.

3.2 Worker Specialization and Labor Market Outcomes

In this section, we characterize how worker specialization influences labor market outcomes. For tractability, we assume that under- and over-qualification are penalized symmetrically, i.e., $\kappa_k^u = \kappa_k^o$, and adopt a two-dimensional ($K = 2$), symmetric benchmark with common parameters across skill dimensions: $\kappa_k = \kappa$, $\gamma_k = \gamma$, and $\alpha_k = \alpha$ for all $k \in \{1, 2\}$.

In this setting, any worker's skill vector can be described by their average level of skill, $\overline{x}$, and the deviation from that average. Specifically, we can write skill vectors as $x = (\overline{x} + c, \overline{x} - c)$, where c captures the degree of skill asymmetry. As documented in Section 2, more specialized workers—holding average skills constant—tend to have more asymmetric skills. Hence we will refer to workers with a higher c as more specialized.

We begin by characterizing the maximum attainable net output for each worker. Under the assumption that $\kappa > 0$, every worker x has a unique best-fit job, $y^*(x)$, that maximizes net output. The corresponding skill requirement in dimension k is given by

$$y_k^*(x_k) = x_k \left(1 + \frac{\alpha}{2\kappa}\right) + \frac{\gamma}{2\kappa}.$$

The best-fit skill requirement is linear in worker skill x_k, with slope $1+\alpha/(2\kappa)$ and intercept $\gamma/(2\kappa)$. Net output at the best-fit skill requirement for worker with skill $x = (\overline{x}+c, \overline{x}-c)$ is

$$\tilde{f}(x, y^*) = \frac{\gamma^2}{\kappa} + \gamma \left[\frac{\alpha}{2\kappa} + 1\right] 2\overline{x} + \alpha \left[\frac{\alpha}{4\kappa} + 1\right] 2(\overline{x}^2 + c^2).$$

This expression is increasing in the average skill, $\overline{x}$, and in the skill asymmetry, c, of the worker. Recall that among workers with the same average skill, more specialized workers have more asymmetric skills. This implies that conditional on average skill, more specialized workers have a higher net output at their best fit. Moreover, the output gain of specialized workers is increasing in the strength of complementarity, α, and is decreasing in the strength of the mismatch penalty, κ. It is insightful to calculate the loss in net output relative to net output at the best fit

$$\tilde{f}(x, y^*) - \tilde{f}(x, y) = \kappa \|y - y^*\|^2, \tag{3}$$

which shows that the loss in net output increases quadratically in the job's Euclidean distance to $y^*(x)$.

These findings have two important implications. First, the same Euclidean distance of y from the best fit y^* implies an equal decline in the net output of a given worker relative to their best fit, regardless of the skill vector of the worker, x. Second, the set of points at which the net output of worker x is $\Delta > 0$ below their best fit is given by a circle

$$\sum_{k=1}^{2} (y_k - y_k^*)^2 = \frac{\Delta}{\kappa}, \tag{4}$$

with radius $\sqrt{\Delta/\kappa}$ centered around their best fit, y^*. These observations imply that the difference in net output at the best fit between any two workers is maintained on any given circle around their respective best fits. This mechanism underlies the gains from specialization: more specialized workers achieve higher net output around their respective best fit. The result requires both $\alpha > 0$ (complementarities) and $\kappa > 0$ (mismatch penalties), highlighting the joint role of both forces.

Finally, we characterize the worker's reservation utility and acceptance set. The acceptance set of workers, $S^+(x)$, is defined by the reservation utility, $rU(x)$, such that all jobs with net output greater than $rU(x)$ are accepted. Based on (4), the acceptance region is a circle around the best fit of the worker, and the radius of the circle depends on the reservation utility. Note that finding the reservation utility is equivalent to finding the maximum acceptable net output loss, Δ^*, where $rU(x) = \tilde{f}(x, y^*) - \Delta^*$. Using these observations and the expression for net output loss (from (3)) in the equilibrium value of unemployment given in (2), we obtain that the optimal Δ^* solves

$$(r+\delta)\tilde{f}(x,y^*) = (r+\delta)\Delta^* + \beta\lambda \int_{\|y^*-y\|<\sqrt{\Delta^*/\kappa}} \left[\Delta^* - \kappa\|y^*-y\|^2\right] dF(y).$$

Observe that the integrand in square brackets is positive on the region of integration, as $\kappa\|y^*-y\|^2 < \Delta^*$, and hence the integral itself is increasing in Δ^*. Therefore, the right-hand side of the above equation is increasing in Δ^*. Since net output at the best fit is higher for more specialized workers, the left-hand side of the above equation is higher as well. This implies that among workers with the same average skill level, more specialized workers will optimally have a higher Δ^*, and hence a wider acceptance region. This is illustrated

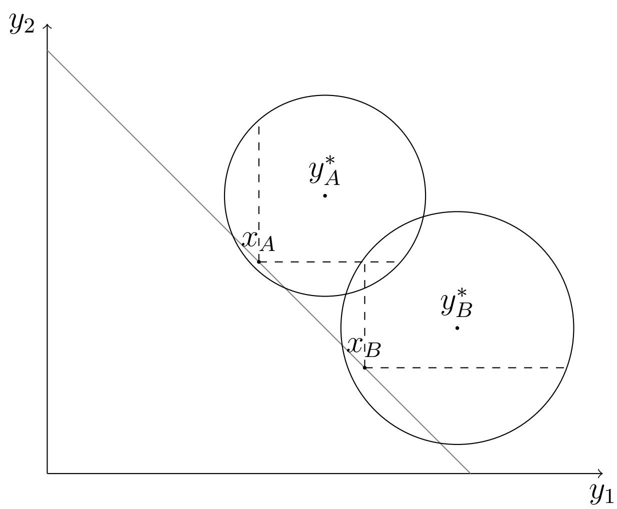


Figure 3: Specialization and Acceptance Sets.

Notes: The figure illustrates the acceptance sets for a non-specialized worker x_A and a specialized worker x_B in the case of two skill dimensions, with identical parameters across dimensions and symmetric penalties for under- and over-qualification.

in Figure 3, where the diagonal gray line shows points with the same average skills, and $x_A = (\overline{x}, \overline{x})$ represents a generalist worker, and $x_B = (\overline{x}+c, \overline{x}-c)$ represents a specialized worker. The acceptance region of each worker is a circle around their respective best fits, and the specialized worker's acceptance region has a larger radius. Ultimately, whether the wider acceptance region leads to a higher or lower acceptance probability and whether it leads to higher or lower expected wages depends on the distribution of job offers, $F(y)$.

To set a benchmark, consider the case of a uniform distribution of job offers, with density p, and with a support sufficiently wide for the acceptance region of worker x to fall within its boundaries. In this case, the maximum acceptable net output loss, Δ^*, is pinned down by

$$\tilde{f}(x, y^*) = \Delta^* \left(1 + \frac{\beta\lambda p\pi\Delta^*}{2(r+\delta)\kappa}\right).$$

In line with our findings in the general case, the optimal Δ^* is larger for more specialized workers, as they attain higher values of $\tilde{f}(x, y^*)$. The acceptance probability is

$$P(x) = \int_{\|y^*-y\|<\sqrt{\Delta^*/\kappa}} p dy = p\pi\frac{\Delta^*}{\kappa},$$

which is increasing in Δ^*. Thus, more specialized workers have a higher job-finding probability.

The value of unemployment is

$$U(x) = \frac{\tilde{f}(x, y^*) - \Delta^*}{r} = \frac{\beta\lambda p\pi(\Delta^*)^2}{2r(r+\delta)\kappa},$$

which is also increasing in Δ^*, and therefore is higher for more specialized workers.

Expected wages are

$$E\left[w(x, y)\right] = \frac{\beta\Delta^*((r+\delta)\kappa + \lambda p\pi\Delta^*)}{2r(r+\delta)\kappa} + \frac{\kappa\int_{\|y^*-y\|<\sqrt{\Delta^*/\kappa}}\sum_k(\max(0, x_k - y_k)^2 dF(y)}{p\pi\Delta^*/\kappa}.$$

The first term is increasing in Δ^*, while it is not straightforward to determine whether the second term is increasing or decreasing in Δ^*.[9] Nonetheless, if wages are mostly determined by net output, rather than by the disutility suffered by workers if they are over-qualified, then expected wages will also be higher for more specialized workers.[10] Therefore, in the case

[9] In Figure 3, the region where a worker suffers a disutility is the lower left part of the acceptance region, separated by dashed lines passing through the skill vector of the worker. As it can be seen on the graph, for specialized workers the area where disutility is incurred is likely to be larger relative to the area of the circle, and the quadratic penalty is also likely to be larger.

[10] If the over-qualification of a worker reduces the output of the match, rather than causing disutility for the worker, then expected wages are given by

$$E\left[w(x, y)\right] = \frac{\int_{S^+(x)}\beta\tilde{f}(x, y) + (1-\beta)rU(x)dF(y)}{P(x)} = rU(x)\frac{r+\delta+\lambda P(x)}{\lambda P(x)} = \frac{\beta\Delta^*((r+\delta)\kappa + \lambda p\pi\Delta^*)}{2r(r+\delta)\kappa},$$

of a uniform job offer distribution with interior acceptance regions, we find that conditional on average skill, more specialized workers have a higher value of unemployment, a higher exit rate from unemployment, and are likely to have higher expected wages as well. In this setting, and in line with Smith (1776), who highlighted the advantages of specialization at the firm level, worker specialization can similarly enhance labor market outcomes.

However, in the data, specialized workers are not only distinguished by asymmetric skill profiles. As shown in Section 2.2, they also face fewer employment opportunities in nearby occupations. This implies that the density of $F(y)$ is lower around the best-fit occupations of more specialized workers. While this reduces their likelihood of exiting unemployment, their productivity near the best fit remains unaffected by the distribution of job offers. In the next section, we quantitatively assess how labor market outcomes vary with specialization, allowing part of the worker's optimal acceptance set to lie outside the support of $F(y)$.

3.3 Numerical Illustration

In the following, we numerically examine the equilibrium job-acceptance rate $P(x)$ and the expected wage $E\left[w(x,y)\right]$. We continue to focus on the case of two skills, $K = 2$. As before, we assume that parameters are common across skill dimensions, i.e., $\gamma_k = \gamma$ for all k, $\alpha_k = \alpha$ for all k, and $\kappa_k^u = \kappa_k^o = \kappa$ for all k. We define skills on a uniform grid over $[0, 1]$, with job offers drawn from a uniform distribution $F(y)$. For simplicity, we consider a case without worker displacement such that jobs are indefinite once matched.[11] Model parameters λ, r, and β are set according to established values in the literature, while we systematically vary the magnitude of the mismatch penalty κ given $\gamma = \alpha = 1$.[12]

To convey economic intuition, we show in Figure 4 how matching sets and net output vary with κ, when considering workers with either specialized skills $x = (0.2, 0.8)$, shown in the left column, or non-specialized skills $x = (0.5, 0.5)$, shown in the right column. The skill vector of the worker is represented as a white dot in the figure, whereas the best fit, $y^*(x)$, is shown as a blue dot. The optimal acceptance regions are denoted with black lines. We

which is higher for more specialized workers, as shown above.

[11] Worker skills are assumed to follow a uniform distribution $W(x)$, and the induced equilibrium distribution of employment across jobs is computed as

$$N(y) = \int \int_{S^+(x)} dF(y)\, dW(x).$$

[12] Specifically, we set $r = 0.10$ and $\lambda = 0.39$, in line with Lise and Postel-Vinay (2020). Finally, we set $\beta = 0.5$, following common values suggested by either the Hosios (1990) condition or symmetric Nash bargaining.

vary κ across rows in the set $\{5, 20, 50\}$, representing a low, medium and a high degree of mismatch penalties.

The figures illustrate two key insights. First, consider the case of a high mismatch penalty, shown in the top row of Figure 4. Here, the optimal skill requirement $y^*(x)$ closely aligns with the worker's skill vector, and the acceptance regions lie entirely within the support of the skill domain. In this setting, the more specialized worker achieves both a higher job-finding probability $P(x)$ and higher expected wages $E[w(x, y)]$, resulting in a higher value of unemployment $U(x)$. This outcome reflects the theoretical result established in the previous section: in the interior of the skill domain, more specialized workers enjoy superior labor market outcomes. Second, these conclusions do not necessarily hold when mismatch penalties are weaker. As shown in the middle and bottom rows—corresponding to lower values of κ with $\kappa = 20$ and $\kappa = 5$, respectively—the acceptance sets for the specialized worker (and, in the former case, also for the generalist) partially lie outside the support of the job offer distribution. In such cases, the optimal skill requirement lays to the right of the worker's skill - due to productivity gains at higher skill requirement jobs - and the specialized worker no longer necessarily enjoys a higher job-finding probability. With a moderate mismatch penalty, the specialized worker still achieves a higher unemployment value $U(x)$, driven by higher expected wages. However, when mismatch penalties are low, the specialized worker may face both a lower exit probability and a lower value of unemployment, despite a continued wage premium at accepted jobs. Taken together, these results indicate that high mismatch penalties, κ, alone do not imply lower job-finding rates for specialized workers. In fact, when mismatch penalties are sufficiently large, specialized workers may accept jobs at higher rates than generalists in this setting.

In summary, the framework predicts that, in the presence of both complementarity gains and mismatch penalties, greater specialization can be associated with higher expected wages but lower job-finding rates.[13]. In the sections that follow, we assess these theoretical predictions against empirical evidence.

[13] While our model abstracts from productivity dynamics for expositional clarity, a dynamic framework could accommodate features such as on-the-job skill adaptation (as in Lise and Postel-Vinay (2020)) or time-varying match-specific shocks. Similarly, allowing for parameter heterogeneity would offer greater flexibility in matching empirical patterns, though such extensions lie beyond the scope of our analysis. These considerations are however pursued in the companion paper Holzheu (2022), where neural networks are used to solve an economy with specialized skills

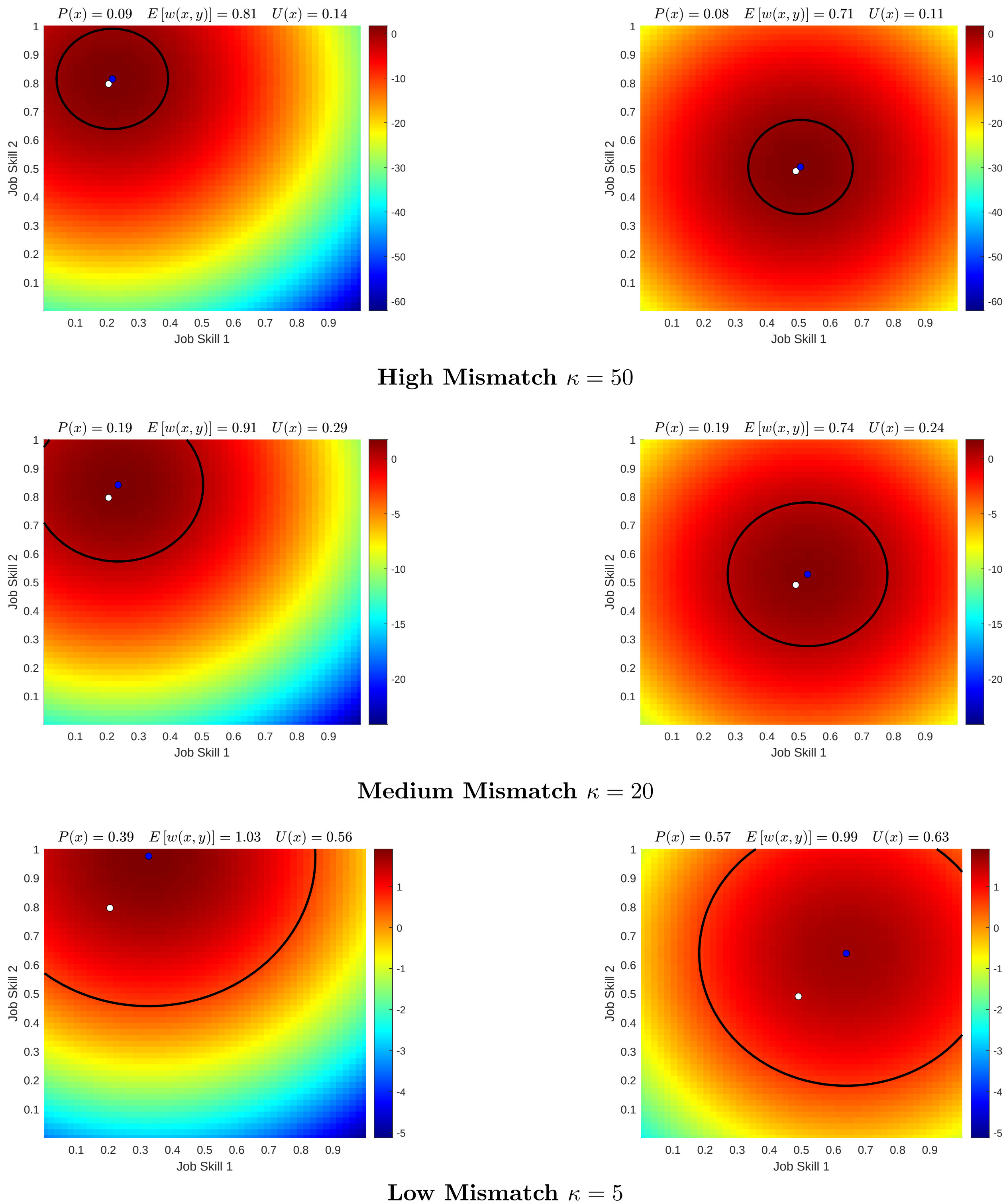


Figure 4: Complementarity, Net Output and Matching Sets.

Notes: The figures show heatmaps of net output $\tilde{f}(x, y)$ and the optimal acceptance regions with black lines for a specialized skill set (left panels) and a non-specialized skill set (right panels) in a two-dimensional skill space. Parameters are set to $\alpha = \gamma = 1$, while κ varies across rows. The worker's skill vector is indicated by a white dot, and the best fit skill requirement is shown as a blue dot.

4 Data and measurement

In the following, we outline our data sets, the definition of displaced worker, the sample, as well as the variables used in our analysis.

Labor Market Data Our empirical analysis draws on data on displaced workers from two sources: (1) the *Displaced Worker Supplement* (DWS) of the CPS for the United States, and (2) the panel version of the administrative matched employer-employee *DADS* dataset for France. The U.S. sample spans 1996–2020, and the French sample covers 2007–2019. Using data from both countries allows us to assess the generality of our findings across different institutional settings, particularly given notable differences in labor market regulation. Each dataset also offers distinct advantages. The U.S. DWS identifies reasons for job loss, enabling us to isolate involuntary separations and relate to a well-established displacement literature (e.g., Neal (1995)). The French matched data provide rich worker histories, detailed characteristics, and universal-level coverage, and can be linked to the firm registry to accurately track mobility and firm closures.

Displaced workers For our analysis it is crucial to consider only displaced workers for whom the reason of separation is exogenous to the quality of the worker-firm match and who did not quit their job voluntarily. Our main definition of displacement follows from the DWS definition and considers workers as displaced whenever they left their previous employer involuntarily due to firm closure.[14] This definition is more restrictive than most previous work that defines displacements as involuntary separations during mass lay-offs, some of which also use the DWS for their analysis (e.g., Neal (1995)). We chose to follow this more restrictive definition for two reasons. First, we aim to harmonize the French and US data sets based on a common definition of displacement. Second, while mass lay-offs can still give rise to the selection of laid-off workers based on the quality of the worker-firm match, a firm closure applies to all workers indiscriminately. We therefore expect our more restrictive measure to address potential remaining concerns about worker selection. For France, we complement the DADS Panel with information from the firm registry BODACC, and following Cahuc et al. (2021), we consider displacements as worker separations at liquidating firms. For both samples, we show that results differ when using mass lay-off events instead of firm closures, suggestive of worker selection in this sample.

[14] Specifically, from the survey year 1998 onward, the DWS considers workers as displaced if they had lost or left a job due to layoffs or shutdowns, were not self-employed and did not expect to be recalled to work within the next six months. Workers are also asked whether their firms have been shutting down.

Sample Our sample is restricted to workers who have experienced a displacement event in the last 3 years between the age of 20 and 64 in the private sector.[15] Table 1 summarizes our main sample of displaced workers across the two data sets. In terms of the number of

	US	France
Years	1996-2020	2007-2019
Specialization	0.31	0.30
Average skills	0.57	0.57
Weeks w/o work	11.98	45.77
No weeks w/o work	0.16	0.08
Post-displ. separation rate	0.23	0.43
Post-displ. log real wage	6.42	4.27
Age	39.03	38.30
Tenure at lost job	4.62	3.87
Experience	19.75	15.45
Female	0.41	0.22
Last log real wage	6.54	4.36
Lost job in manufacturing	0.21	0.21
Last firm size		189.88
# Workers	2697	18307
# Firms		11648
# Observations	2697	18800

Table 1: Summary statistics

Notes: The table shows summary statistics across samples. Note that wages in the US DWS are weekly wages whereas they are measured at a daily frequency in France. The number of firms, workers and observations is based on the sample for the analysis of duration of non-employment.

observations, the French data set is roughly seven times larger than the US data set. The average specialization index is comparable across the two samples, as well as the average skill level. The average age, experience, and tenure at the last job and the share of female workers is slightly higher in the US sample. The share of observations in manufacturing is comparable in the two data sets.

Main Variables In our analysis, our main dependent variables are the duration of non-employment after displacement and the wage at the first job after displacement. The duration

[15]Note that some of the literature on displacement, such as Davis et al. (2011), impose a lower limit of at least 3 years of previous tenure at the past job for their sample. This seems not to be the right approach in this setting given that experience within the occupation rather than within the job is the more decisive factor in our setting, yet is unobserved in the US sample. Moreover, Lise and Postel-Vinay (2020) show heterogeneity in the learning rates across skills, such that any tenure threshold would be arbitrary. We consider heterogeneity in our results based on worker experience in Section 5.1.

of non-employment is directly observed in both data sets, either through a survey question (as in the DWS) or as the time span until the next work spell following a displacement in the administrative data set. People spend on average roughly 4 times as long without work in France after displacement, compared to the US. Note that in the US data set, 16% of workers have less than 1 week of non-employment between jobs, which is high relative to the 8% in the French data set. Both data sets feature information on the wage after displacement. For comparability, we restrict attention to workers with one job since displacement in the US sample. The log wage gap between pre- and post-displacement wages is larger in the US with 12% compared to 9% in France.

5 Empirical results

We next provide empirical evidence on the negative and positive effects of specialization. In Section 5.1, we estimate a series of regression specifications using data on displaced workers, a setting in which job separations are plausibly exogenous and reflect firm-side economic shocks rather than low match-specific surplus. In Section 5.2, we use our model to interpret our empirical findings.

5.1 Regression results

Empirical Specification In our empirical strategy, we test how pre-displacement specialization is associated with post-displacement outcomes. For worker i displaced at time t, we estimate:

$$Y_{i,\tau} = \alpha \, \mathrm{Spec}_{i,j(i,t),t} + X_{i,t}\beta + \epsilon_{i,t},$$

where $Y_{i,\tau}$ denotes the outcome measured at horizon τ, and $\mathrm{Spec}_{i,j(i,t),t}$ is the specialization index of worker i's last job $j(i,t)$ prior to displacement.[16] The control vector $X_{i,t}$ includes the average skill level ($\overline{x}_{i,j(i,t),t} = \sum_k^K x_{j(i,t),k}$) of worker i at their pre-displacement job converted to an index between 0 and 1, age, gender, labor market experience, tenure at the last job, as well as the log wage at the last job. Including average skill as a control reflects the theoretical insight from Section 3, where we show that our variables of interest vary with specialization conditional on average skill. For the US sample, we further control for education. In the French sample we control for worker fixed effects, estimated with a standard AKM specification as in Abowd et al. (1999) on pre-displacement wages.

[16] In the absence of a theory-driven measurement of specialization, we replicate our analysis using four alternative measures of specialization. These measures all share the feature that both individual skill profiles and the economy-wide skill distribution play a role. As shown in Table 7 in the Appendix, the results are robust to these alternative specifications.

We examine two outcomes: (a) the duration until re-employment (in weeks), and (b) the log wage upon re-employment. These outcomes reflect the dual nature of specialization. While greater specialization may lengthen non-employment duration due to fewer suitable job opportunities, it can also result in higher re-employment wages through improved match quality. Table 2 summarizes the main regression results.

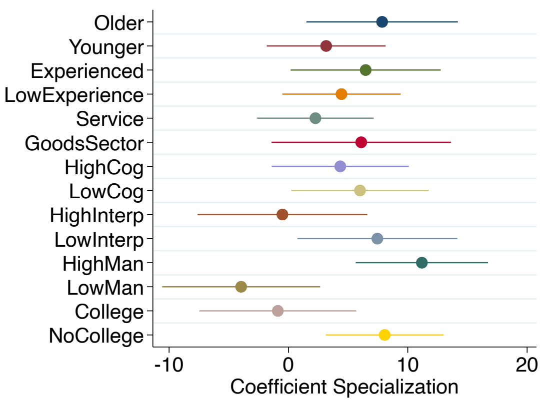
	Weeks w/o work			Log real wage		
	(1)	(2)	(3)	(4)	(5)	(6)
			US			
Specialization	3.947*	4.082*	5.171*	0.734*	0.630*	0.264*
	(0.041)	(0.036)	(0.010)	(0.000)	(0.000)	(0.017)
Average skills		-1.821	0.155		0.998*	-0.0819
		(0.444)	(0.951)		(0.000)	(0.573)
Observations	2697	2697	2697	677	677	677
			FR			
Specialization	5.041^{+}	6.076*	5.434^{+}	0.448*	0.437*	0.0904*
	(0.053)	(0.020)	(0.064)	(0.000)	(0.000)	(0.000)
Average skills		-21.25*	-10.26*		0.253*	0.0455
		(0.000)	(0.008)		(0.000)	(0.152)
Observations	18800	18800	13411	16315	16315	10745
Controls	w/o Skill	w/ Skill	+Controls	w/o Skill	w/ Skill	+Controls

Table 2: Regression Results

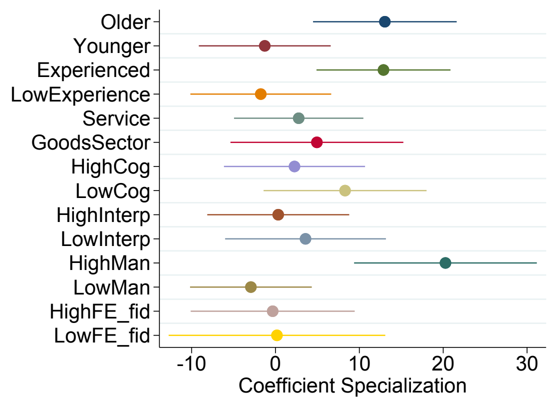
Notes: The table shows results of a regression of weeks without work and entry wages on previous specialization and controls. Column (1) and (4) do not control for skills, column (2) and (5) control for average skills, column (3) and (6) additionally control for the baseline set of controls, which includes age, gender, education (for the US) or AKM worker FE (for France) and pre-displacement experience, tenure and log wage. See text for details. Results are weighted using sampling weights for the US. Values in brackets represent p-values, $^{+}$ $p < 0.10$, * $p < 0.05$.

Negative effect of specialization The left panel of Table 2 shows the results for the duration of non-employment following displacement. Across specifications, higher specialization is associated with longer non-employment spells. Column (1) includes only the specialization index. Column (2) controls for pre-displacement average skill level, which tends to be positively correlated with specialization. In addition, higher skill levels likely enhance match productivity directly, possibly leading to shorter non-employment durations. As expected, the coefficient on specialization increases in magnitude once the skill level is accounted for, consistent with opposing effects of specialization and general skills. Column (3) adds the full set of worker controls, allowing us to net out key confounders such as experience and tenure, which are likely to shorten non-employment duration independently of specialization.[17]

The regression results suggest that specialization meaningfully affects non-employment duration, even among workers with similar average skill levels. For example, a pressing machine operator ($\overline{x} = 0.19$, Spec $= 0.81$) spends 16–18 days longer in non-employment than a proofreader with the same average skill level but lower specialization (Spec $= 0.33$). Among high-skill occupations, managers in education ($\overline{x} = 0.82$, Spec $= 0.76$) face 19–21 more days of non-employment than managers in food services (Spec $= 0.20$) with identical skill levels.



(a) US



(b) France

Figure 5: Non-employment duration – Heterogeneity analysis

Notes: The panels show the coefficients on specialization for non-employment duration for different groups of displaced workers. Specifications control for age, gender, year as well as the log wage at the last job. Older workers are above age 40, all other criteria cut the sample at the mean and correspond to the job before separation. High FE fid and Low FE fid refer to firms with high and low AKM fixed effects, respectively.

Figure 5 shows that the effect of specialization on non-employment duration is heterogeneous across workers. The impact is larger for older and more experienced individuals, and particularly pronounced among those in occupations with high manual skill requirements. In France, the effect is stronger for workers in jobs with low cognitive demands; in the US, for those in jobs with low interpersonal demands and without a college degree. These patterns suggest that the negative effects of specialization are concentrated among lower-skilled

[17]Using an alternative sample of workers displaced during mass layoffs yields insignificant coefficients (see Appendix B.3), highlighting the importance of our preferred sample based on firm closures. Intuitively, layoffs may be selective—targeting lower match-quality workers—while firm closures avoid this selection, making them more appropriate for isolating the effect of specialization.

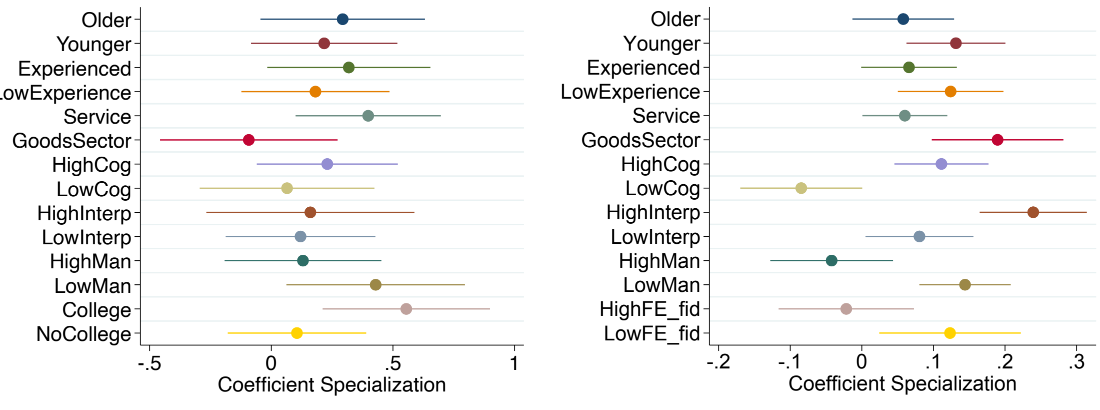
workers.

Positive effect of specialization The right panel of Table 2 presents regression results for workers' first post-displacement wage. We find that entry wages increase with pre-displacement specialization. Column (4) includes only the specialization index; Column (5) adds controls for pre-displacement average skill level, which is likely to raise wages across matches. Column (6) includes the full set of baseline controls, accounting for additional confounding factors. The magnitude of the effect is economically meaningful. Using our previous example of the two types of managers, the more specialized worker earns 5 percent more in France and 15 percent more in the US.

At first glance, our finding that specialization increases expected wages may seem to contrast with Macaluso (2025), who shows that workers in locally skill-remote occupations experience larger income losses following displacement. Macaluso compares outcomes across individuals with identical skill vectors who face different job opportunity distributions. In terms of our framework, this corresponds to holding x and $f(x, y^*)$ constant while varying $F(y)$. This isolates the negative effects of specialization due to reduced local opportunities. In contrast, we compare workers with different skill vectors holding average skills constant, allowing both the positive and the negative aspects of specialization to manifest. While Macaluso identifies the location-specific effect of a fixed skill vector by controlling for occupation fixed effects, we examine variation across skill sets conditional on average skills and find that more specialized jobs are associated with higher expected wages.[18]

To further support our results on the positive effect of specialization, we examine separation rates in the first post-displacement job (Appendix Table 6 and Figure 12) and find that they decline with prior specialization conditional on average skill, consistent with improved match quality and stronger post-displacement prospects for more specialized workers. Figure 6 shows that the positive effects of specialization on re-employment wages vary across worker types. The gains are largest for younger, less experienced workers, and for those with strong cognitive and interpersonal skills but low manual skill intensity—suggesting greater complementarity benefits for higher-skilled workers.

[18]In Appendix B.4, we reconcile results by replicating Macaluso's approach and examining wage changes around displacement as a function of specialization. Consistent with our main findings, we find that specialization is positively associated with wage changes. While Macaluso (2025) focuses on within-occupation variation in local skill demand, we analyze cross-occupation differences in specialization and find that more specialized workers face smaller wage losses. We further show that our results hold when the analysis is conducted across 442 metropolitan areas and nine broad U.S. regions, in addition to our baseline specification treating the national labor market as a whole.



(a) Log real wages – US

(b) Log real wages – France

Figure 6: Entry wages – Heterogeneity analysis

Notes: The panels show the coefficients on specialization for different groups of displaced workers for wages on re-employment. Specifications control for age, gender, year as well as the log wage at the last job. Older workers: above age 40. All other criteria cut the sample at the mean and correspond to the job before separation. High FE fid and Low FE fid refer to firms with high and low AKM fixed effects, respectively.

Taken together, these findings support the proposed mechanisms through which specialization shapes labor market outcomes. More specialized workers experience lower job-finding rates but benefit from higher match quality, as reflected in higher re-employment wages and lower separation rates. The heterogeneity analysis further indicates that these effects are unevenly distributed: lower-skilled workers bear the brunt of the negative consequences of specialization and benefit least from its advantages, while higher-skilled workers experience the reverse.

5.2 Implications

To assess the implications of our empirical findings, we turn to the theoretical framework outlined in Section 3. According to our empirical findings, greater specialization raises expected wages but lowers job-finding probabilities. The net effect—whether specialization raises or lowers $U(x)$—ultimately depends on the relative strength of these two channels. To determine which effect dominates under our estimated regression coefficients, we apply the equilibrium conditions of the model.

Specifically, we calibrate the key parameters κ and α to match the model's equilibrium outcomes for job acceptance rates and wages given specialization to the estimated regression coefficients for France. We proceed in four steps to align the model with the empirical data.

First, to align the level of analysis with the model—where outcomes are defined at the occupation level (i.e., for a given x)—we re-estimate the effect of specialization on outcomes aggregated at the occupation-year level. The resulting coefficients, reported in Table 11 in the Appendix, closely resemble our baseline results. Second, we implement the same occupational skill requirements, occupational employment shares, $N(y)$, and specialization measures in the model as in the data (see Section 2), setting $K = 3$ accordingly. This step effectively discretizes the skill distribution and defines the set of skill vectors x and skill requirements y that we consider to the occupations observed in France. We use the offer distribution $F(y)$, as obtained in Section 2.2 based on administrative data on vacancy postings at the occupation level. We adopt the same benchmark values for labor market parameters from Lise and Postel-Vinay (2020) as in Section 3, additionally setting $\delta = 0.02$. Third, we apply the same occupation weights as in the displaced worker sample in the French data, ensuring that the model-based regression gives the same weight to each skill vector as in the empirical analysis. We denote this distribution by $D(x)$. We average all distributions $(N(y), D(x), F(y))$ across the years 2010 to 2019. Finally, we consider the inverse of the likelihood of job finding to approximate the duration of unemployment. We then run the regressions on the model's equilibrium outcomes and calibrate κ and α by minimizing the sum of squared differences between the model-based and empirical regression estimates, conditional on γ. The resulting calibrated parameters as well as the regression coefficients based on model outcomes are shown in Table 12 in the Appendix.

We then use the calibrated parameters to compute equilibrium unemployment across skill sets. Specifically, we calculate $U(x)$ over the observed job distribution $N(y)$ and examine its relation with specialization, conditional on average skill level. Results for $\gamma = 0.2$ are shown in Figure 16.[19] Figure 16 represent results for three skill levels in three colors: in blue we show $U(x)$ for skills sets at the median skill level, in green for skill sets with average skill 0.05 below the median, and in red for skill sets 0.05 above the median.[20] The shaded region represents the confidence interval around a weighted linear regression line representing the best fit by skill group.

Two key insights emerge from this analysis. First, conditional on average skill, the value of unemployment, $U(x)$, is weakly decreasing with specialization. This pattern suggests that, in the French economy, the negative effects of specialization—arising from the scarcity of specialized jobs in the offer distribution—tend to outweigh its positive effects, which stem

[19] Appendix B.5 presents analogous figures for different γ values, which are nearly indistinguishable from Figure 16 except for the level of $U(x)$.

[20] Note that (1) we targeted the results of the regression conducted on the entire sample, not stratified by skill level, and (2) that we keep the parameters of the model, that is α and γ, fixed across skill groups.

from higher match productivity in well-aligned jobs. The importance of the job offer distribution, $F(y)$, becomes particularly apparent when comparing these results to a counterfactual setting with uniformly distributed offers, holding all else equal. As shown in Figure 17 in the Appendix, under a uniform offer distribution, $U(x)$ increases with specialization for low- and medium-skill groups, highlighting the extent to which equilibrium outcomes are shaped by the distribution of job opportunities.

Second, the figure confirms that, on average, higher-skilled workers exhibit higher values of unemployment, $U(x)$. However, this relationship does not hold uniformly across all skill profiles: some higher-skilled occupations display lower $U(x)$ than those with slightly lower average skills. In our framework, this non-monotonicity arises from reduced access to suitable job opportunities. Consequently, increases in skills do not necessarily translate into improved labor market prospects when accompanied by greater specialization—even if, on average, higher skills are associated with higher unemployment values.

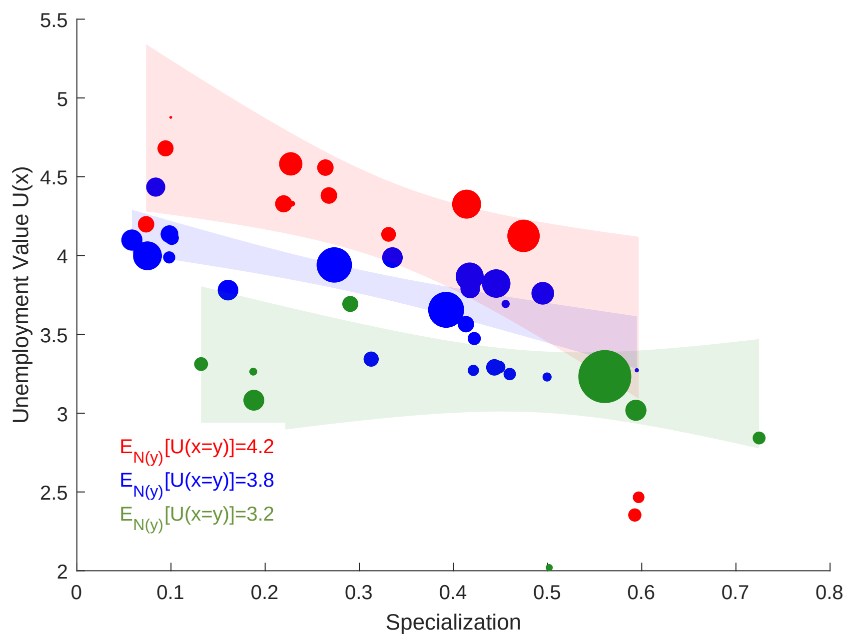


Figure 7: Unemployment Value for Empirical French $F(y)$

Notes: The figure plots the unemployment value $U(x)$ for three representative skill levels—median (0.468 ± 0.005, blue), high (0.518 ± 0.005, red), and low (0.418 ± 0.005, green)—using the empirical job offer distribution $F(y)$ observed in France. Each point corresponds to an empirical skill vector x, with bubble size reflecting employment weights $N(y)$, so that larger bubbles indicate occupations with a larger employment share. The shaded regions show confidence intervals around the weighted linear regression lines, which represent best-fit trends within each skill group.

6 Conclusion

This paper shows that worker specialization—defined as the average distance between a worker's skill set and those prevalent in the economy—has both positive and negative implications for labor market outcomes. We begin by empirically characterizing specialization along two dimensions: (i) skill asymmetry—workers tend to be strong in some skills and weak in others—and (ii) a relative scarcity of skill-close job opportunities in the labor market. We then incorporate both features into a random search model with mismatch penalties and skill-job complementarity. The model predicts that specialization raises expected wages in well-matched jobs but reduces job-finding rates due to the lower density of suitable offers.

We empirically test these predictions using data on exogenously displaced workers in the US and France. Consistent with the model, we find that, conditional on average skill, more specialized workers experience longer non-employment spells but receive higher wages upon re-employment. These patterns hold across both of these institutional contexts. The negative aspect of specialization is especially pronounced for lower-skilled workers, who benefit less from complementarity gains and face higher mismatch risk due to the lack of well-fitting jobs. Higher-skilled workers, by contrast, are more likely to benefit from specialization through better match quality. Using a calibrated version of our model disciplined by the estimates obtained from the empirical analysis, we find that the value of unemployment is weakly decreasing in specialization on average, suggesting that in France the scarcity of suitable job offers can outweigh the wage gains from improved fit.

Our analysis is conducted in a partial equilibrium setting. Future work could extend the theoretical framework to include general equilibrium forces, heterogeneity in matching technologies, or dynamic elements such as on-the-job learning. We see this paper as a first step toward a theoretical understanding of how specialization, and hence the structure of skill portfolios relative to skill demand, shapes labor market outcomes conditional on the average skill level.

The results highlight that skill acquisition yields heterogeneous returns depending not only on skill level but also on specialization. While specialized workers command higher wages in well-matched jobs, they face greater risks due to potentially longer unemployment spells. In contrast, generalists find jobs more quickly but at lower wages. These trade-offs offer a unified explanation for heterogeneity in post-displacement outcomes and suggest policy relevance for both education and insurance design. Broader skill development may help mitigate downside risks, especially for low-skill workers, while well-designed social insurance systems can support risk-taking in skill specialization by cushioning the costs of mismatch.

Declaration of generative AI and AI-assisted technologies in the writing process
During the preparation of this work the authors used ChatGPT in order to check grammar, text formulations and spelling. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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A Appendix to Section 2

A.1 Skill measures

To get a sense of the main components of each skill measure, in Table 3 we list the top 25 descriptors contributing to our measure of cognitive, manual and interpersonal skill requirements.

	Cognitive skills	Manual skills	Interpersonal skills
1	Engineering & Technology	Responsible for Others' Health & Safety	Coordination
2	Flexibility of Closure	Inspecting Equipment, Structures, or Material	Psychology
3	Systems Analysis	Depth Perception	Social Perceptiveness
4	Information Ordering	Response Orientation	Resolving Conflicts & Negotiating with Others
5	Estimating the Quantifiable Characteristics of Products, Events, or Information	Reaction Time	Coaching & Developing Others
6	Systems Evaluation	Multilimb Coordination	Monitoring
7	Complex Problem Solving	Operating Vehicles, Mechanized Devices, or Equipment	Management of Personnel Resources
8	Physics	Gross Body Equilibrium	Problem Sensitivity
9	Making Decisions & Solving Problems	Cramped Work Space, Awkward Positions	Guiding, Directing, & Motivating Subordinates
10	Technology Design	Wear Common Protective or Safety Equipment	Instructing
11	Mathematical Reasoning	Operation & Control	Developing & Building Teams
12	Category Flexibility	Performing General Physical Activities	Service Orientation
13	Analyzing Data or Information	Operation Monitoring	Therapy & Counseling
14	Mathematics	Speed of Limb Movement	Coordinating the Work & Activities of Others
15	Visualization	Static Strength	Assisting & Caring for Others
16	Deductive Reasoning	Auditory Attention	Frequency of Conflict Situations
17	Problem Sensitivity	Glare Sensitivity	Speech Clarity
18	Number Facility	Gross Body Coordination	Learning Strategies
19	Critical Thinking	Extremely Bright or Inadequate Lighting	Speech Recognition
20	Inductive Reasoning	Spatial Orientation	Time Sharing
21	Mathematics	Extent Flexibility	Negotiation
22	Drafting, Laying Out, & Specifying Technical Devices, Parts, & Equipment	Sound Localization	Speaking
23	Perceptual Speed	Exposed to Hazardous Equipment	Persuasion
24	Science	Exposed to Contaminants	Education & Training
25	Speed of Closure	Peripheral Vision	Establishing & Maintaining Interpersonal Relationships

Table 3: Top 25 descriptors in each skill measure

A.2 Dimensionality reduction

If in the data several descriptors measure the same skill, then there are two types of issues that can arise when raw skill measures are used to calculate skill distances. The first issue arises if not all descriptors that measure the same (or similar) skills have the same value for each occupation. The second issue arises if one type of skill is captured in more descriptors than another.

	occupation			
	A	B	C	D
Gross Body Coordination	5	1	1	1
Multilimb Coordination	1	5	1	1
Complex Problem Solving	1	1	5	1
Mathematics Knowledge	1	1	1	5
Manual skill	3	3	1	1
Cognitive skill	1	1	3	3

Skill measure

	occupation			
	A	B	C	D
A	0	32	32	32
B	32	0	32	32
C	32	32	0	32
D	32	32	32	0
A/B	0	0	8	8
C/D	8	8	0	0

Distance measure

Table 4: Skill distance mis-measurement with similar but not perfectly correlated descriptors

The first issue is illustrated in Table 4 where we consider four occupations, A, B, C, and D. The top of the left panel shows that each occupation is characterized by their skill requirements in four descriptors: 'Gross Body Coordination', 'Multilimb Coordination', 'Complex Problem Solving', and 'Mathematics Knowledge'. A simple way to reduce the number of skill dimensions is to take the average of the first two descriptors as the manual requirement, and the average of the last two descriptors as the cognitive requirement, shown in the bottom half of the table, shown in the bottom part of the left panel. In this example, occupations A and B require high manual skills, while occupations C and D require high cognitive skills. We would therefore expect someone who is a good fit for occupation A to be a better fit for occupation B than for occupation C and D, and someone who is a good fit for occupation C to be a better fit for occupation D than for A and B. However, the top right panel shows that the pairwise distance based on the raw skill requirement vectors is 32 between any two occupations, implying that the skill distance measured this way is the same between occupation A and B as it is between A and C. On the other hand, the distances based on the reduced number of skill requirement vectors is zero between A and B and between C and

D, and 8 between any other pair of occupations, as shown in the bottom panel on the right. The skill distances based on the reduced number of skill vectors reflect better the differences in skill requirements between occupations.

	occupation A	B	C
Gross Body Coordination	5	1	1
Multilimb Coordination	5	1	1
Complex Problem Solving	1	5	1
Social Perceptiveness	1	1	5
Manual skill	5	1	1
Cognitive skill	1	5	1
Interpersonal skill	1	1	5

Skill measure

	occupation A	B	C
A	0	48	48
B	48	0	32
C	48	32	0
A	0	32	32
B	32	0	32
C	32	32	0

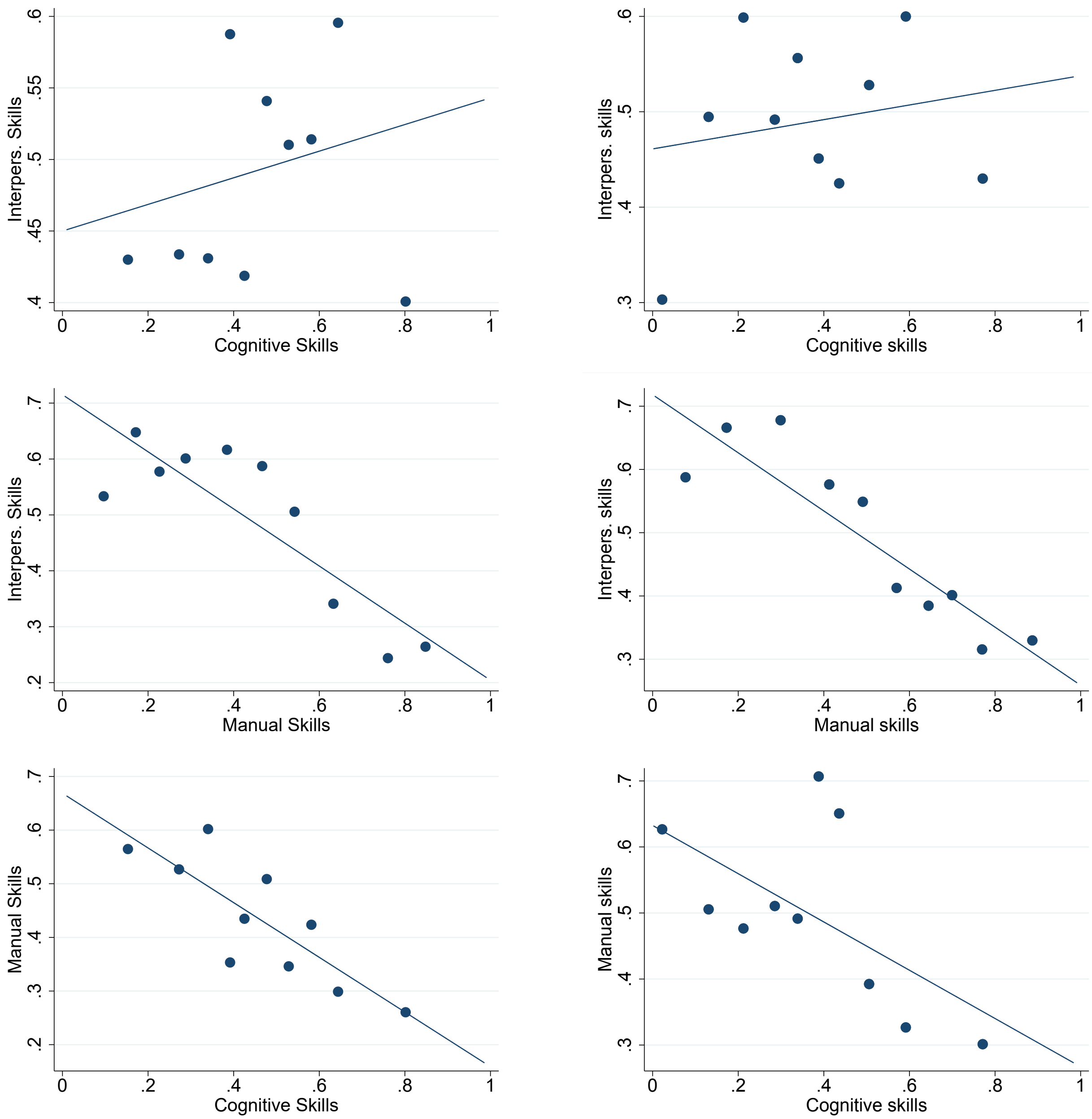
Distance measure

Table 5: Skill distance mis-measurement with uneven number of descriptors across skills

Table 5 provides an illustration of the second issue. The top of the left panel shows the different raw skill measures in each row, for 3 occupations A, B and C. There are two descriptors for manual skills: ‘Gross Body Coordination‘ and ‘Multilimb Coordination Measure‘, and one descriptor each for cognitive and interpersonal skills. The bottom panel on the left shows skill measures collapsed to the three dimensions (by taking the average of the corresponding descriptors): manual, cognitive and interpersonal. Each occupation requires high skills in only one skill type: occupation A in manual skills, occupation B in cognitive skills and occupation C in interpersonal skills. Based on this, we expect all occupations to be equidistant from each other. The right panel shows the pairwise distances between any two occupations based on the raw skill descriptors in the top and based on the collapsed skill measures in the bottom, calculated as the sum of squared differences across all skill measures. Based on the raw skill descriptors the distance between occupation A and the other two is larger than the distance between occupation B and C, thus it seems that occupation A is further apart from the others. The distance measures based on the collapsed skill measures are the same between any two occupations, thus reflecting the fact that each occupation requires high skills in only one type of skill.

These two simple examples demonstrate the importance of reducing the number of skill dimensions before calculating skill distances. In practice, rather than manually assigning each skill descriptor from ONET to a broad skill category, we employ a PCA with rotations to extract cognitive, manual and interpersonal skills from the almost 200 descriptors.

A.3 Cross-skill relationship



(a) US

(b) France

Figure 8: Cross-skill correlations

Notes: The figures show binscatter plots of the correlation across skills in the French and in the US data.

In our data sets (rotated) skill measures are weakly correlated in the economy, as can be seen in Figure 8. Specifically, the population-weighted correlation between manual and cognitive skills is -0.38, between manual and interpersonal skills it is -0.58, and between cognitive and interpersonal skills it is 0.08. This fact implies that on average, workers cannot be excellent in all three skill dimensions at the same time. As jobs differ with respect to their requirements, it is natural to consider some jobs as having a better or worse fit to a given skill portfolio.

A.4 Skill requirements

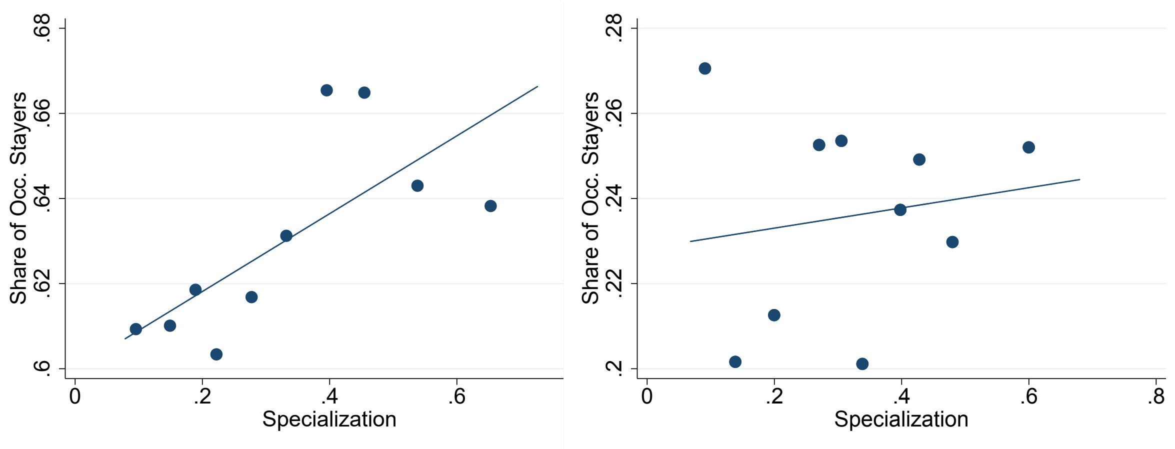
In what follows we show that occupational skill distances based on our skill requirement measures have economic meaning. If skill requirements are economically meaningful, then very specialized workers should be more likely to stay in their occupation following unemployment, and individuals should move to occupations that are closer to their previous occupation than the distance on average to other occupations.

If workers with specialized skills are indeed less suited, on average, for other roles in the job market, we would expect that they would exhibit a higher tendency to remain in their last occupation following a period of unemployment. To illustrate this empirical pattern, Figure 9 presents the relationship between our specialization measure and the percentage of individuals who remain in their respective occupation after experiencing a period of unemployment.[21] The figure demonstrates that, on average, occupations with a higher degree of specialization tend to have fewer instances of workers changing occupations following a period of unemployment. As anticipated, individuals set apart from the broader job market, in occupations with distinct skill requirements, exhibit a lower inclination to switch careers. This observation suggests that workers with greater specialization could face greater challenges in securing a suitable job.

To define job switchers, we calculate the weighted average occupational distance of job switchers for each occupation. Let $\omega_{j,o}$ denote the fraction of occupation j workers who move to occupation o after going through an unemployment spell, implying that $\sum_{j \neq o} \omega_{j,o} = 1$.[22] The occupational switching distance for occupation j is then calculated as $\sum_{j \neq o} \omega_{j,o}(y_{j,k} - y_{o,k})^2$. This is the weighted average distance of occupation j to other occupations to which occupation j workers move to after going through an unemployment spell. If our measure of skills has economic content, individuals should move to occupations that are closer to their

[21] To calculate the occupation-stayer shares we use the ASEC data set for the US and the cross-sectional DADS for France as these are representative of the universe of jobs in the two countries. We impose the same sample selection as in our displaced worker sample, that is we focus on full-time workers in age groups 20-64 in the private sector.

[22] We calculate these from the ASEC data set for the US and the cross-sectional DADS for France as these are representative of the universe of jobs in the two countries. We impose the same sample selection as in our displaced worker sample, that is we focus on full-time workers in age groups 20-64 in the private sector.



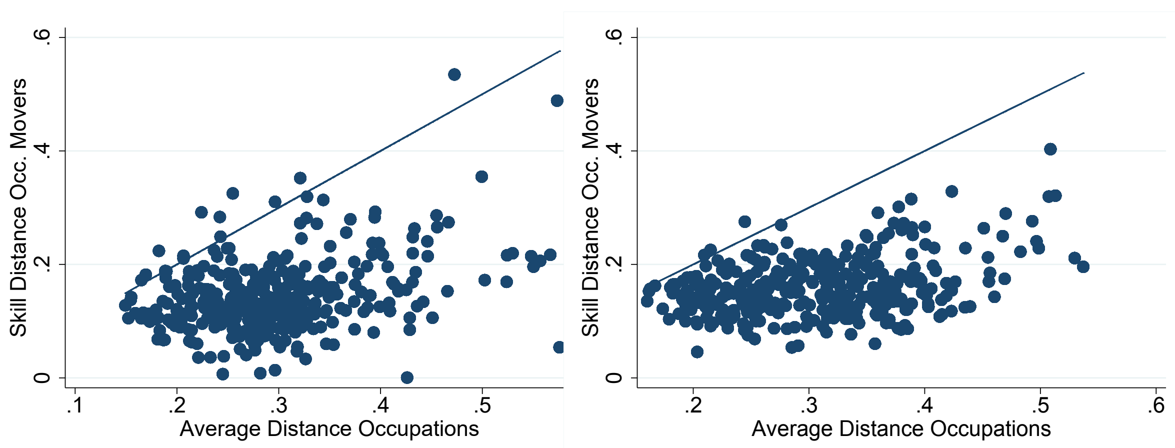
(a) US

(b) France

Figure 9: Occupation switching and Specialization

Notes: The graphs show binned scatter plots of the likelihood of staying in the same occupation after layoff against our specialization measure.

skill portfolio than the average occupation. Figure 10 shows that this pattern holds true in the data. The scatter plots show for each occupation the average skill distance from all other occupations (on the x-axis) and average occupational distance of switchers after layoff (on the y-axis), as well as the 45 degree line. The average occupational distance of switchers is almost always below the 45 degree line, implying that people move to occupations that are closer to them than the average occupation in the economy.



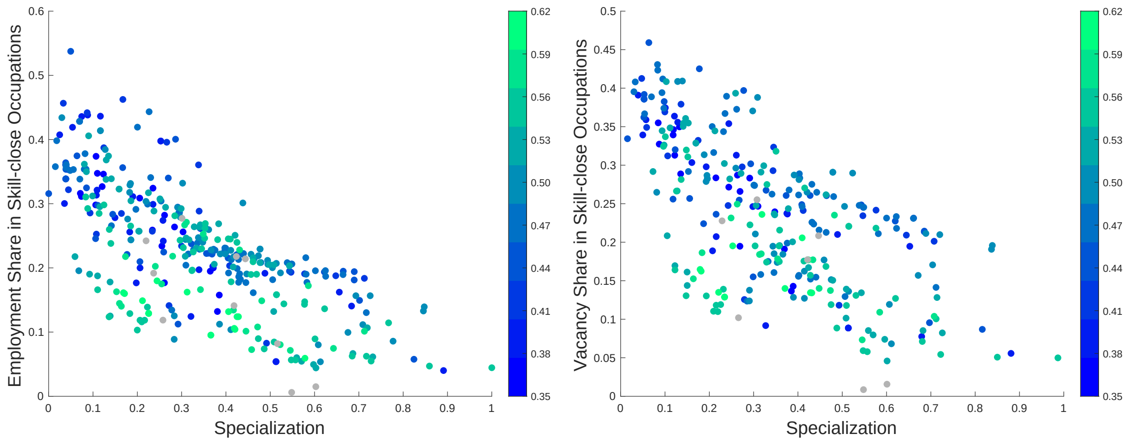
(a) US

(b) France

Figure 10: Occupation switching distance and average distance

Notes: The figures show scatter plots showing for each occupation the average skill distance from all other occupations (on the x-axis) and average occupational distance of switchers after layoff (on the y-axis), as well as the 45 degree line. The left panel shows this for the US, while the right panel shows this for France.

A.5 Employment and vacancy distribution across occupations



(a) Employment shares

(b) Vacancy shares

Figure 11: Employment and employment opportunities

Notes: The panels show the share of employment (on the left) and the share of vacancies (on the right) in occupations closer to the given occupation than the 25th percentile of pair-wise skill distances against the specialization of a given occupation. Specialization and employment and vacancy shares are measured in the year 2010. Occupations are binned by average skill level, with colors indicating different skill levels according to the colorbar. The dots in gray show occupations outside the range of the colorbar. Average skills are calculated as the simple average across the $K = 3$ skill dimensions.

B Appendix to Section 5

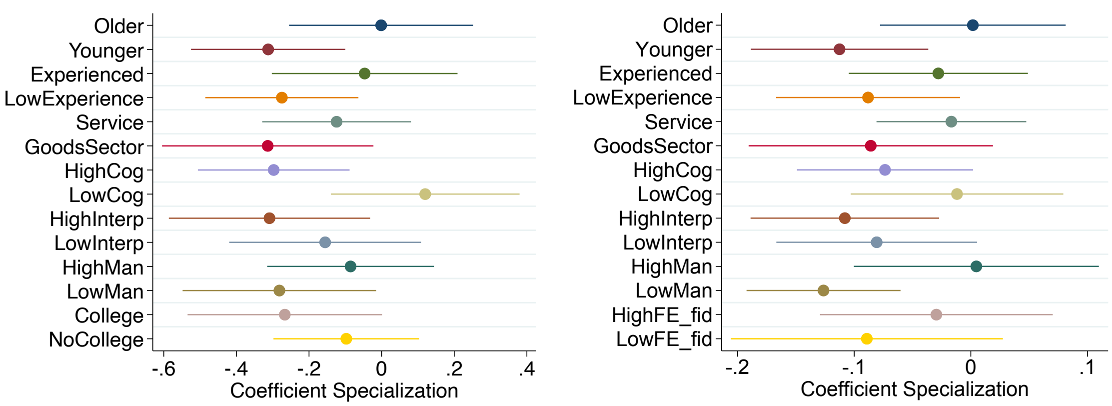
B.1 Results on worker separation

Measurement Due to differences in the available information on post-displacement outcomes, we measure separation rates slightly differently in the US and French samples. The US DWS contains information about the number of jobs held since displacement together with the time since displacement. Hence, for the US data, we construct the separation rate as the likelihood of having more than one job for workers displaced in the last year. The French administrative data set contains information on whether workers separated from their first job after displacement in the first year. In the French dataset, we calculate the separation rate as the probability that a worker leaves their initial job within the first year following displacement. The post-displacement separation rate is almost twice as high in the French as compared to the US sample.

	Separation		
	(1)	(2)	(3)
	US		
Specialization	-0.203*	-0.200*	-0.167*
	(0.010)	(0.012)	(0.042)
Skills		-0.0356	0.0279
		(0.708)	(0.788)
Observations	876	876	876
	FR		
Specialization	-0.194*	-0.187*	-0.0589*
	(0.000)	(0.000)	(0.035)
Skills		-0.161*	-0.124*
		(0.000)	(0.000)
Observations	16336	16336	10756
Controls	w/o Skill	w/ Skill	+Controls

Table 6: Regression results for separations

Notes: The table shows results of a regression of separation rates on previous specialization and controls. Column (1) does not control for skills, column (2) does not impose controls but includes average skills, column (3) controls for the baseline set of controls, which includes age, gender, education (for the US) or AKM worker FE (for France) and pre-displacement experience, tenure and log wage. Results are weighted using sampling weights for the US. Values in brackets represent p-values, $^{+}$ $p < 0.10$, * $p < 0.05$.



(a) Separation – US

(b) Separation – France

Figure 12: Separation – Heterogeneity analysis

Notes: The panels show the coefficients on specialization for different groups of displaced workers for separation from the first job after displacement. Specifications control for age, gender, year as well as the log wage at the last job. Older workers: above age 40. All other criteria cut the sample at the mean and correspond to the job before separation. High FE fid and Low FE fid refer to firms with high and low AKM fixed effects, respectively.

B.2 Different measures of specialization

With our specialization measure we aim to measure how well-fitted a worker's skills are to the economy in general. The less well-fitted they are, the more specialized the worker is. Since there is no established way of measuring this, we propose four different ways to measure specialization. Our first, baseline measure is the average distance between the worker's skill set and the skill requirement of all jobs in the economy, as defined in the main text of the paper. The second is the distance between a worker's skill set and the average skill requirement across all jobs in the economy.[23] The third is the share of jobs in the economy of which the skill requirement is more than a specified cutoff distance away from the worker's skill set. The fourth considers the distances only if the worker's skills are below the skill requirement in occupation o. This would be in line with a model where the mismatch penalty only arose in case of the worker having lower skills than required by the job, thus the skill distances between pairs of occupations are not symmetric.

Using the same notation as in the main text of the paper, the average skill requirement in dimension k at time t in the economy is $E[y_{k,t}] = \sum_{o=1}^{O} n_{o,t} y_{o,k}$. Our second measure of worker specialization is then

$$Spec_{i,t}^2 = \sum_{k=1}^{K} (x_{i,k} - E[y_{k,t}])^2,$$

which measures the distance between the worker's skill set and the average skill requirement in the economy at time t.

For our third measure we need to first define the cutoff distance, beyond which jobs are considered too far to be viable for a given worker. To do so, we first measure the pairwise distance between the skill requirement of any two jobs in the economy, resulting in a set of skill requirement distances: $\{dist_{o,j}\}$ for $o = 1, .., O$ and $j = o, ..., O$, where the pairwise distance between job o and j is $dist_{o,j} = \sum_{k=1}^{K} (y_{o,k} - y_{j,k})^2$. We define the cutoff distance as the median distance of this set, and denote it by $dist_{med}$. Our third measure is defined as

$$Spec_{i,t}^3 = \sum_{o=1}^{O} n_{o,t} I \left\{ \sum_{k=1}^{K} (x_{i,k} - y_{o,k})^2 > dist_{med} \right\},$$

[23]From the factorization in (1) it can be shown that our specialization measure is equivalent to this alternative measure up to a constant shifter. To see this note that

$$\sum_k (x_k - E[y_k])^2 = \sum_k E[y_k]^2 + \sum_k x_k^2 - 2\sum_k x_k E[y_k] = Spec(x) + \sum_k E[y_k]^2 - \sum_k E[y_k^2].$$

which measures the share of jobs in the economy at time t that are more than a cutoff distance away from the worker's skill set.

The fourth measure of specialization only accounts for under-qualification:

$$Spec^4_{i,t} = \sum_{o=1}^{O} n_{o,t} \left(\sum_{k=1}^{K} (\min\{x_{i,k} - y_{o,k}, 0\})^2 \right).$$

	Weeks w/o work	Separation	Log real wage
		US	
Specialization	5.171*	-0.167*	0.264*
	(0.010)	(0.042)	(0.017)
Specialization II	4.814*	-0.161*	0.267*
	(0.016)	(0.047)	(0.015)
Specialization III	3.435+	-0.137+	0.191+
	(0.055)	(0.057)	(0.055)
Specialization IV	10.93*	-0.547*	0.849*
	(0.020)	(0.004)	(0.001)
Observations	2697	876	677
		FR	
Specialization	5.434+	-0.0908*	0.169*
	(0.064)	(0.000)	(0.000)
Specialization II	6.145*	-0.0865*	0.168*
	(0.035)	(0.000)	(0.000)
Specialization III	6.127*	-0.0963*	0.178*
	(0.036)	(0.000)	(0.000)
Specialization IV	4.853	-0.194*	0.364*
	(0.350)	(0.000)	(0.000)
Observations	13411	11789	11775

Table 7: Comparison - Regression results

Notes: The table shows results across four measures of specialization. All columns control for the baseline set of controls: age, gender, education (for the US) or AKM worker FE (for France) and pre-displacement experience, tenure and log wage. Results are weighted using sampling weights for the US. Values in brackets represent p-values, $^{+}$ $p < 0.10$, * $p < 0.05$

The results in Table 7 show that while the magnitude of the effects differ across specifications, all specialization measures point in the same direction.

B.3 Different sample of displaced workers

As discussed in Section 4, displaced workers are commonly identified as those who involuntarily separate during mass layoff events. In the main analysis, we adopt a more restrictive definition, focusing only on workers who lost their jobs due to firm closure. We expect that this more restrictive measure addresses potential concerns about worker selection. In Table 8 and 9 we show the results when also considering workers displaced during mass layoff events. If the less well fitted workers are laid off first, then we expect a smaller effect of specialization.

	Weeks w/o work			
	(1)	(2)	(3)	(4)
		US		
Specialization	-0.464	0.0408	1.579	5.171*
	(0.655)	(0.969)	(0.143)	(0.010)
Skills		-3.981*	-4.810*	0.155
		(0.003)	(0.001)	(0.951)
Observations	9330	9330	9330	2697
		FR		
Specialization	2.344	3.444	2.849	5.434^{+}
	(0.307)	(0.134)	(0.267)	(0.064)
Skill Level		-20.71*	-10.24*	-10.26*
		(0.000)	(0.002)	(0.008)
Observations	23276	23276	16683	13411
Controls			All	+Closure

Table 8: Non-employment duration – Regression results

Notes: The table shows regression results for a regression of weeks of non-employment after displacement on specialization. Column (1) does not and column (2) does control for skills, column (3) controls for the baseline set of controls: age, gender, education (for the US) or AKM worker FE (for France) and pre-displacement experience, tenure and log wage. Column (4) additionally restricts the sample to workers displaced from closing plants. Results are weighted using sampling weights for the US. Values in brackets represent p-values, $^{+}$ $p < 0.10$, * $p < 0.05$

This is indeed confirmed in Table 8, as the coefficients are smaller in magnitude and not significant when including workers displaced during mass layoffs in column (3), compared to our more restrictive sample in column (4). We also see smaller positive effects in the US in Table 9 when comparing column (3) to (4) and column (7) to (8). These results suggest that there might be some negative selection of workers at mass layoff events.

	Separation				Log real wage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					US			
Specialization	-0.0985*	-0.0999*	-0.112*	-0.167*	0.413*	0.232*	0.132*	0.264*
	(0.009)	(0.009)	(0.005)	(0.042)	(0.000)	(0.003)	(0.041)	(0.017)
Skills		0.0101	0.0348	0.0279		1.312*	0.270*	-0.0819
		(0.830)	(0.488)	(0.788)		(0.000)	(0.001)	(0.573)
Observations	3433	3433	3433	876	3428	3428	3428	677
Controls			All	+Closure		All	+Closure	
					FR			
Specialization	-0.198*	-0.191*	-0.0572*	-0.0562*	0.471*	0.459*	0.0912*	0.0926*
	(0.000)	(0.000)	(0.028)	(0.044)	(0.000)	(0.000)	(0.000)	(0.000)
Skill Level		-0.147*	-0.102*	-0.124*	0.275*	0.0575+	0.0449	
		(0.000)	(0.002)	(0.000)		(0.000)	(0.052)	(0.158)
Observations	18763	18763	12386	10752	18741	18741	12374	10741
Controls			All	+Closure			All	+Closure

Table 9: Positive effects – Regression results

Notes: The table shows results of a regression of entry wages and separation rates on previous specialization and controls. Column (1) does not control for skills, column (2) does not impose controls, column (3) controls for the baseline set of controls, which includes age, gender, education (for the US) or AKM worker FE (for France) and pre-displacement experience, tenure and log wage. Results are weighted using sampling weights for the US. Values in brackets represent p-values, $^{+}$ $p < 0.10$, * $p < 0.05$.

B.4 Comparison to Macaluso (2023)

Using the CPS-DWS dataset, Macaluso (2025) demonstrates through a regression analysis of wage changes pre- and post-displacement that workers who are geographically more skill-remote pre-displacement encounter more pronounced declines in earnings after finding a new job. Since Macaluso's skill remoteness measure is comparable to our specialization measure, this finding is in apparent contrast with our results of a positive correlation of post-displacement wages and specialization. In this section, we explore the reasons for these seemingly contradictory findings.

We conclude that these two results are indeed just seemingly contradictory. Macaluso's specification relies on variation in skill demand across different geographical locations (further studied in Macaluso et al. (2019)) and compares the outcomes of individuals with the same skill vector across different locations. In our empirical analysis – in line with our model – we compare the outcomes of individuals with different skill vectors in an environment with a common distribution of skill demand. Based on our model we can only make predictions about the outcomes of individuals with different skill vectors in a common environment.

To show this, we proceed in two steps. First, we point to key differences in the construction of Macaluso's skill remoteness and our specialization measure. The key differences are in the measurement of skills, in the fineness of occupation categories and in the definition of local labor markets. In a second step, we conduct the same analysis as in Macaluso (2025), but for a range of occupation categories and local labor market definitions. Crucially, we conduct the analysis with occupation fixed effects, as in Macaluso (2025) and without occupation fixed effects, as in our baseline analysis. We then show that we can replicate both the negative result in Macaluso (2025) and our positive result. Moving step-by-step from Macaluso's skill remoteness towards our specialization measure, and running the regressions with and without occupation fixed effects, we pinpoint the conditions under which the negative results are maintained. Our analysis suggests that Macaluso's results are only maintained when considering variations in the outcomes within broad occupation groups due to local variations in skill demand.

Measuring skill remoteness We compute the following measure of skill remoteness for occupation i at time t in location l for L locations in total

$$Spec_{i,l,t} = \sum_{o=1}^{O} \lambda_{o,l,t} \left(\frac{1}{K} \sum_{k=1}^{K} |x_{i,k} - y_{o,k}| \right),$$

which is the local occupational employment share weighted average distance of a worker's skill portfolio from other occupation-specific skills. This skill remoteness measure differs from our specialization metric in three key dimensions:[24]

- It employs $K = 35$ ONET skill descriptors s, in contrast to our baseline approach, which utilizes three principal components derived from all 199 ONET descriptors.
- Skill remoteness considers $O = 22$ broad occupation groups (denoted as O), whereas our baseline methodology encompasses 352 occupation groups.
- The analysis of skill remoteness spans across $L = 442$ metropolitan areas contrasting with our baseline specification, which focuses on a single labor market ($L = 1$).

To implement the measure of skill remoteness, we follow Macaluso (2025) as closely as possible. We leverage the Bureau of Labor Statistic's Occupational Employment Statistics (OES) dataset to obtain local occupational employment shares, $\lambda_{o,l,t}$, and use the CPS-DWS metropolitan region variable at a worker's displacement residence location to identify

[24] Note also that in our specialization measure we use the sum of squared distances, rather than the sum of absolute distances. In this section we compute all distances as the sum of absolute distances for consistency.

a worker's location.[25] Due to differences in occupation measures before 1999, we focus on a sample with years 1999-2020.

As in Macaluso (2025), we compute a measure *above* that is one if an occupation is above the current local median value of skill remoteness. We compute a similar measure based on our specialization measure, indicating if an occupation is above the median of all economy-wide specialization values in the particular year. In addition to these two measures, we also compute several measures that differ in terms of the fineness of the occupation categories, and the definition of the labor market.

Macaluso's level of analysis differs from ours in two aspects. First, it considers 22 broad occupation groups, whereas we look at 352 finer occupational categories, and second, distances are weighted using local employment shares in 442 areas. Therefore we measure skill distances (and hence differences in specialization) both within the 22 broad occupation groups, and across these groups, whereas Macaluso's measure only captures between group skill distances (and hence differences in skill remoteness). This is an important difference, as 50.92% of the variation in our specialization measure is within broad occupation groups.[26] Second, Macaluso calculates skill remoteness across 442 local labor markets, whereas we consider the entire economy to be a single labor market. Besides these two definitions of labor markets, we also consider the 9 census regions as separate local labor markets. We perform the analysis with both broad and fine occupation categories across the 442 metropolitan areas and across the 9 census regions.

Regression analysis To understand the source of differences between our results and those in Macaluso (2025), we analyze the following regression:

$$\Delta y_{i,j(i,t),t} = \alpha \, above_{i,j(i,t),t} + X_{i,t}\beta + \epsilon_{i,t}, \tag{5}$$

where $\Delta y_{i,j(i,t),t}$ denotes the wage change before and after displacement at the first job[27] and $X_{i,t}$ contains a vector of covariates. As explained earlier, the indicator $above_{i,j(i,t),t}$ is 1 if individual i's pre-displacement job at time t and firm $j(i,t)$ is more than the local median distance from other jobs, i.e., i had a locally skill-remote job at displacement. We run the above regression for all the different versions of the *above* measure discussed previously. To

[25] Note that in the CPS-DWS, location information is either missing or indicates a non-metropolitan area for 28% of observations. As a result, we are unable to assign a skill-remoteness measure to these cases.

[26] This corresponds to the $1 - R^2$ from a regression of our specialization measure on 22 occupation group fixed effects interacted with year. When estimating the regression separately by year, the resulting $1 - R^2$ values range from a minimum of 0.4196 to a maximum of 0.6242.

[27] We only compare the wage with a 1-year lag to be in line with the rest of our analysis where we consider starting wages at the first job after displacement.

conform with the sample used in Macaluso (2025), we consider all forms of displacement, and include only those individuals who have not moved since their displacement. Table 10 shows the point estimates obtained for α, as well as their significance level.

# Occupations # Areas	22 442 (1)	22 9 (2a)	22 9 (2b)	352 442 (3a)	352 442 (3b)	352 9 (4a)	352 9 (4b)	352 1 (5)
35 raw skills	**-0.103***	-0.305*	0.0496	-0.0720	0.00380	-0.0335	0.0226	0.0322^{+}
baseline skills	-0.0342	-0.0880	0.0067	-0.0350	0.0474*	0.0445	0.0787*	**0.0777***
Occupation FE	X	X		X		X		
Average skill			X		X		X	X
Observations	4862	4867	4867	4716	4716	4840	4840	4866

Table 10: Estimates of α for different measurements of skill remoteness

Notes: The table shows the point estimates of α from regression (5), using sampling weights, on the sample of all displacement events. Each entry is the point estimate based on a different calculation of *above* using different skill measures in each row, and different occupation groups and geographical boundaries in each column. $^{+}$ $p < 0.10$, * $p < 0.05$.

In Table 10 the top row is based on Macaluso's skill measurement whereas the bottom row is based on our skill measurement. The first row of column (1) reflects the finding in Macaluso (2025) whereas the second row in column (5) reflects our findings. We show a negative and significant coefficient of -0.10 for the Macaluso estimate and a positive and significant coefficient of 0.077 for our setting. Between these two cells, we show the point estimates in various settings to establish the importance of each difference between the analysis in Macaluso (2025) and ours. The columns on the left feature 22 broad occupation groups, whereas those on the right feature 352 fine occupation categories. Moving from left to right for a given occupation definition, we reduce the number of geographic regions. Importantly, the set of controls used differs across columns. In columns 1, 2a, 3a and 4a we include the same controls as Macaluso in her analysis: fixed effects for occupation group (22 or 352 depending on the column), region, industry, gender, marital status, race, education and recession, as well as the log of city employment. In columns 2b, 3b, 4b and 5 we follow our baseline analysis and do not include occupation fixed effects, but control for the average level of skills in the occupation (22 or 352 occupations and skills calculated according to the row). Table 10 shows that in columns 1, 2a, 3a and 4a the point estimates are negative with one exception (though often not significant), whereas in columns 2b, 3b, 4b and 5 the point estimates are positive (again, not always significant).

Given that in columns 1, 2a, 3a and 4a we include occupation fixed effects, the negative point estimate is identified from variations in local demand leading to different skill remoteness measures across locations for the same occupation. Note, however, that in column 3a and

4a the negative point estimates are not significant, implying that this result only holds when conducting the analysis at the level of broad occupation groups. The interpretation of this result is that after displacement from a given broad occupation, local demand determines the expected wage loss. This wage loss is larger the further the local demand is from the skills required in this broad occupation.
Since in columns 2b, 3b, 4b and 5 we do not control for occupation fixed effects, the positive significant estimate is identified from variations in skill remoteness across occupations (in column 5 only across occupations). The interpretation of this result is in line with the predictions of our model: the expected wage of individuals with remote (specialized) skills is higher (once they find a suitable job), due to their skills being especially well suited to the requirements in acceptable jobs. The point estimates are only significant in columns 3b, 4b and 5, when we look at fine occupation categories, i.e. when skill requirements are measured at the level of fine occupations, implying that variation within broad occupation categories is important.

In light of these results, the contrast between the two findings is much less stark. Macaluso's result derives from variation in skill remoteness across locations for a given broad occupation group. It compares the outcomes of individuals with the same skill vector across labor markets with different skill requirement distributions. Our result stems mostly from variation in the productivity of skills across fine occupation groups. We compare the outcomes of individuals with different skill vectors in a single labor market with a common skill requirement distribution. The predictions of our model pertain to the latter case, as we can only make statements about the outcomes of different skill vectors in a common environment.

B.5 Unemployment value for different calibrations

Regressions at occupation-year level In Section 5 we consider regressions at the worker-level. Since our model outcomes are calculated at the occupation-level, in Table 11 we run regressions in our two samples at the equivalent level, by collapsing the data at the occupation-year level. The results confirm those ran on individual data, where we control for worker and firm characteristics as well. We target the coefficient estimates in the table below for France in Section 5.2.

	Weeks w/o work	Log real wage
	US	
Specialization	4.086^{*}	0.486^{+}
	(0.039)	(0.000)
Observations	1321	1321
	FR	
Specialization	6.076^{+}	0.439^{**}
	(0.082)	(0.000)
Observations	2454	2466

Table 11: Regression results on occupation level data

Notes: The table shows regression results across the two samples collapsed at the occupation-year level. We control for the skill level index. Results are weighted using sampling weights for the US. Values in brackets represent p-values, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Model fit Table 12 shows the parameter estimates together with the regression estimates at these best-fitting values.

	Calibrated		Coefficients	
γ	α	κ	$1/P(x)$	$E[w]$
0.00	13.24	26.83	0.44	6.67
0.20	15.50	29.85	0.44	6.21
0.40	16.29	32.52	0.44	6.22
0.80	19.13	40.66	0.44	6.27

Table 12: Estimation Results

Notes: The table shows best fit estimation results for α and κ given values for γ as well as the best fitting regression coefficients, mimicking the empirical regression specifications for duration of unemployment $1/P(x)$ and expected wages $E[w]$.

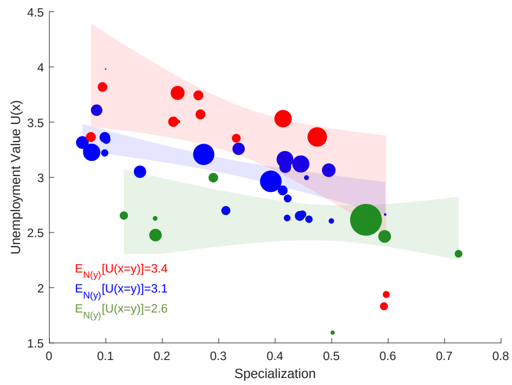


Figure 13: $\gamma = 0.001$

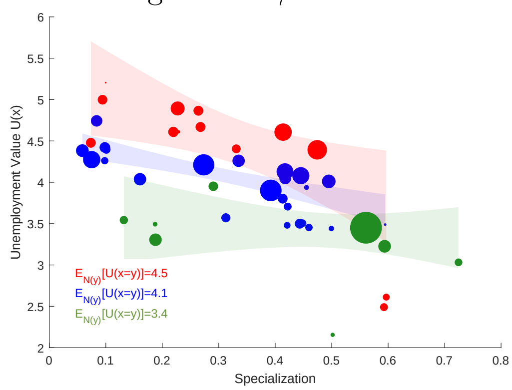


Figure 14: $\gamma = 0.4$

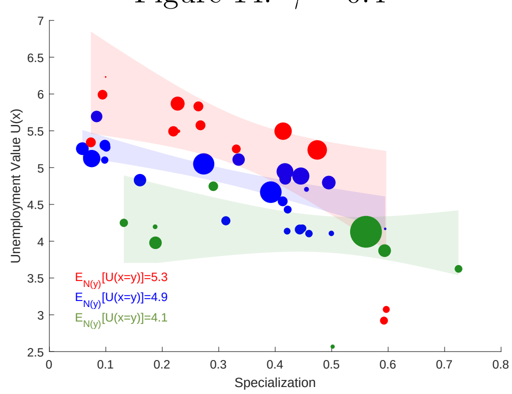


Figure 15: $\gamma = 0.8$

Figure 16: Unemployment Value across different γ

Notes: The figures plots the unemployment value $U(x)$ for three representative skill levels—median (0.468 ± 0.005, blue), high (0.518 ± 0.005, red), and low (0.418 ± 0.005, green)—using the empirical job offer distribution $F(y)$ observed in France. Each row considers a different value of γ and α, κ accordingly. Each point corresponds to an empirical skill vector x, with bubble size reflecting population weights $N(y)$, so that larger bubbles indicate more populous occupations. The shaded regions show confidence intervals around the weighted linear regression lines, which represent best-fit trends within each skill group.

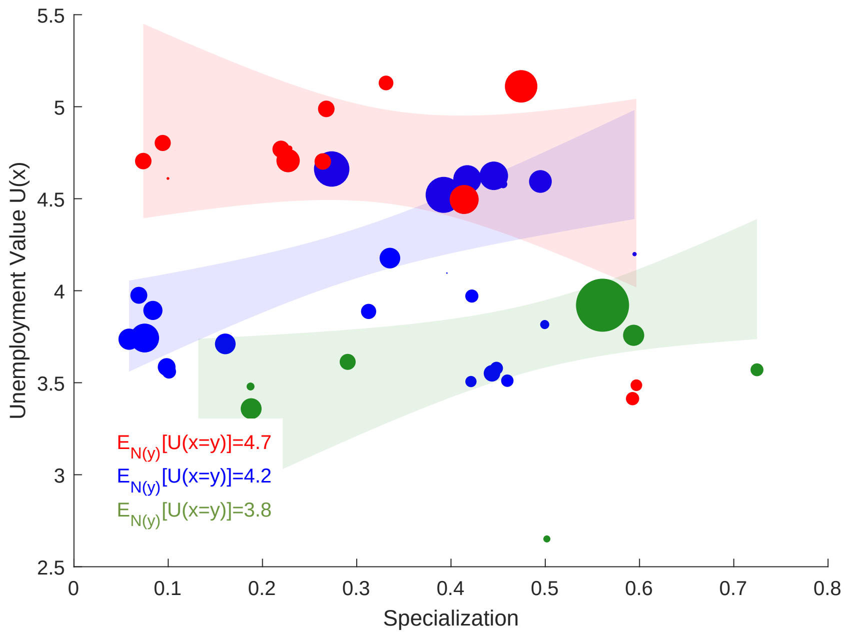


Figure 17: Unemployment Value for Uniform Offer Distribution

Notes: The figure plots the unemployment value $U(x)$ for three representative skill levels—median (0.468 ± 0.005, blue), high (0.518 ± 0.005, red), and low (0.418 ± 0.005, green)—using the uniform job offer distribution $F(y)$. Each point corresponds to an empirical skill vector x, with bubble size reflecting population weights $N(y)$, so that larger bubbles indicate more populous occupations. The shaded regions show confidence intervals around the weighted linear regression lines, which represent best-fit trends within each skill group.