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THE TWO FACES OF WORKER SPECIALIZATION

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The Two Faces of Worker Specialization*

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Abstract

Can specialization – the average distance of the worker's skill set from skill profiles prevalent in the economy – confer both positive and negative returns? We quantitatively show in a random search framework that more specialized workers i) suffer larger mismatch penalties on average, leading to lower job finding rates, but ii) enjoy higher gains from worker-firm complementarity in well-fitted jobs, reflected in higher starting wages and lower separation rates. The theoretical model indicates that the acquisition of more specialized skills may or may not yield an augmented lifetime income for workers. Hence, the acquisition of more specialized skills can come at a loss of lifetime income for some workers. Informed by the model, we analyze the labor market outcomes of exogenously displaced workers in the US and in France and provide empirical evidence for the two faces of worker specialization.

JEL Classification: J24, J41, J63, J64

Keywords: Specialization, Skills, Displacement

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1 Introduction

The influence of worker skills on labor market outcomes has been extensively explored in the literature. Generally, skills are considered assets with non-negative labor market returns. Although the literature distinguishes between the degree of transferability of skills across jobs, spanning from general purpose to purely job-specific skills, earlier studies have asserted that skills impact labor market outcomes either positively or not at all. Yet, recent research on multidimensional skill sets has contended that various skills can both enhance and diminish a worker's match productivity, contingent on the specific job in question (Lise and Postel-Vinay (2020), Lindenlaub and Postel-Vinay (2020), Lindenlaub and Postel-Vinay (2023)). A given worker's skill can therefore be an asset in some circumstances and a liability in other circumstances. So far, micro-economic evidence for the non-positive effects of skill set characteristics on labor market outcomes is scant (e.g., Gathmann and Schönberg (2010), Lamo et al. (2011)). Recent evidence derives from differences in labor demand within broad occupation groups in geographically distinct labor markets (Macaluso (2023)) and seemingly contrasts with findings of positive wage premia due to specialized education (Leighton and Speer (2020), Silos and Smith (2015)).

In this paper, we disentangle and reconcile these different insights. To do so, we introduce the concept of skill set specialization, which quantifies the extent to which a worker's skill set deviates on average from the skill profiles prevalent in the economy. We show that this measure is an important predictor of workers' labor market outcomes, over and beyond the average level of their skills. Our analysis reveals that specialization, conditional on the level of worker skills, can improve certain labor market outcomes such as wages upon successful matching, while worsening other outcomes such as job finding rates. Intuitively, depending on the relative size of the negative and the positive effect, average earnings can fall or rise with specialization. In our analysis, we proceed in two steps. First, we quantitatively show in a random search framework that specialized skills entail a higher mismatch penalty on average across jobs, but offer higher complementarity benefits in well-fitted jobs. Second, guided by simulation results from the quantitative model, we test for the presence of both the negative and the positive effects of specialization using data on exogenously displaced workers in the US and in France. The theory together with the empirical data allows us to interpret our empirical findings. Theoretically, we show that the net effect of specialization is not positive for all workers and that some workers indeed loose from acquiring specialized skills. This insight resonates with reported worker disenchantement in highly specialized occupations such as manufacturing and reports of reduced willingness of young workers to adapt highly specialized jobs.

To illustrate our concept of specialization, we can draw parallels from the world of sports. Take, for instance, a sprinter competing in the 50m race—a specialist in short-distance running. In contrast, consider a decathlete who competes in the 100m race and nine other events. According to our definition, the decathlete exhibits lower specialization across the field of athletics compared to the sprinter. Likely, the sprinter would not excel in a range of disciplines of the decathlon (including the pole vault), and the decathlete would not win over a sprinter in the 50m race. The greater divergence of the sprinter's skill set from requirements of other disciplines implies a higher mismatch penalty on average compared to the decathlete, making him a worse contender in the average discipline in athletics. However, the sprinter's skill in running is arguably a better fit to the 50m discipline than the decathlete's, earning him a higher chance of winning the 50m race.[1] In the labor market, specialization affects workers' fit to various labor market opportunities. Workers' specialization amplifies both the returns in a particular field and their exposure to labor market risks. For instance, among displaced workers, specialized individuals may take more time to secure a new job, as their specific skills may render them less productive, on average, across various job types while making them exceptionally well-suited to a particular set of jobs. Once they secure a well-matched job, their specialized skills become an asset, leading to increased productivity. This trade-off is a fundamental aspect of specialized skill portfolios.

To understand the interplay between mismatch penalties and complementarity gains for specialized skill portfolios, we develop a parsimonious random search framework, building on Lise and Postel-Vinay (2020) and Mortensen and Pissarides (1994). The framework clarifies that specialized workers can have a lower probability of matching because they suffer from a larger mismatch penalty in the economy on average. Yet, specialized workers can be more productive in the smaller set of well-fitted jobs due to their larger gains from worker-job complementarity. This is because more specialized skill sets tend to feature more asymmetric skill portfolios, with high skills in some dimensions, but low skills in other dimensions. The high skills can create high returns with suitable, high requirements jobs. The distribution of jobs and the magnitude of mismatch penalties and complementarity gains determine the extent of these effects in the economy. We leverage our model to quantitatively show that

[1]Naturally, 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).

specialization co-varies with longer non-employment duration and with higher entry-wages conditional on skill levels. Our simulation exercise informs our empirical strategy to uncover these negative and positive effects of specialization.

To empirically study the presence of these trade-offs, we analyze microeconomic data for mobility events from two countries: the United States and France. Specifically, we investigate the variation in worker outcomes following displacement for individuals with diverse skill portfolios, allowing us to distinguish between variation in average skill levels and skill set specialization. As mobility decisions are in general endogeneous to the worker-firm match, we choose a sample of displaced workers to address the potential endogeneity of worker-firm separation prior to matching with a new firm. Our analysis reveals two key findings. First, we demonstrate that higher pre-displacement specialization leads to extended periods of non-employment. Second, higher pre-displacement specialization is associated with higher post-displacement entry wages and lower post-displacement separation rates. The heterogeneity analysis suggests that specialization can exert particularly pronounced adverse effects on the labor market outcomes of lower-skilled workers. We conjecture that this derives from the fact that these workers experience only limited complementarity gains while experiencing potentially large mismatch effects. Overall, these findings suggest that increasing specialization alone, while keeping skills fixed, can have detrimental effects on labor market outcomes. Policy makers should therefore aim at designing broad education opportunities without focusing exclusively on excellence in a few select fields, especially for low skill workers.

Our findings challenge the consensus view that higher skills uniformly improve labor market prospects. In our quantitative model we show that higher average skills can lead to worse labor market outcomes. This is because skill portfolios differ both with respect to skill level and skill set specialization, and these two competing forces can create instances in which a higher level of average skills can worsen labor market outcomes due to a simultaneously higher degree of specialization. In this sense, we show that increasing the level of skills can, but not necessarily does, worsen labor market outcomes. Our theoretical insights help to reconcile the findings of specialization premia of education (Leighton and Speer (2020), Silos and Smith (2015)) and specialization penalty of displaced workers (Gathmann and Schönberg (2010)) by showing that both can be true for different sets of worker skills and for different labor market outcomes. We hence provide a unifying interpretation to these seemingly contradictory findings.

This paper is first and foremost related to the literature on multidimensional skills (Lise and Postel-Vinay (2020), Alon and Fershtman (2019), Gibbons and Waldman (2004), Lindenlaub and Postel-Vinay (2020), Lindenlaub and Postel-Vinay (2023), Lindenlaub (2017), Lamo et al. (2011), Guvenen et al. (2020)). The paper is also related to the large literature on worker displacement. In particular, it is related to the literature documenting that displaced workers who switch industries (Neal (1995), Parent (2000), Carrington and Fallick (2017), Kletzer (1996)) and/or occupations (Kambourov and Manovskii (2009), Milgrom (2023)) suffer larger earnings losses and that task and occupational skill distance is an important determinant of wage losses (Gathmann and Schönberg (2010), Ormiston (2014), Nawakitphaitoon and Ormiston (2015)). The paper is closely related to Dustmann and Meghir (2005) and Neal (1995) who also use displaced workers to study transferable skills. Our work is complementary to two recent analysis with a focus on the outcomes of displaced workers with multidimensional skills across different labor markets, Macaluso (2023) and Hernandez Martinez et al. (2022).[2] Differently from Macaluso (2023), we do not consider variations in labor demand across different locations for a small set of broad occupation groups but instead analyze differences in skill returns across fine occupation groups in broad labor markets. While Macaluso (2023) answers the question of how location affects displacement outcomes for a given skill, we analyze which skill sets are more favorable to possess after a displacement event in a given labor market.

The paper proceeds as follows. First, we develop a framework to articulate the mechanisms in section 2. We then describe our data sets and motivate our analysis by characterizing our skill and specialization measure in more detail in section 3. We then describe our empirical results in section 4 before concluding in section 5.

2 Mechanism

In this section, we establish a simple framework to assess the influence of specialization on a worker's expected labor market prospects. Our primary focus is on demonstrating how the expected duration of unemployment, the likelihood of job separation, and the initial wage upon reemployment are contingent on the degree of specialization. This framework builds upon Lise and Postel-Vinay (2020), which incorporates a multidimensional production function in a random search setting. Our production function, like theirs, features a mismatch penalty and complementarity gains. Our framework deviates from their model by considering stochastic shocks to output, which allow for endogenous separations, and Nash bargaining without on-the-job search as in Mortensen and Pissarides (1994). We first describe the setting of the theoretical framework and how mismatch penalties and comple-

[2] Relatedly, Grigsby (2022) shows that closely related occupations experience similar wage responses after a demand shock in one occupation.

mentarity gains drive the two aspects of specialization (subsection 2.1). We then demonstrate the negative and positive effects of specialization in a quantitative illustration of the framework (section 2.2). This section prepares our subsequent empirical analysis by providing guidance on the relevant empirical objects and their expected covariance in the presence of complementarity gains and mismatch penalties.

2.1 Framework

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 a technology vector $y = \{y_1, ..., y_K\}$, $y_k \in \mathbb{R}_+$ in the same K skill dimensions. The output of a worker depends on their own skills, on the technology of the firm that the worker is matched with, and on a time-varying match-specific idiosyncratic productivity, z. We denote the match-specific output by $f(x, y, z)$. Employed workers receive wages $w(x, y, z)$ and unemployed workers receive flow unemployment benefit b. Both workers and firms are risk neutral and discount the future at rate r. Unemployed workers sample jobs from the exogenously given distribution $F(y)$ at rate λ. A new match starts with match-specific idiosyncratic productivity $z_0 = 0$, and thereafter, match productivity is redrawn from the distribution $G(z)$ at rate ξ. Importantly, there is no on-the-job search. Matches are destroyed exogenously at rate δ and can be destroyed endogenously if the match-specific productivity z becomes too low. We assume that learning is stochastic: the skills of the worker fully adjust to the skill requirements of the firm at rate π.

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

$$f(x, y, z) = \sum_k \left(\alpha_k y_k + \alpha_{kk} x_k y_k - \kappa_k (x_k - y_k)^2\right) + z,$$

where α_k, α_{kk} and κ_k are assumed to be non-negative for all K dimensions.[3] The terms $\kappa_k (x_k - y_k)^2$ capture a mismatch penalty between worker skills and firm skill requirements, while the terms $\alpha_{kk} x_k y_k$ allow for complementarity between worker skills and job skill requirements. The penalty for mismatch and the reward for complementarity are inherently

[3] This specification is equivalent to the sum of flow production and flow disutility of work in Lise and Postel-Vinay (2020). A further simplification is that in our specification the κ_k parameters do not depend on whether the worker's skills are below the firm's skill requirements (which reduces flow production in Lise and Postel-Vinay (2020)), or above (which increases the flow disutility of work in Lise and Postel-Vinay (2020)). Since it is the sum of flow production and flow disutility of work that determines match formation in Lise and Postel-Vinay (2020), in their work, as in ours, both over- and under-qualification reduce the flow surplus of a match.

linked. Even in the absence of the complementarity term ($\alpha_{kk} = 0$), output is higher if x matches y due to a lower mismatch penalty. And similarly, in the absence of the mismatch penalty ($\kappa_k = 0$), output is lower if x and y are very different as the complementarity term is depressed. Including both of these terms in the output function allows us to vary the strength of each component. These two terms can drive the negative and positive aspects of specialization, as we discuss in more detail below.

Specialization We define the specialization of a worker as having a set of skills that is distant from the skill combinations typically used in the economy. In the context of our model, the specialization of a worker with skill set x is

$$Spec(x) \equiv \int_y \sum_k (x_k - y_k)^2 dN(y),$$

where $N(y)$ is the distribution of employment across jobs y.[4,5] To better understand the aspects of skill sets that correlate with our measure of specialization, it is useful to factorize it in the following way

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

where E denotes the expected value over the distribution $N(y)$.[6] Assume that economy-wide skills are normalized such that $E[y_k]$ is equal for all skill dimensions k. It can be shown that if two individuals a and b have the same average skill level, such that $\sum_{k=1}^K x_{ka}/K = \sum_{k=1}^K x_{kb}/K$, then the one with a higher specialization measure, $Spec_a > Spec_b$, will also have a more asymmetric skill set, $\max_k x_{ka} - \min_k x_{ka} > \max_k x_{kb} - \min_k x_{kb}$. To see this, note that the last term in the decomposition will be the same for two such individuals, yet $\sum_k x_{ka}^2 > \sum_k x_{kb}^2$ whenever a has a more asymmetric skill set than b due to Jensen's

[4]We define specialization in terms of the distribution of filled jobs in the economy, $N(y)$, rather than in terms of the distribution of vacant jobs, $F(y)$. We chose this definition as data on filled jobs is more readily available and reflects better the long term demands for skills.

[5]Note that our specialization measure counts over- and under-qualification of worker skills relative to job skill requirements equally. If the flow surplus of a match would only penalize the under-qualification of workers, then a measure that only counts under-qualification would be more appropriate. In Appendix section C.2 we show that our empirical results hold with such a specialization measure as well.

[6]This factorization further shows that our specialization measure is equivalent to another skill distance measure, the distance to the average skill requirement in the economy $\sum_k (x_k - E[y_k])^2$ (up to a constant shifter). To see this note that

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

inequality. Our definition of specialization hence reflects the intuitive notion that a more asymmetric skill set (such as for a sprinter) is also a more specialized skill set, conditional on the skill level. To discuss how specialization impacts labor market outcomes, we next set-up the value functions of firms and workers.

Value functions Let $U(x)$ denote the value of an unemployed worker, $W(x, y, z)$ the value of an employed worker, and $J(x, y, z)$ the value of a filled job. Let us denote the joint surplus of the match by $S(x, y, z) = J(x, y, z) + W(x, y, z) - U(x)$. Given linear preferences over income $S(x, y, z)$ is independent of the wage, i.e. of the way in which the total surplus is shared by the worker and the firm. We assume that firms and workers engage in Nash bargaining over the firm-worker surplus with a relative weight β of workers such that

$$W(x, y, z) - U(x) = \frac{\beta}{1-\beta} J(x, y, z).$$

The Bellman equation for the value of unemployment satisfies

$$rU(x) = b + \lambda \int_y \max\{0, (W(x, y, z_0) - U(x))\} dF(y) = b + \beta\lambda \int_y S(x, y, z_0)^+ dF(y). \quad (1)$$

The value of an unemployed worker is equal to the flow value b and the expected capital gain from becoming employed $\lambda \int_y \max\{0, (W(x, y, z_0) - U(x))\} dF(y)$. The last equality is obtained from the sharing rule $W(x, y, z_0) - U(x) = \beta S(x, y, z_0)$, where we denote $S(x, y, z)^+ \equiv \max\{0, S(x, y, z)\}$. Note that matching is based on a mutual decision by the worker and the firm, and the match is only formed if the surplus is positive.

The value function of employed workers satisfies:

$$\begin{aligned} rW(x, y, z) &= w(x, y, z) + \xi \int_{R(x,y)}^{\infty} W(x, y, z') - W(x, y, z) dG(z') \\ &+ \xi G(R(x, y))(U(x) - W(x, y, z)) \\ &+ \pi(W(y, y, z) - W(x, y, z)) + \delta \left(U(x) - W(x, y, z)\right). \end{aligned}$$

Employed workers receive wage $w(x, y, z)$ and benefit from the option value of being in the current match, the value of which depends on changes occurring to the match. First, the option value is composed of the expected value of changes to the match productivity z. As standard, the optimal choice whether to continue the match takes the form of a reservation value $R(x, y)$, such that if $z' > R(x, y)$, the match continues at value $W(x, y, z')$, and if $z' \leq R(x, y)$, the match is destroyed and the worker receives unemployment value $U(x)$. It is important to note that the reservation productivity depends on both the worker's skill set, x, and the firm's skill requirements, y. This implies the following expected capital gains due to changes in match productivity relative to the current worker value: $\xi \int_{R(x,y)}^{\infty} W(x,y,z') - W(x,y,z) dG(z')$ from remaining employed and $\xi G(R(x,y))(U(x) - W(x,y,z))$ from endogenously separating. Second, the option value varies with the gains due to adaptation to the firm's skill requirements with value $W(y,y,z)$ which increases the option value by $\pi(W(y,y,z) - W(x,y,z))$. Finally, if the worker is exogenously displaced, they receive a value $U(x)$ such that the expected change in value is $\delta\left(U(x) - W(x,y,z)\right)$.

Finally, the value of a filled job for the firm satisfies:

$$\begin{aligned} rJ(x,y,z) &= f(x,y,z) - w(x,y,z) + \xi \int_{R(x,y)}^{\infty} J(x,y,z') - J(x,y,z) dG(z') \\ &+ \xi G(R(x,y))(0 - J(x,y,z)) \\ &+ \pi(J(y,y,z) - J(x,y,z)) + \delta\left(0 - J(x,y,z)\right). \end{aligned}$$

The flow yield of a filled job is just the profit from the filled job, that is $f(x,y,z) - w(x,y,z)$. As for the worker's value, the option value of the job to the firm is composed of three terms. First, if the match draws a new productivity z' and it is above the reservation productivity $R(x,y)$, the firm enjoys a value $J(x,y,z')$ such that the expected gain in value is $\xi \int_{R(x,y)}^{\infty} J(x,y,z') - J(x,y,z) dG(z')$. Otherwise, the match dissolves and leads to a full loss of the match value to the firm with expected value $\xi G(R(x,y))(0 - J(x,y,z))$ if $z' \leq R(x,y)$. Worker learning leads to an increase in value to $J(y,y,z)$ with expected gain $\pi(J(y,y,z) - J(x,y,z))$. Finally, the match can be exogenously destroyed, leading as well to a full loss of match value with expected gain of $\delta\left(0 - J(x,y,z_0)\right)$.

Bringing together these three value functions, we can express the worker-firm surplus as

$$\begin{aligned} \left(r + \xi + \pi + \delta\right) S(x,y,z) &= f(x,y,z) + \xi \int S(x,y,z')^{+} dG(z') \\ &+ \pi\left(S(y,y,z) + (U(y) - U(x))\right) - rU(x) \end{aligned} \tag{2}$$

Using the negotiation protocol, we can express wages as:[7]

$$w(x,y,z) = \beta f(x,y,z) + (1-\beta)\left(\pi + r\right) U(x) - \pi(1-\beta)U(y). \tag{3}$$

Specialization and labor market outcomes We aim to analyze the impact of workers' specialization on the probability of matching, starting wages and on the separation proba-

[7] See Appendix section A.1 for details.

bility once matched.

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

$$P(S(x,y,z_0) \geq 0) = \int_y I\left(S(x,y,z_0) \geq 0\right) dF(y) \equiv \int_{y \in S^+(x)} dF(y),$$

where $S^+(x)$ denotes the set of jobs y with which the worker's surplus is non-negative. The probability of matching therefore depends on the distribution of surplus that the worker could generate with the various firms y. The worker-firm surplus is increasing in the flow output and decreasing in the value of unemployment, as can be seen in (2). Via flow output we expect that more specialized workers, whose skills are on average further away from job skill requirements, have a lower probability of drawing an acceptable match, i.e., the $S^+(x)$ set is smaller for workers with a higher $Spec(x)$ measure. This is because these workers will have a large mismatch penalty with a larger set of firms y, leading to a higher fraction of available jobs with non-positive surpluses.

Expected starting wages among acceptable matches are given by

$$E(w(x,y,z_0)|y \in S^+(x)) = \frac{\int_{y \in S^+(x)} [\beta f(x,y,z_0) + (1-\beta)\left(\pi + r\right) U(x) - \pi(1-\beta)U(y)] dF(y)}{P(S(x,y,z_0) \geq 0)}.$$

The expected starting wages depend on flow output and the value of unemployment in acceptable matches. For a given average skill level, more specialized workers have more asymmetric skills. These workers – if well fitted to their job's skill requirements – enjoy larger complementarity gains than workers with more symmetric skills, due to Jensen's inequality. Unless offset by the lower value of unemployment, we expect more specialized workers to have higher expected output among the smaller set of acceptable matches.

Finally, the probability of separation is

$$P(\text{separation}|y \in S^+(x)) = \frac{\int_{y \in S^+(x)} [\delta + \xi G(R(x,y))] dF(y)}{P(S(x,y,z_0) \geq 0)},$$

which is increasing in the expected reservation productivity $R(x,y)$. The reservation productivity is implicitly defined as the productivity at which $S(x,y,R(x,y)) = 0$. From (2) we can see that $R(x,y)$ is lower if the flow output (net of the idiosyncratic component) is higher and if the value of unemployment is lower. Following the same reasoning as for expected starting wages, we expect more specialized workers to have a higher expected output in the smaller set of acceptable matches, and hence a lower reservation probability and a lower probability of separation.

Given the complex interplay of flow output and the option value of unemployment in determining surplus, it is instructive to consider a parameterized version of such an economy. This exercise informs us about the net effect of specialization on labor market outcomes through the direct effect via flow output and the indirect effect via the value of unemployment. In what follows, we parametrize our model to quantitatively study the impact of worker specialization on labor market outcomes. By varying the strength of the mismatch penalty and of complementarity gains we explore how these two forces shape the impact of specialization on our outcomes of interest.

2.2 Quantitative illustration

Parameterization To illustrate these mechanisms quantitatively, and assess the role of the mismatch penalty, κ_k and the gain from complementarity, α_{kk}, we solve for $S(x, y, z)$ and $U(x)$ using equations (1) and (2). To do this, we parametrize the economy as follows. We adopt the setting in Lise and Postel-Vinay (2020) and choose three skill dimensions. We set unemployment benefit b and production function parameters as they do, with the modification that we set the parameter κ to the average of all κs in their framework. We assume a normal distribution $N(0, \sigma^2)$ for $G(z)$ and set $\sigma = 0.17$. We set the rent sharing parameter at $\beta = 0.30$, the learning rate at $\pi = 0.10$ and the arrival rate of idiosyncratic productivity shocks at $\xi = 0.30$. We set the job destruction rate at $\delta = 0.05$ and the job offer arrival rate at $\lambda = 0.20$. We measure skill requirements and specialization for each occupation as described in detail in Section 3.1. Finally, we use the empirically observed vacancy distribution $F(y)$, obtained from data on French job postings at *Pôle Emploi*.[8] We calculate the surplus and the value of unemployment for workers with skill vector x from the set of occupational skill requirements, y. Given our specification, the problem has 7 state variables (3 from x, 3 from y and 1 from z). To solve such a high dimensional problem, we use neural networks leveraging the solution method from our own work in the companion paper Bárány and Holzheu (2023).

Expected surplus analysis For a first impression of the variance of labor market outcomes in our model, we consider the expected surplus of a worker (conditional on matching), $E[S(x, y)^+ | S(x, y) > 0]$ and overall across matches $E[S(x, y)^+]$ at different levels of average skills and specialization. Figure 1 shows the expected surplus and the average skill level, in blue for jobs with a specialization measure at least one standard deviation above the mean, and in yellow for jobs with specialization measure at least one standard deviation below

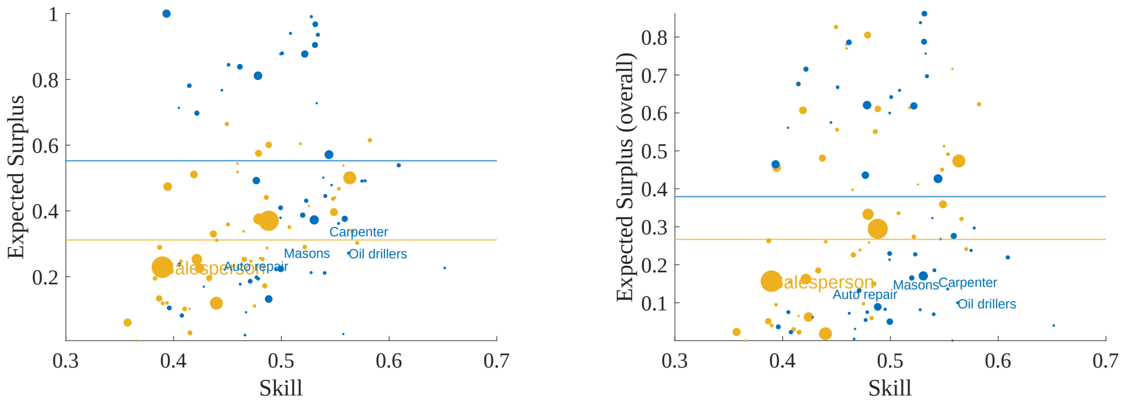
[8] Vacancy data from the French *Pôle Emploi* contains all vacancies posted at the unemployment agency's job board including occupation codes.

the mean. The horizontal lines indicate the average surplus for each of the two groups. As expected, we find that highly specialized jobs have on average higher expected surplus, as shown by the blue horizontal line laying above the yellow line. This figure shows that for a given average skill level, the expected surplus varies significantly, with the blue dots typically higher than the yellow ones. This means that it is not only the skill level but also the specialization that determines expected surplus and hence labor market experiences. We also find that skills on average increase expected surplus. However, we see that higher skills do not uniformly improve labor market outcomes. To see this, consider the set of occupations denoted in blue. These are highly specialized occupations such as auto repair technicians or carpenters. While these jobs have higher expected surplus conditional on matching than for the salesperson (left figure), they feature lower expected surplus overall, given a lower likelihood of matching (right figure). In other words, accumulation of more skills at the expense of a balanced portfolio can imply lower expected surplus. It is in this sense that the accumulation of specialized skills can *in some circumstances* create worse labor market prospects.

Labor market outcomes We next turn to the analysis of specialization and labor market outcomes in our model. Figure 2 shows the probability of matching and the expected wage across acceptable matches against specialization for the baseline parametrization of the production function. The figure shows that the baseline simulation generates a negative relationship between match probability and specialization and a positive relationship between expected wages and specialization. This is consistent with the intuition developed earlier whereby the likelihood of a positive surplus decreases in specialization, and the expected surplus among acceptable matches increases in specialization.

While this figure is consistent with our mechanism, we can go a step further and use the simulated data to understand how specialization co-varies with expected labor market outcomes conditional on a worker's skill level. We do this in Table 1, where we show parameter estimates from a regression of the likelihood of matching as well as of the expected entry wage on specialization and average skills, weighted by the empirical frequency of jobs in the economy. We perform this exercise for the set of baseline parameters, for a no mismatch penalty case ($\kappa_k = 0$), and for a no complementarity gains case ($\alpha_{kk} = 0$). The exercise shows that only for the specification with both mismatch penalty and complementarity gains terms, we find a highly significant ($p < 0.001$) regression estimate for both the expected matching frequency and the expected entry wage.[9] We hence conclude that our model predicts a negative and

[9]Section A.2 in the Appendix shows the equivalent of Figure 2 for these two parameterizations, and the figures there confirm that both the mismatch penalty and the complementarity gains channel is needed for this result.



(a) $E[S(x,y)^+|S(x,y)>0]$

(b) $E[S(x,y)^+]$

Figure 1: Expected surplus

Notes: The figures show scatter plots of the expected surplus and the skill of a worker, for both high (blue - 1 standard deviation above the mean) and low (orange - 1 standard deviation below the mean) specialization workers. The left figure conditions surplus to be positive while the right figure computes the average surplus when larger than zero. The horizontal lines represent the average surplus for high versus low specialized workers. The size of the dots represents the relative frequency of jobs in the economy. The occupations marked in blue are selected as examples such that they have higher expected surplus conditional on matching than a salesperson but lower expected surplus overall.

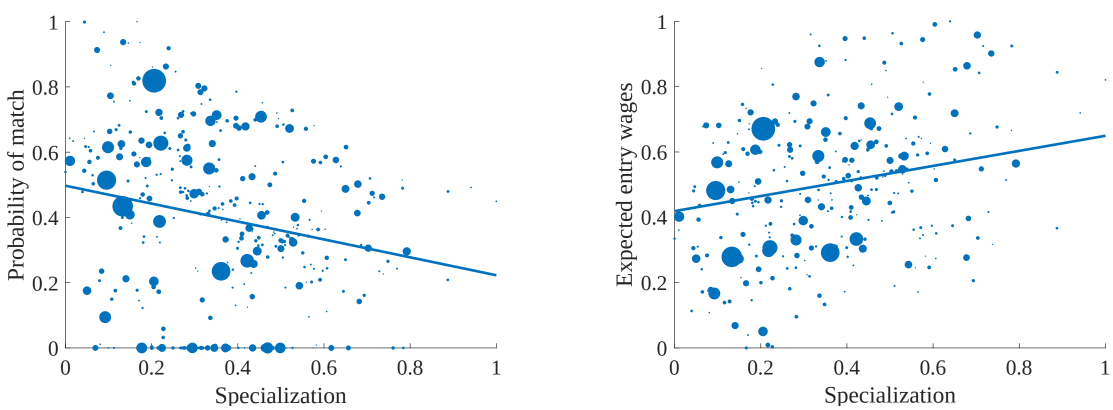


Figure 2: Match probability and expected entry wage

Notes: The figure show scatter plots of the probability of matching with a randomly sampled firm (on the left) and the expected entry wage across firms with which the worker would match (on the right), both plotted against the specialization of the worker. The size of the dots represents the relative frequency of jobs in the economy.

	Match probability	Entry wage
Baseline: $\kappa_k \neq 0, \alpha_{kk} \neq 0$		
Specialization	-0.409**	0.289**
	(0.000)	(0.000)
No Mismatch: $\kappa_k = 0$		
Specialization	-0.085*	0.109*
	(0.048)	(0.015)
No complementarity: $\alpha_{kk} = 0$		
Specialization	-0.395**	0.065
	(0.000)	(0.257)

Table 1: Simulation Regressions

Notes: The table shows the results of a regression of the likelihood of matching and expected entry wages on specialization, controlling for the skill level index. The regression is run on simulated data based on different parameter combinations. The regression is performed at the occupation level across 347 occupations, weighted by their empirical size. Values in brackets represent p-values, * $p < 0.05$, ** $p < 0.001$.

a positive effect of specialization on labor market outcomes and that both effects can be uncovered in a regression exercise.

Given these insights, we now turn to the empirical data to search for the empirical equivalent of the negative and positive aspect of specialization. In what follows, we describe the data and demonstrate, among exogenously displaced workers, that more specialization leads to a higher duration of non-employment, but, once a suitable job is found, also to higher job stability and higher entry wages. The results of these regressions mirror those obtained from simulated data in Table 1. Thus, specialization impacts the labor market outcome of workers both via the mismatch and the complementarity channel as predicted in this quantitative exercise.

3 Data and measurement

In the following, we outline our data sets, the sample, as well as the variables used in our analysis. In particular, we define and describe our measure of specialization and the empirical equivalent of the sample of displaced workers in subsection 3.1. We then use our data to provide suggestive evidence of our mechanism in subsection 3.2.

3.1 Data overview

Worker data sets In our empirical analysis, we use data sets for two different countries: (1) for the US, we leverage the *Displaced Worker Supplement* (DWS) and the *Annual Social and Economic Supplement* (ASEC) of the *Current Population Survey* (CPS); (2) for France we use the administrative matched employer-employee data set *Déclarations annuelles des données sociales* in both the panel and the cross-sectional version (DADS). Our samples cover the years 1996-2020 for the US and 2007-2019 for France. The different country data sets enable us to reach conclusions that extend beyond a particular country's setting especially in light of differences in labor market regulations between the two countries.

Skill requirements 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 principle 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)).[10]

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. This procedure further allows us to preserve most of the information contained in the data while obtaining a meaningful measure of broad skill requirements. For example, some of the most important contributors to manual skill requirements, besides 'Multilimb Coordination', are 'Gross Body Equilibrium', 'Performing General Physical Activities', 'Speed of Limb Movement', 'Gross Body Coordination'. Some of the most important contributors to cognitive skill instead are 'Complex Problem Solving', 'Mathematics' or 'Perceptual Speed'. In Table 5 in the Appendix we list the 25 most important descriptors contributing to each of our three skill requirement measures. This reduction in dimensionality is especially important when thinking about skill distances across occupations. To see this, consider two cases. In the first case, the researcher observes a set of highly correlated measures of the

[10] After performing the PCA, we then collapse these skill measures to the occupation codes used in the data.

same skill (type 1), each observed with noise. In the second case, the researcher observes the same set of noisy measurements of skill type 1 and an additional measure of a different skill type (type 2). While in the first case, dimensionality reduction simply improves on the precision of the measurement of skill type 1 and hence of skill differences, in the second case it avoids over-counting differences in the first as compared to the second skill type, therefore reflecting true skill differences. In Appendix section B.2 we provide more details on this important point. In summary, reducing the number of skill measurements when calculating skill distances is crucial - not only does it condense information, but it also accurately represents the genuine disparities among various multidimensional skill sets.

To integrate the skill and labor market data, we map SOC occupation codes to French DADS occupation codes (similarly to Laffineur and Mouhoud (2015) and Laffineur (2019)) and to US DWS harmonized occupation codes (similarly to Acemoglu and Autor (2011) and Lise and Postel-Vinay (2020)). In our data sets, (rotated) skill measures are weakly correlated in the economy (see scatter plots in Appendix section B.4). 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 a worse fit to a given skill portfolio.[11]

Specialization Following the theoretical framework presented in Section 2, we measure specialization as the weighted average of the pairwise distances between the worker's skill set and the skill requirement of all jobs in the economy at a given point in time:

$$Spec_{i,t} = \sum_{o=1}^{O} \lambda_{o,t} \left(\sum_{k=1}^{K} (s_{i,k,t} - s_{o,k})^2 \right).$$

In the above expression $s_{o,k}$ is the skill requirement of occupation o in dimension k, $\lambda_{o,t}$ is the share of job o in the economy at time t, such that $\sum_{o=1}^{O} \lambda_{o,t} = 1$, and $s_{i,k,t}$ is the skill of worker i in dimension k in period t. In practice we will assume that the worker's skill set is identical to the skill requirement of their last job, such that $s_{i,k,t} = s_{j,k}$ if the worker's last job before time t was in occupation j. To facilitate interpretation, we normalize the

[11] We confirm that our measure of skill requirements has economic meaning. If skill requirements are economically meaningful, then individuals should move to occupations that are closer to their previous occupation than the distance on average to other occupations. We show this to be true in Figure 8 in Appendix section B.3, which demonstrates that people who switch occupations after an unemployment spell switch to occupations that in terms of skill requirements are closer to their skill portfolio than other occupations in the economy are on average.

specialization measure on the unit interval.

This measure quantifies how different a worker's skill set is on average relative to all jobs in the economy and hence expresses the singularity of the worker's skill set. If a job is very specialized, its skill requirements will be very far from the majority of jobs, and this will be reflected in a high specialization measure. If, on the other hand, a job is not very specialized, then it will be close to many other jobs in terms of skill requirements, and this will be reflected in a low specialization measure. For instance, consider engineers and hairdressers; these are professions characterized by a high degree of specialization, with engineers focusing on cognitive skills and hairdressers specializing in manual skills. Conversely, professions like pharmacists and secretaries are less specialized, as they necessitate a combination of both interpersonal and cognitive skills. Note that our specialization measure is similar in spirit to local skill remoteness used in Macaluso (2023), but we measure skills differently, and our measure is constructed based on finer occupation categories and focuses on the whole economy.[12]

Since there is no established way of measuring specialization in the literature, in Appendix section C.2 we propose three alternative measures. These measures are: (1) the distance between a worker's skill set and the average skill requirement across all jobs in the economy, and (2) 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. Measure (3) 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. In Table 9 in the Appendix we show that the empirical results are very similar when using these alternative specialization measures, and larger when using measure (3).

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.[13] 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

[12]Macaluso's skill remoteness is based on 35 raw skill descriptors from ONET, for 22 broad occupation groups, and for 442 metropolitan areas. We compare our and Macaluso's measure and results in detail in Appendix section C.3.

[13]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.

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 and second, we aim to reduce the scope for worker selection. 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. We avoid this selection by focusing on firm closures, where firms cannot choose which workers to retain.

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.[14] Table 2 summarizes our main sample of displaced workers across the two data sets. In terms of the number of 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 index. 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.

In our analysis, our main dependent variables are the duration of non-employment after displacement, the separation rate and the wage at the new job. The duration 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. Given different information about post-displacement outcomes in the US and in the French data, we measure the separation rate slightly differently in the two 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

[14] 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 the results section.

	US	France
Years	1996-2020	2007-2019
Specialization	0.31	0.30
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 2: Summary statistics

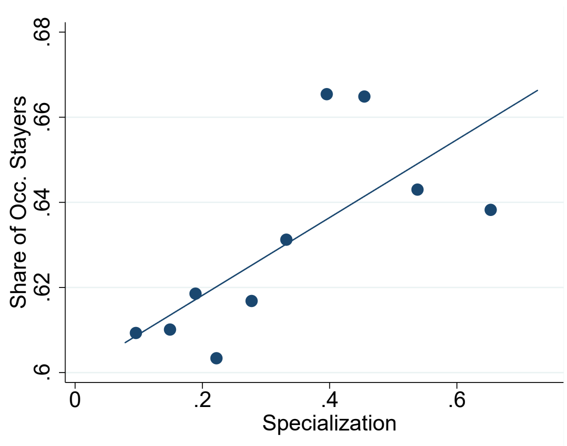
Notes: The table shows summary statistics across samples. Note that wages in the US DWS are weekly wages whereas they are measured at a daily frequency in France. The number of firms, workers and observations is based on the sample for the analysis of duration of non-employment.

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. Both data sets feature information on the wage at the new job. 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.

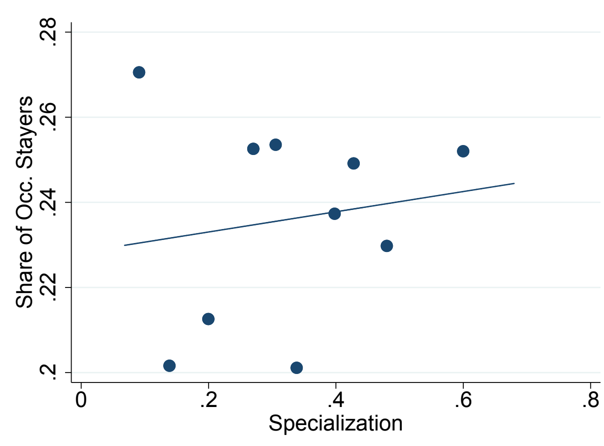
3.2 Empirical content of specialization

In the following we illustrate the empirical content of our measure of specialization. First, we show that higher specialization correlates with a higher share of occupational stayers in the data. This suggests that mismatch penalties are present in the data. Second, we show that skill asymmetry, commonly associated with specialized skills, is strongly positively correlated with our measure of specialization. This suggests that workers can expect specialization premia based on skill complementarities. These findings give empirical support to our specialization measure and provide motivation for our empirical analysis in the next section.

Specialization and occupation switchers 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 3 presents the relationship between our specialization measure and the percentage of individuals who remain in their respective occupation after experiencing a period of unemployment.[15] 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, in line with the concept of a mismatch penalty discussed in Section 2.



(a) US



(b) France

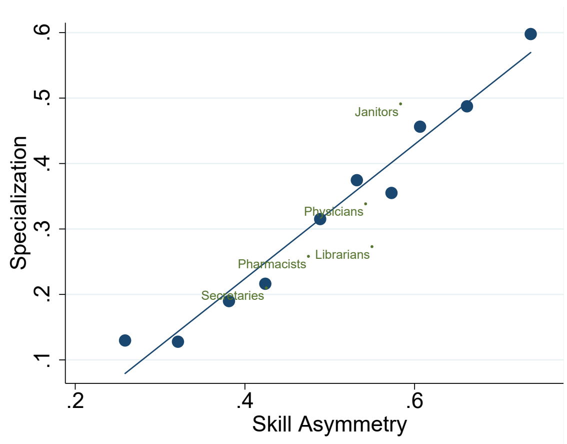
Figure 3: Occupation switching and Specialization

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

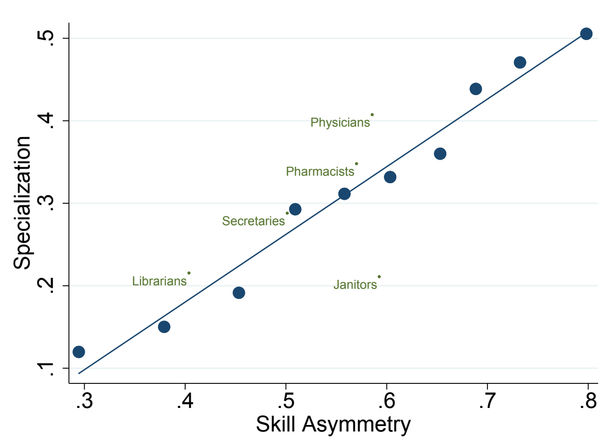
Specialization and skill asymmetry We define skill asymmetry across different skill dimensions within a job as $asym(s_j) = \max_k s_{j,k} - \min_k s_{j,k}$. This measure indicates the

[15]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.

extent of variation in requirements across different skills. Higher values signify greater disparities in skill requirements. It captures the conventional concept of specialized skills, where a worker possesses exceptionally strong skills in one area while potentially lacking skills in another. It's important to distinguish this individual-level specialization from our broader definition of specialization at the economy-wide level. While skill asymmetry allows us to compare individual skills, specialization measures how unique a worker's skill set is in relation to other workers in the economy. Recall from Section 2 that our specialization measure increases in skill asymmetry, given an average level of skills and the distribution of job skill requirements. We now show that this is also true empirically. Although skill asymmetry and specialization are distinct concepts, skill asymmetry and specialization co-vary positively in the data as shown in Figure 4. In other words, workers with more uneven skill sets are, on average, further removed from the typical jobs found in the economy. This observation is significant because it aligns with the idea that specialized workers, when matched with the right jobs, can be more productive due to larger complementarity gains from asymmetric skill portfolios, as discussed in Section 2.



(a) US



(b) France

Figure 4: Skill Asymmetry and Specialization

Notes: The figures show binned scatter plots of the specialization of skills against the asymmetry of skills. The asymmetry of skills is the spread of skills across manual, cognitive and interpersonal skills. Note that specialization is calculated at the yearly level and occupational characteristics are weighted by employment shares across occupations.

For instance, consider engineers who primarily focus on designing new products without direct customer interactions, emphasizing cognitive skills over interpersonal ones. This specialization in cognitive skills potentially enables engineers to attain higher levels of expertise in that domain compared to pharmacists, who also allocate time to customer interactions, thereby honing their interpersonal skills besides their cognitive skills. This contrast implies that engineers possess a more lopsided skill set compared to pharmacists. In essence, the pharmacist's skill set is more balanced and aligns better, on average, with various jobs in the economy, making them less specialized than engineers. The engineer, however, can potentially benefit from higher complementarity gains at the right job due to their higher cognitive and lower interpersonal skills, i.e., due to their more asymmetric skill set. While these patterns are suggestive in nature, the next section presents results from an analysis of displaced workers in support of the negative and positive effects of specialization.

4 Empirical results

In the following, we provide empirical evidence regarding the negative and positive effects of specialization formally through different regression specifications. While the previous motivating evidence has hinted at the possibility of these effects, selection effects could drive the observed results. In the following, we use data on displaced workers to study the relationship between labor market outcomes and specialization. By using the displaced worker sample, we can be confident that the job separation of the worker was not driven by low worker-firm surplus but by economic conditions at the firm.

In our empirically strategy, we follow the theoretical model analysis and replicate the cross-skill analysis conducted there. Specifically, we test for worker i displaced at time t whether specialization before displacement correlates with a set of outcome variables $Y_{i,\tau}$

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

where $Spec_{i,j(i,t),t}$ is the specialization index of the last job $j(i,t)$ of worker i before displacement at time t.[16] For $Y_{i,\tau}$ we examine a) the duration until re-employment $T_{i,t}$, as well as b) the re-employment wage $w_{i,j(i,t+n),t+n}$ and c) separation probability $Sep_{i,j(i,t+n),t+n}$. These outcome variables can capture the two aspects of specialized skills. On the one hand, a worker with specialized skills is on average worse fitted to jobs in the economy, which can increase the duration of non-employment. On the other hand, once a more specialized dis-

[16] We also conduct our analysis with four alternative measures of specialization, notably building on Macaluso (2023) and Lise and Postel-Vinay (2020). Table 9 in the Appendix shows that our results hold with these different measures of specialization. Note that we here present individual-level regressions, while our simulation analysis in Table 1 is conducted at the occupation level. We choose this in order to allow for additional worker and firm-level covariates in the regression. We show results at the occupation-year level in Table 8 in the Appendix. The results are qualitatively and quantitatively similar.

placed worker finds a job, the match productivity is likely to be higher, leading to higher wages upon re-employment and a lower probability of separating from the new job in the first year. The control vector $X_{i,t}$ includes the skill index defined as the average skill level ($\overline{s}_{i,j(i,t),t} = \sum_k^K s_{j(i,t),k}$) 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. 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.

Negative effect of specialization Table 3 summarizes the results across specifications for the duration on non-employment after displacement and shows that workers with higher specialization face longer periods of non-employment. In column (1) we do not control for

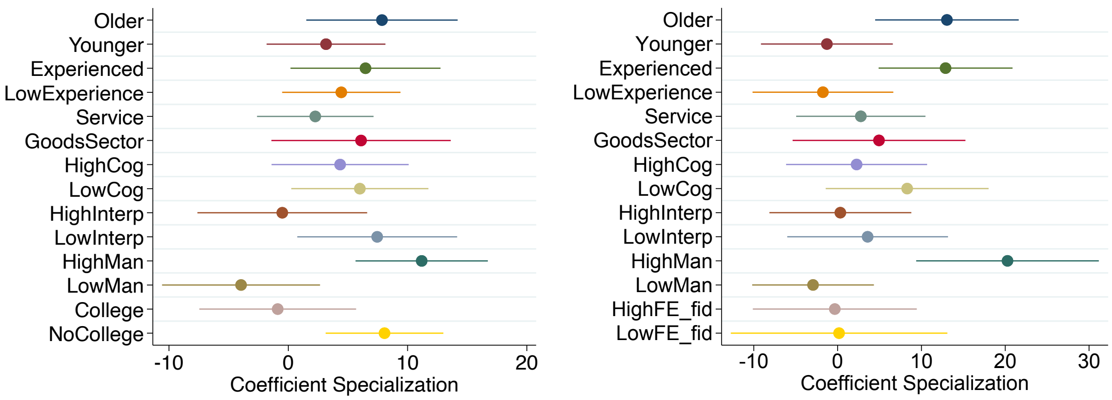
	Weeks w/o work		
	(1)	(2)	(3)
		US	
Specialization	3.947^{*}	4.082^{*}	5.171^{*}
	(0.041)	(0.036)	(0.010)
Skills		-1.821	0.155
		(0.444)	(0.951)
Observations	2697	2697	2697
		FR	
Specialization	5.041^{+}	6.076^{*}	5.434^{+}
	(0.053)	(0.020)	(0.064)
Skills		-21.25^{*}	-10.26^{*}
		(0.000)	(0.008)
Observations	18800	18800	13411
Controls	w/o Skill	w/ Skill	+Controls

Table 3: Non-employment duration – Regression results

Notes: The table shows regression results for a regression of weeks of non-employment after displacement on specialization, skill level 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/ AKM worker FE and pre-displacement experience, tenure and log wage. Results are weighted using sampling weights for the US. Values in brackets represent p-values, $^{+}$ $p < 0.10$, * $p < 0.05$.

worker characteristics except for the specialization index. In column (2) we additionally control for the worker's pre-displacement skill level. It is important to control for this, as higher worker skills are likely to increase the productivity of the worker in any match, and hence reduce the duration of non-employment, moreover the level of skills and the index of specialization are positively correlated in our data. As expected, the coefficient on specialization increases after controlling for the skill level as specialization and the skill level affect the non-employment duration in opposite ways. In column (3) we additionally control for other worker characteristics through the full set of control variables. These covariates allow us to control for a set of key confounding factors. First, a worker's general skills as captured through experience or tenure are likely to reduce the duration of non-employment, while specialized skills might increase the duration of non-employment. Controlling for this is crucial in order to separate the effect of generalized skills from specialized skills associated with the last job. Second, we would like to differentiate the effect of specialized skills from idiosyncratic match quality. Hence we control for the pre-displacement wage to proxy for past job match quality. For the administrative data set in France, we further include worker fixed effects estimated from a standard AKM specification. In the US data we control for the worker's level of education. These additional controls allow us to address a potential selection bias, whereby mainly low performing or lower skilled workers are displaced, who are also the workers who take longer to find a new job. The results from this regression show that a pressing machine operator, who has an average skill index of 0.19, and a high specialization index of 0.81 spends on average 16 to 18 days longer looking for a job than a proofreader, whose average skill index is also 0.19, but has a lower specialization index of 0.33. The difference in terms of expected unemployment duration between managers in education and related fields ($\overline{s} = 0.82$, $Spec = 0.76$) and managers in food serving and lodging establishments ($\overline{s} = 0.82$, $Spec = 0.20$) is between 19 and 21 days. Note that if we use a broader definition of displaced workers, those displaced during mass lay-offs instead of firm closures, the coefficients are insignificant, see Appendix C.4. This indicates that the type of selection bias that we avoid by looking at firm closures can be important, especially for the negative aspects of specialization. Intuitively, a firm that sheds a share of its work force is likely to choose to lay-off those with lowest match quality. This selection effect is avoided in our preferred specification focusing on firm closures.

Figure 5 shows that the effect of specialization on non-employment duration varies across workers to some degree. We find that the specialization effect is larger for older and experienced workers. The effect is by far the largest for workers specializing in jobs with high manual skill requirements, while workers in jobs with low cognitive (in France) and low interpersonal skill requirements (in the US) also face a longer non-employment duration. In the US, the effect is larger for workers without college education. These results suggests that the negative effects of specialization hit the less skilled workers the most. In terms of our framework, this implies that the mismatch penalty is relatively strong for this group of workers.



(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.

Positive effect of specialization We aim to analyze the effect of specialized skills on the worker's first post-displacement job. We examine two outcomes: the likelihood of job separation and the wage upon re-employment.

Table 4 shows regression results for both outcomes. First, the table shows that separation rates are decreasing in specialization. Second, the table shows that entry wages after displacement are increasing in pre-displacement specialization. As before, in column (1) we do not consider covariates other than the pre-displacement index of specialization. In column (2) we additionally control for the worker's pre-displacement average skill level. It is important to control for this, as higher worker skills are likely to increase the wages of the worker in any match. In column (3) we additionally control for the baseline set of controls. These covariates allow us to control for a set of key confounding factors, which are likely to affect the worker's wage in any match. Quantitatively these effects are not small, they are significant in both samples and provide evidence that specialized skills can be assets. Using our previous example of the two types of managers, the more specialized one expects to get separated 3 percentage points less in the first year, and expects 5 percent higher wages in France, while in the US they expect to get separated 9 percentage points less, and expects 15 percent higher wages.

At a first glance, these results might appear to contradict the findings in Macaluso (2023) who shows that locally more skill remote workers suffer a larger wage loss after displacement. In Appendix section C.3, we contrast in detail the differences with the results in Macaluso

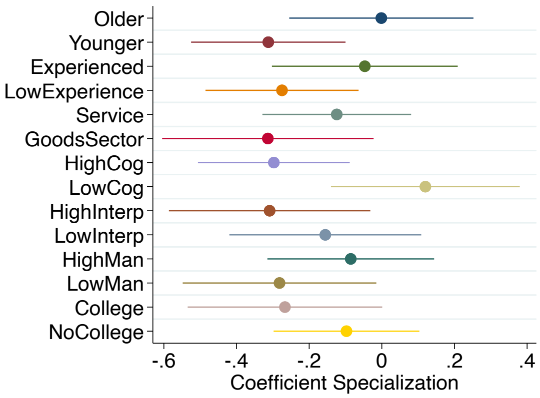
	Separation			Log real wage		
	(1)	(2)	(3)	(4)	(5)	(6)
			US			
Specialization	-0.203*	-0.200*	-0.167*	0.734*	0.630*	0.264*
	(0.010)	(0.012)	(0.042)	(0.000)	(0.000)	(0.017)
Skills		-0.0356	0.0279		0.998*	-0.0819
		(0.708)	(0.788)		(0.000)	(0.573)
Observations	876	876	876	677	677	677
			FR			
Specialization	-0.194*	-0.187*	-0.0589*	0.448*	0.437*	0.0904*
	(0.000)	(0.000)	(0.035)	(0.000)	(0.000)	(0.000)
Skills		-0.161*	-0.124*		0.253*	0.0455
		(0.000)	(0.000)		(0.000)	(0.152)
Observations	16336	16336	10756	16315	16315	10745
Controls	w/o Skill	w/ Skill	+Controls	w/o Skill	w/ Skill	+Controls

Table 4: Separation and entry wages – Regression results

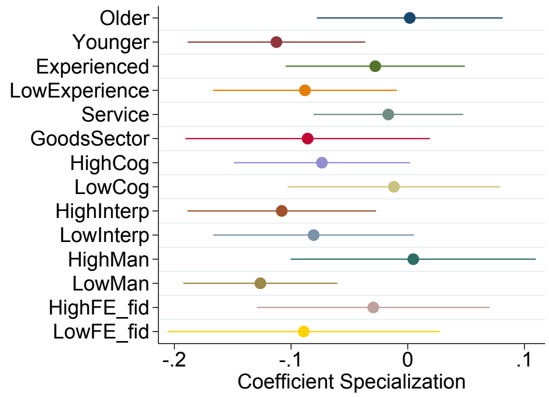
Notes: The table shows results of a regression of separation rates and of entry wages on previous specialization and controls. Column (1) does not control for skills, column (2) does not impose controls, column (3) controls for the baseline set of controls, which includes age, gender, education or AKM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

(2023). In this appendix section, we follow Macaluso (2023) and analyze wage changes before and after displacement and its correlation with specialization. Consistent with our previous results, we find a positive effect of specialization on wage changes. Note that by analyzing wage changes, this specification alleviates potential concerns about the role of unobserved worker-specific factors. This analysis also allows us to clarify the relation of our results to those in Macaluso (2023). In summary, while Macaluso (2023) analyzes variations in local skill demand within broad occupation groups and finds a negative effect of local skill remoteness on wage changes, we focus on cross-skill comparisons across fine occupation groups and find that more specialized occupations have smaller wage losses than less specialized occupations. In this section of the Appendix, we also show that our results are robust for an analysis across 442 metropolitan areas and across 9 broad economic regions of the US in addition to our baseline analysis that treats the whole US economy as a single labor market.

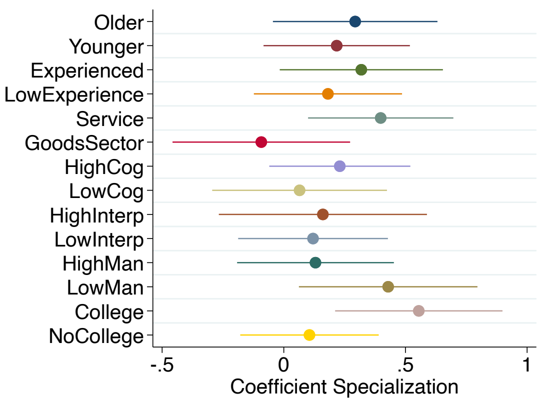
Figure 6 shows that the results in terms of re-employment wages and stability also vary across workers to some degree. For the positive aspects of specialization, the largest effect is on younger, less experienced workers, as well as workers with high cognitive and interper-



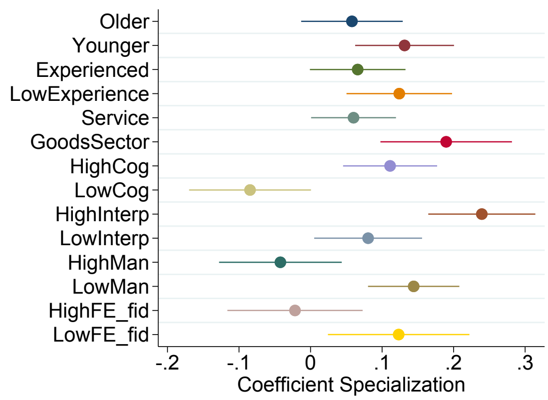
(a) Separation – US



(b) Separation – France



(c) Log real wages – US



(d) Log real wages – France

Figure 6: Separation and entry wages – Heterogeneity analysis

Notes: The panels show the coefficients on specialization for different groups of displaced workers. The first row shows it for separation from the first job, and the second 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.

sonal skills and low manual skills. This implies that the most skilled workers benefit the most from the positive aspects, implying stronger complementarity gains for this group of workers.

These three findings on the effects of specialization support the suggested mechanisms by which specialization influences workers. The results suggest that workers with more specialized skills face lower job finding rates but enjoy increased match quality upon job matching as indicated here by higher wages and lower separation rates upon re-employment. The heterogeneity analysis implies that less skilled workers suffer the largest negative aspects of specialization and benefit the least from the positive aspects, while the opposite is true for the more skilled workers. Based on the analysis in our production function framework, this suggests a difference between these worker groups in the relative strength of the mismatch penalty and of complementarity gains. Specifically these findings suggest that the mismatch penalty is relatively stronger for lower skilled workers, while complementarity gains are relatively stronger for higher skilled workers. These differences in the mismatch penalty can be interpreted as a lesser penalty for individuals with skills exceeding the job requirements and a greater penalty for those with skills falling short of the requirements. The increased complementarity gains for highly skilled workers may arise from disparities across different skill dimensions. For example, there could be a more significant advantage in having high cognitive skills in jobs that demand such skills, as opposed to the advantage of having high manual skills in jobs requiring manual dexterity.

5 Conclusion

This paper adds to the growing body of research which shows that multi-dimensional skills change our understanding of labor markets not simply by expanding the detail of analysis but also by showing trade-offs across skills. We show that multidimensional skill portfolios necessarily imply trade-offs.

In this paper, we have shown that worker specialization gives rise to positive and negative labor market returns. Conditional on a level of skills, more specialized workers face potentially higher complementarity gains at a suitable job but also higher mismatch penalties leading to a larger set of unsuitable jobs. Empirically, we confirm our predictions guided by theory: we find that pre-displacement specialization increases the duration of non-employment while also increasing entry wages and job stability at the new job. Highly specialized workers are, on average, suitably matched to a narrower range of jobs, resulting in a heightened return to previously utilized skills. In contrast, workers with more generalized skill sets have a broader spectrum of jobs available for matching, albeit with lower complementarity gains to previously used skills. By bringing together these two pieces of the economic analysis, we provide a new interpretation to the partial transferability of skills across jobs and show how this changes across workers.

Our results can shed light on worker outcomes after displacement and explain why some workers experience different trajectories after job loss than others. Specialized workers might have enjoyed specialization premia through the complementarity channel before displacement but then suffer the effects of lower job match probabilities after displacement through the mismatch penalty channel. Less specialized workers likely find a job faster but at lower specialization premia. Hence, workers with lower expected wages find employment faster while workers with higher expected wages stay unemployed for longer. These insights are salient for policy makers by showing that large losses upon displacement are the flip-side of complimentarity gains enjoyed before displacement. Social insurance should optimally weigh the incentives to accumulate skills with risky payoffs.

A crucial implication of our analysis is that the acquisition of skills, through both skill level enhancement and specialization in specific domains, may not necessarily lead to positive labor market outcomes for certain workers. This insight carries significant implications for policymakers when considering the provision of educational programs and the need to strike a balance between skill accumulation and specialization. Particularly for low-skilled workers, prioritizing specialization at the cost of skill accumulation is likely to result in adverse labor market consequences.

Finally, our work can also speak to the literature on skill accumulation on the job and its impact on the economy. First, specialization can act as an amplification mechanism of business cycle shocks, a mechanism we explore in Bárány and Holzheu (2023). Second, specialized skills can change the incentives of firms to pay for training on the job. The literature has extensively studied why firms pay for training their workers, providing them with skills that can be used at other firms, contending that the degree of transferability of skills and labor market frictions determine the cost firms are willing to bear for such training (Acemoglu and Pischke (1999)). Our framework introduces another mechanism that can elucidate why firms would pay for training costs. It hinges on the idea that, since the advantages of acquiring a specific skill may also amplify future risks for workers, firms can alleviate the burden on workers by assuming some of the adverse consequences associated with skill acquisition.

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A Appendix to section 2

A.1 Conceptual framework – Wage equation

To derive the wage equation of the worker, we use the Nash surplus sharing rule, yielding

$$\beta J(x,y,z_0) - (1-\beta)W(x,y,z_0) = -(1-\beta)U(x)$$

Using the left-hand side of the previous equation, we find

$$\begin{aligned}
r(\beta J(x,y,z_0) - (1-\beta)W(x,y,z_0)) &= \beta f(x,y,z_0) - \beta w(x,y,z_0) - \beta\xi J(x,y,z_0) \\
&\quad + \beta\xi \int_R^\infty J(x,y,z)dG(z) + \beta\pi(J(y,y,z_0) - J(x,y,z_0)) \\
&\quad + \beta\delta\,(0 - J(x,y,z_0)) \\
&\quad - (1-\beta)w(x,y,z_0) + (1-\beta)\xi W(x,y,z_0) \\
&\quad - (1-\beta)\xi \int_R^\infty W(x,y,z)dG(z) \\
&\quad - (1-\beta)\xi G(R)(U(x)) - (1-\beta)\pi(W(y,y,z_0) - W(x,y,z_0)) \\
&\quad - (1-\beta)\delta\,(U(x) - W(x,y,z_0)) \\
-(1-\beta)rU(x) &= \beta f(x,y,z_0) - w(x,y,z_0) + \xi(1-\beta)U(x) \\
&\quad - \xi(1-\beta)(1-G(R))U(x) - \xi(1-\beta)G(R)U(x) \\
&\quad - \pi(1-\beta)(U(y) - U(x)) \\
&= \beta f(x,y,z_0) - w(x,y,z_0) - \pi(1-\beta)(U(y) - U(x))
\end{aligned}$$

Rearranging this expression, we obtain for wages

$$\begin{aligned}
w(x,y,z_0) &= \beta f(x,y,z_0) - \pi(1-\beta)(U(y) - U(x)) + (1-\beta)rU(x) \\
&= \beta f(x,y,z_0) - (1-\beta)(\pi U(y) - (\pi + r)U(x)) \\
&= \beta f(x,y,z_0) + (1-\beta)\,(\pi + r)\,U(x) - \pi(1-\beta)U(y)
\end{aligned}$$

A.2 Simulation results for other parametrizations

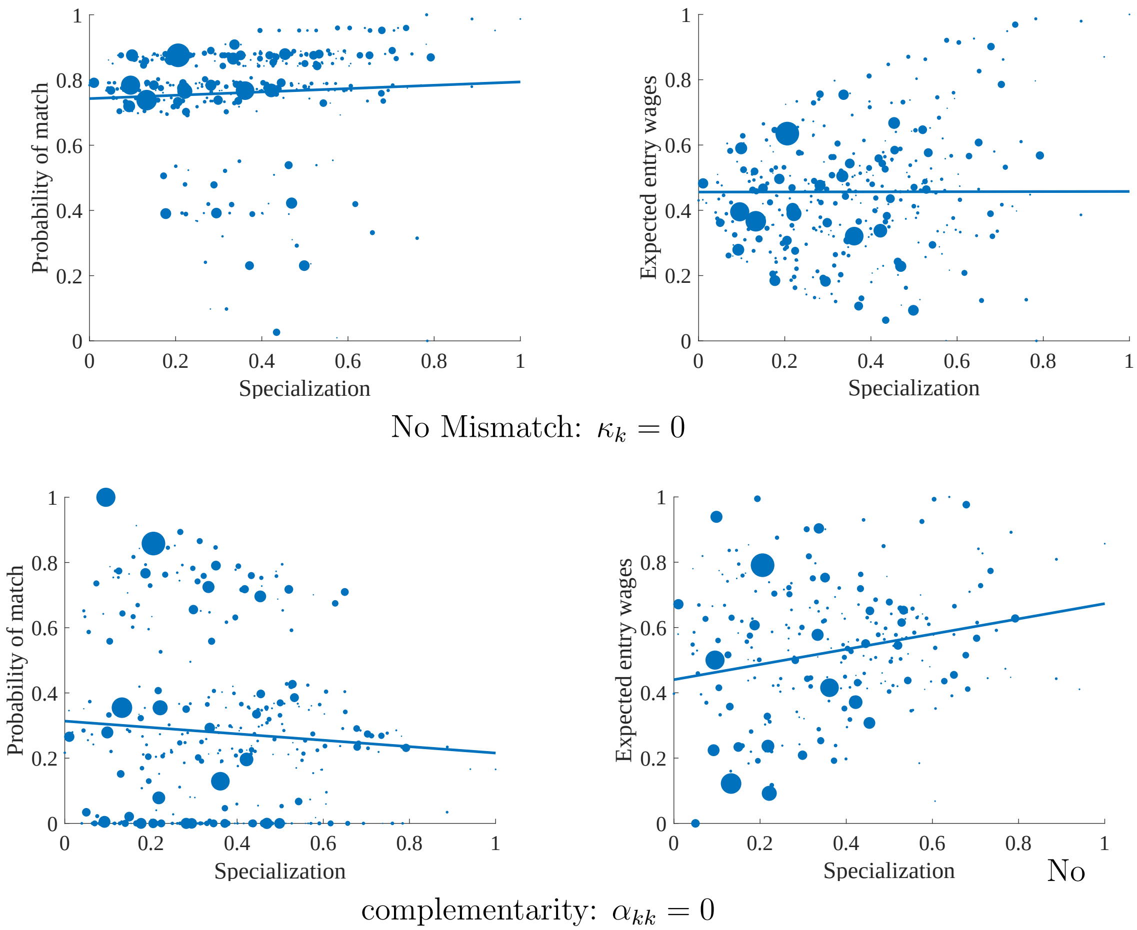


Figure 7: Mismatch penalty and complementarity – alternative parametrizations

Notes: The figures show scatter plots of the probability of matching with a randomly sampled firm (on the left) and the expected entry wage across firms with which the worker would match (on the right), both plotted against the specialization of the worker for different parameter settings.

B Appendix to section 3

B.1 Skill measures

To get a sense of the main components of each skill measure, in Table 5 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 5: Top 25 descriptors in each skill measure

B.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 6: Skill distance mis-measurement with similar but not perfectly correlated descriptors

The first issue is illustrated in Table 6 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

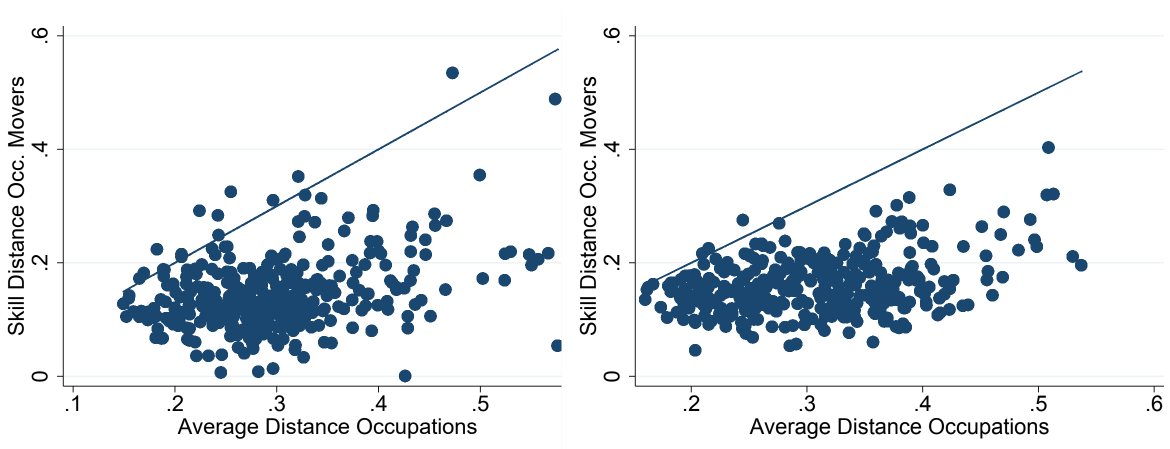
Table 7: Skill distance mis-measurement with uneven number of descriptors across skills

Table 7 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.

B.3 Skill requirements

In what follows we show that occupational skill distances based on our skill requirement measure have economic meaning by considering job switchers. For this we calculate the average skill distance of occupation j to other occupations in the economy, i.e., $\sum_{o\neq j}(s_{j,k} - s_{o,k})^2$. We also 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 $\sum_{j\neq o}\omega_{j,o} = 1$.[17] The occupational switching distance for occupation j is then calculated as $\sum_{j\neq o}\omega_{j,o}(s_{j,k} - s_{o,k})^2$. 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 skill portfolio than the average occupation. Figure 8 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

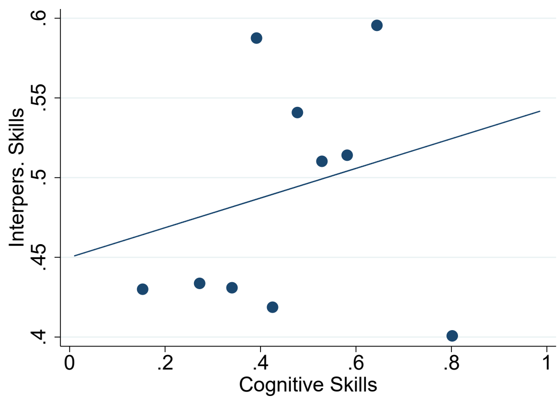
(b) France

Figure 8: Occupation switching distance and average distance

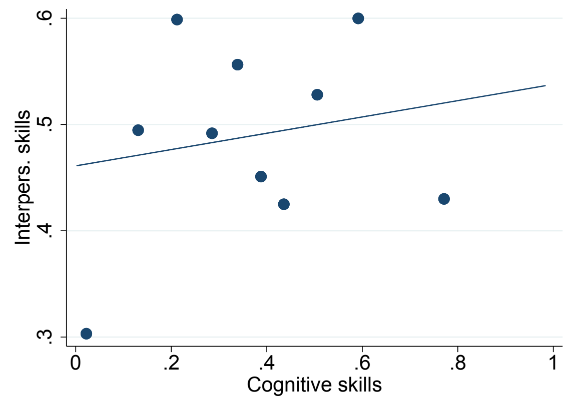
Notes: The figures show scatter plots showing for each occupation the average skill distance from all other occupations (on the x-axis) and average occupational distance of switchers after layoff (on the y-axis), as well as the 45 degree line. The left panel shows this for the US, while the right panel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

[17] 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.

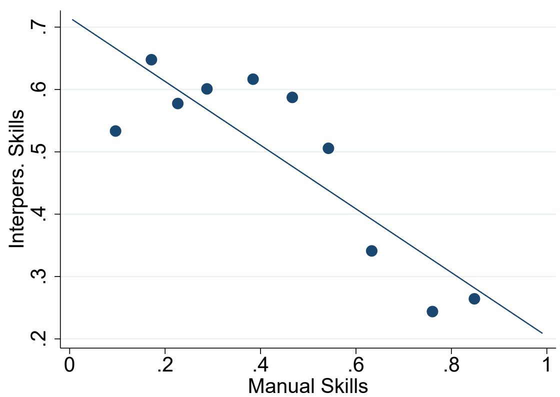
B.4 Cross-skill relationship



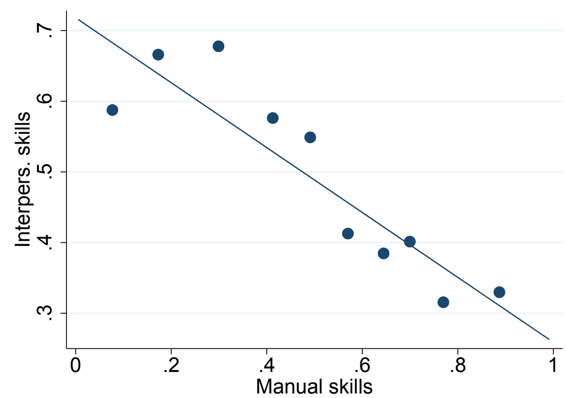
(a) US – interpersonal and cognitive



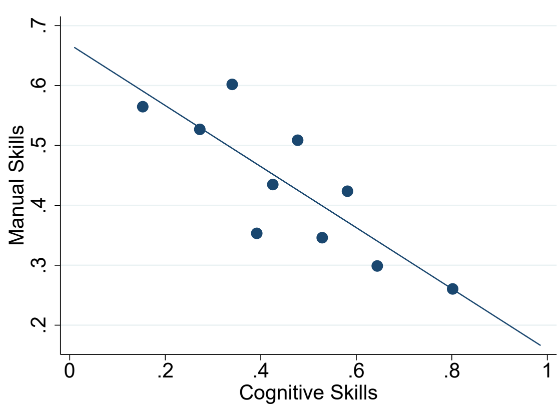
(b) France – interpersonal and cognitive



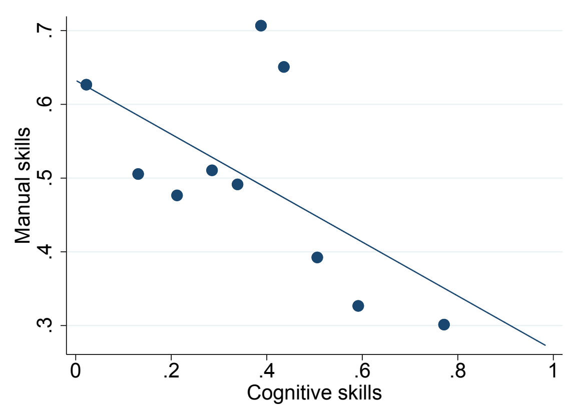
(c) US – interpersonal and manual



(d) France – interpersonal and manual



(e) US – cognitive and manual



(f) France – cognitive and manual

Figure 9: Cross-skill correlations

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

C Appendix to section 4

C.1 Equivalent of regressions on simulated data

In Section 2 in Table 1 we show the results of a regression of the probability of matching and starting wages at the new job on the specialization index and skill level index. This regression is performed at the occupation level. In Table 8 we run an equivalent regression in our two samples 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.

	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 8: 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, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

C.2 Different measures of specialization

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. 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 is similar to our baseline measure but contains only skill distances based on under-qualification, 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 $E[s_{k,t}] = \sum_{o=1}^{O} \lambda_{o,t} s_{o,k}$. Our second measure of worker specialization is then

$$Spec^2_{i,t} = \sum_{k=1}^{K} (s_{i,k,t} - E[s_{k,t}])^2,$$

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 $dist_{o,j} = \sum_{k=1}^{K} (s_{o,k} - s_{j,k})^2$. We define the cutoff distance as the median distance in this set, and denote it by $dist_{med}$. Our third measure is defined as

$$Spec^3_{i,t} = \sum_{o=1}^{O} \lambda_{o,t} I \left\{ \sum_{k=1}^{K} (s_{i,k,t} - s_{o,k})^2 > dist_{med} \right\},$$

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:

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

The results in Table 9 show that while the magnitude of the effects differ across specifications, all specialization measures point in the same direction.

	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)
Observations	13411	11789	11775

Table 9: 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/AKM worker FE and pre-displacement experience, tenure and log wage. Results are weighted using sampling weights for the US. Values in brackets represent p-values, $^{+}$ $p < 0.10$, * $p < 0.05$

C.3 Comparison to Macaluso (2023)

Using the CPS-DWS dataset, Macaluso (2023) 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 (2023), but for a range of occupation categories and local labor market definitions. Crucially, we conduct the analysis with occupation fixed effects, as in Macaluso (2023) and without occupation fixed effects, as in our baseline analysis. We then show that we can replicate both the negative result in Macaluso (2023) 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

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

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:[18]

- 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 (2023) 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 a worker's location.[19] Due to differences in occupation measures before 1999, we focus on a sample with years 1999-2020.

As in Macaluso (2023), 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.[20] Second,

[18]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.

[19]Note that in the CPS-DWS, for 28% of observations the location is either unobserved, or the individual is not located in a metropolitan area. Therefore, we cannot assign a skill-remoteness measure to these observations.

[20]This is $1 - R^2$ from regressing our specialization measure on the 22 occupation group fixed effects interacted with the year. When running the regression year-by-year of the specialization measure on the 22 occupation group fixed effects, the lowest value we get for $1 - R^2$ is 0.4196, and the highest is 0.6242.

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 (2023), we analyze the following regression:

$$\Delta y_{i,j(i,t),t} = \alpha\, above_{i,j(i,t),t} + X_{i,t}\beta + \epsilon_{i,t}, \tag{4}$$

where $\Delta y_{i,j(i,t),t}$ denotes the wage change before and after displacement at the first job[21] 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 conform with the sample used in Macaluso (2023), 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	22	22	22	352	352	352	352	352
# Areas	442	9	9	442	442	9	9	1
	(1)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(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 (4), 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 (2023) whereas the second row in column (5) reflects our findings. We show a negative

[21] 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.

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 (2023) 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.

C.4 Different sample of displaced workers

As discussed in Section 3 a frequently used method to identify displaced workers is to look at workers who involuntarily left their jobs during a mass layoff event. In the main text we conduct the analysis focusing on a more restrictive definition of displacement; we consider only workers who involuntarily left their jobs following firm closure. We expect that this more restrictive measure addresses potential concerns about worker selection. In Table 11 and 12 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 11: 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/AKM worker FE 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 11, 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 12 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 12: 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/ AKM worker FE and pre-displacement experience, tenure and log wage. Results are weighted using sampling weights for the US. Values in brackets represent p-values, $^{+}$ $p < 0.10$, * $p < 0.05$.