Searching for Job Security: Occupational Choice and Skill Mismatch

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Abstract

Occupations differ significantly in job loss risk. Combining data from the CPS, O*NET, and the NLSY, we present three facts. First, job separation risk is heterogeneous across occupations. Second, manually (cognitively) intensive occupations feature more (less) separation risk. Third, workers with greater cognitive (manual) ability sort away from (into) manually (cognitively) intensive occupations, conditional on worker attributes. We interpret these facts through a search model with multidimensional skill sorting. The key assumption is that occupational skill requirements jointly determine match output and separation risk. Skill-correlated risk affects job-acceptance sets, inducing workers to sacrifice match quality for job security. This can weaken (strengthen) sorting along the manual (cognitive) dimension and generate asymmetric cross-skill sorting patterns. The decentralized economy can be inefficient, because workers value job security more than the constrained planner, generating skill mismatch. Quantitatively, the decentralized economy produces 0.56 percent less output than the planner's allocation. A simple skill-based unemployment insurance policy can restore half of the output loss.

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1 Introduction

Wages are not the only consideration for workers when choosing an occupation. Job security also matters: job loss can cause large immediate income losses and leave lasting scars on future earnings and human capital accumulation (Jacobson, LaLonde, and Sullivan, 1993; Huckfeldt, 2022; Schmieder, Von Wachter, and Heining, 2023). Studies of occupational choice have typically focused on how workers sort into occupations whose skill requirements align with their abilities, documenting, for example, that workers with higher manual abilities sort into occupations with higher manual skill requirements (Lise and Postel-Vinay, 2020; Lindenlaub and Postel-Vinay, 2023). It remains unclear, however, how differences in job-loss risk across occupations affect this sorting and whether workers forgo better skill matches for greater job security.

We study the implications of *skill-correlated separation risk*, the correlation between occupational skill requirements and the risk of job loss. Because occupational skill requirements are correlated with job risk, the same occupational features that determine worker suitability and wages affect expected job duration. This creates a potential tradeoff for worker occupational choice: the gains from a good skill match must be weighed against how long employment is expected to last. A worker whose abilities are well suited to a risky occupation may therefore prefer a safer occupation that uses those abilities less effectively, trading match quality for greater job security.

Empirically, we document three motivating facts on skill-correlated separation risk. First, separation risk varies substantially across occupations, even after accounting for worker characteristics and aggregate conditions. Second, this variation maps systematically into occupational skill requirements. Using data from the CPS and the SIPP, we find that workers employed in occupations with greater manual requirements have higher separation rates, while those with greater cognitive requirements have lower separation rates. These relationships hold even when controlling for wages, which explain little additional variation in separation risk. Third, worker abilities and occupational requirements exhibit asymmetric cross-sorting patterns. Using worker panels constructed from the NLSY, we find that workers with greater cognitive ability tend to not be sorted into manually intensive occupations. However, workers with higher manual abilities do not exhibit the same pattern of sorting away from cognitively-intensive occupations. Measures of empirical mismatch indicate that manually-able workers tend to be underqualified along the cognitive dimension, while cognitively-able workers tend to be overqualified along the manual dimension. Although these patterns do not establish that separation risk causes occupational sorting, together they are consistent with workers

trading off skill match quality against job security.

To interpret these facts, we develop a dynamic model of the labor market with two-sided multidimensional heterogeneity in worker abilities and occupational requirements. Match output depends on how well worker abilities align with occupational requirements. Workers search while both unemployed and employed, and wage contracts are determined through sequential auctions (Postel-Vinay and Robin, 2002). Our key departure from existing multidimensional sorting models (Lise and Postel-Vinay, 2020; Lindenlaub and Postel-Vinay, 2023) is to allow occupational separation rates to depend on skill requirements.

Because occupational requirements determine both match productivity and expected job duration, separation risk changes the effective complementarity between worker abilities and occupational requirements. With homogeneous risk, workers rank occupations by match output monotonically. This monotonicity fails when occupational skill requirements change the expected job duration. When separation risk rises with manual requirements and falls with cognitive requirements, match value obtains an additional premium from lower manual and higher cognitive requirements. Consequently, for example, a manually skilled worker may accept an occupation with lower manual requirements if it provides sufficient job security. Skill-correlated separation risk thus affects workers' job-acceptance sets. This creates a force that weakens sorting along the manual dimension while strengthening sorting along the cognitive dimension, giving rise to asymmetric cross-sorting patterns in equilibrium.

To assess the welfare implications of this channel, we characterize a social planner's problem facing the same skill-correlated separation risk and labor market frictions. When separation risk is homogeneous across occupations, workers and the planner rank occupations identically according to match output. With heterogeneous risk, both workers and the planner value job duration, but they need not value it equally. As long as firms have some bargaining power over equilibrium wages, workers do not capture all the gains from future employment. We show they consequently value their future prospects after job loss less than the planner does. This undervaluation of future job prospects matters more for potential matches with riskier occupations, where workers are more likely to lose their current job and have to rely on future opportunities. This force can make risky occupations disproportionately unattractive, leading workers to sacrifice too much match quality for security. The wedge is clearest at the top of the job ladder, where no valuable on-the-job offers remain: workers require a larger increase in match output than the planner to compensate for higher separation risk. Because separation risk is tied to occupational skill requirements, this wedge tilts workers too far away from manual requirements and toward cognitive requirements relative to the

planner, sacrificing worker-occupation fit.

The model is brought to the data to quantify these various equilibrium channels. We calibrate the model to match the observed distributions of worker abilities and occupational requirements, worker–occupation sorting patterns, and wage-related moments. To isolate the effect of skill-correlated separation risk, we compare the calibrated economy with a counterfactual in which separation risk is homogeneous across occupations, but chosen to match the average, baseline employment-to-unemployment transition rate. Under skill-correlated separation risk, job-acceptance sets tilt away from manual requirements as workers trade match quality for security. Aggregate employment rates change little, but we find that lower average match quality meaningfully reduces aggregate output by 0.67% relative to the homogeneous-risk counterfactual.

We then compare the decentralized economy with the allocation chosen by a planner facing the same heterogeneous separation risk. The decentralized economy produces 0.56% less output than the planner's allocation. Approximately 70 percent of this gap is due to workers responding more strongly than the planner to skill-correlated separation risk, while the remainder comes from a changed unemployment-to-employment acceptance margin. Therefore, workers overvalue job security relative to the planner, and the resulting skill mismatch is quantitatively important in generating aggregate efficiency losses.

Finally, we use the model to study a stylized unemployment-insurance policy in which benefits increase with workers' manual ability. These benefits are financed by a lump-sum tax on employed workers, while the government runs a balanced budget. Greater insurance after job loss makes workers with strong manual abilities more willing to accept risky manual occupations in which their skills are productive. Allowing for moderate skill-based unemployment insurance raises aggregate output by 0.26%, recovering almost half of the output gap between the decentralized and planner allocations. Therefore, we find evidence that even moderate targeting of unemployment policies can meaningfully mitigate efficiency losses of skill-correlated separation risk.

Literature Review. We build most directly on work studying multidimensional worker–job sorting. Lindenlaub (2017) characterizes assignment when workers and firms differ along multiple dimensions, while Lindenlaub and Postel-Vinay (2023) study multidimensional sorting under random search. Lise and Postel-Vinay (2020) develop and estimate an on-the-job search model in which workers possess multiple skills and jobs differ in their corresponding requirements. Their framework provides the basis for our measurement of worker abilities and occupational requirements, along with the rank-based measures of empirical mismatch

developed by Guvenen et al. (2020).

Related models generate mismatch through learning about comparative advantage or other information frictions (Papageorgiou, 2014; Baley, Figueiredo, and Ulbricht, 2022). Our departure is to allow the same occupational requirements that determine match output to also determine separation risk. Occupational requirements then affect both the productivity and expected duration of a match. This changes the effective complementarity between worker abilities and occupational requirements: local complementarity in match surplus depends not only on the production technology, but also on how separation risk varies across skill requirements. As a result, the occupation that maximizes a worker's match output does not necessarily maximize the value of the match.

Our paper also relates to the growing literature on job security and the cost of displacement. Job loss produces large and persistent earnings losses (Jacobson, LaLonde, and Sullivan, 1993; Schmieder, Von Wachter, and Heining, 2023), in part because displaced workers lose human capital and fall to lower positions on the job ladder (Huckfeldt, 2022). Several papers study how incomplete insurance distorts job mobility and matching with one-dimensional productive heterogeneity (Huang and Qiu, 2026; Clymo et al., 2026). Lehner, Talesara, and Wickard (2026) exploit survey, experimental, and administrative data to show that workers indeed care about separation risk and prefer safer jobs. The paper closest to our mechanism is Jarosch (2023), which shows that workers climb a job ladder in security as well as wages and that the loss of a stable job accounts for an important share of displacement costs. However, the nature of job security differs between the two settings. In Jarosch (2023), stability is a job attribute distinct from the worker's comparative advantage, so seeking security means moving up the job ladder. In our model, security is bundled with occupational skill requirements. Moving toward security therefore means moving across skill space and can reduce the quality of the worker–occupation match.

Moreover, we connect research on non-wage job attributes to the productive role of unemployment insurance. Workers are willing to trade earnings against amenities and other job characteristics (Rosen, 1986; Sorkin, 2018; Maestas et al., 2023), and occupational earnings risk can itself affect career choice (Dillon, 2018). We contribute to this literature by measuring occupation-specific separation risk and showing that it is systematically related to task content, even after conditioning on occupational wages. This means that choosing a safer job may also change the quality of the worker-occupation match, implying that job security cannot be separated from the productive characteristics of the occupation.

Finally, skill-based separation risk creates a role for unemployment insurance related to

that featured in Acemoglu and Shimer (1999), where insurance encourages risk-averse workers to seek riskier, more productive jobs. In our model, workers are risk neutral; however, an inefficient wedge arises because workers do not appropriate the full social value of future matches formed after unemployment. A recent strand of work studies how benefits affect reservation wages, search, and subsequent match quality (Shimer and Werning, 2008; Nekoei and Weber, 2017). Relative to these works, our policy exercise demonstrates how unemployment benefits can also change sorting across occupational skill requirements in a multidimensional setting. When benefits are targeted towards workers whose productive skills are concentrated in riskier occupations, insurance can tilt private acceptance decisions towards the production-efficient allocations of a social planner.

2 Data

This section describes the primary data sources and variable definitions we use throughout the empirical analysis. We use three primary data sources. We construct occupational separation rates using the Current Population Survey (CPS). To construct occupation skill attributes we use occupational skill requirement data sourced from O*NET. Finally, we use the NLSY79 to track a representative panel of workers for whom we can infer underlying ability measures. Appendix A provides additional details on data construction and cleaning.

Occupation-Specific Separation Rates. The primary objects that motivate both the empirical and theoretical analysis are occupation-level separation rates. To construct occupation-specific separation rates we use the CPS. The CPS is suitable for our purposes for two reasons. First, it is a large, monthly, and nationally representative survey of labor transitions with a long time series. Second, it has harmonized occupation data for workers.[1] We use a monthly CPS sample of non-ASEC households from 1994-2019. We restrict our sample to include workers aged 60 or below and to individuals currently in the labor force. We measure a job separation as when a worker transitions from employed to unemployed by employment status.

The occupations we consider in our analysis are 2010 occupation Census codes, harmonized for all periods in our sample of the CPS. We posit that the average separation rate for an occupation consists of the true occupational separation rate, time-varying aggregate separation factors, and worker-specific characteristics. To decompose the occupation-specific

[1]The Longitudinal Employer-Household Dynamics (LEHD) data on administrative worker earnings is ill-suited for this purpose because occupation is not widely recorded.

separation rate we estimate the following regression

$$\delta_{j,t} = \alpha + \delta_t + \delta_{\mathcal{O}} + \Gamma' X_{j,t} + \varepsilon_{j,t} \,, \tag{1}$$

where $\delta_{j,t}$ is an indicator for whether a worker (j) separated from their job to unemployment in a given month (t). We residualize out the occupational separation rate, $\delta_{\mathcal{O}}$, from time-varying aggregate separation risk, δ_t, and a vector of worker characteristics $X_{j,t}$.[2] For the remainder of the analysis, we use $\delta_{\mathcal{O}}$ as an occupation-specific measure of labor market unemployment risk.

Occupational Skill Requirements. We obtain a vector of skill requirements associated with an occupation $\mathbf{y}$ by using occupational data from O*NET (the Occupational Information Network). O*NET is a database sponsored by the US Department of Labor which characterizes occupations by the skills, knowledge, abilities, and work context associated with the occupation. To map O*NET measures to the subsequently defined NLSY79 worker panel, we use crosswalks from O*NET-SOC codes to Census 2000 occupations and then to Census 1990 occupation definitions, which are the occupation codes used in our NLSY panel.

We follow earlier work documented in Lise and Postel-Vinay (2020), and use a large set of underlying occupational descriptors from O*NET. We then perform a Principal Component Analysis (PCA) on the O*NET descriptors for each occupation and keep the first three principal components. The three PCA components are then rotated by linearly recombining them to construct three separate measures: a cognitive component, a manual component, and an interpersonal component. To do so, the linear recombination must satisfy the following requirements (i) the mathematics descriptor loads exclusively on the first component, (ii) the mechanical descriptor loads exclusively on the second component, and (iii) the social perceptiveness descriptor loads on the third component. We then rescale the indices to be in the range $[0, 1]$.

NLSY79 and Worker Abilities. We use the 1979 National Longitudinal Survey of Youth (NLSY79) to construct an annual panel linking workers' labor-market outcomes to occupation-level separation rates and skill requirements. We follow standard sample-selection and cleaning procedures for the NLSY79 (Farber and Gibbons, 1996; Guvenen et al., 2020). Our baseline sample is the cross-sectional male sample. We focus on respondents whose labor-market entry is observed in the survey, excluding individuals who were already attached to full-time work at the start of the panel. Full-time attachment is defined as at least 1,200

[2] For worker characteristics we use gender, race, marital status, educational attainment, and age.

annual hours, and we require at least two consecutive full-time years.

We exclude individuals with more than two years of military service and drop military employment observations. For respondents who return to school early in their career, we treat the later re-entry into the labor market as the relevant career start and drop earlier observations. We also drop observations after the last reported job and remove workers with repeated or extended spells of nonemployment. The final analysis sample requires valid occupation and industry codes, age, schooling, ASVAB scores, and wage information; excludes observations before age 16 and observations classified as still in school; and trims wage outliers within interview wave.[3]

We follow Lise and Postel-Vinay (2020) and construct worker ability measures using the NLSY79 ASVAB assessment, together with non-cognitive and demographic measures. We first form occupation-level skill requirements, denoted by y^{cog}, y^{man}, and y^{int}, from O*NET as described above. We then use these occupation skill measures to assign each worker an education-implied skill profile: O*NET reports the required education level for each occupation, and we collapse the occupation-level cognitive, manual, and interpersonal requirements to the education level. This generates the average skill content of occupations associated with each education category.

Worker abilities are then estimated from one observation per individual. We use the ten ASVAB subtests, the Rosenberg self-esteem score, the Rotter locus-of-control score, body mass index, and the education-implied O*NET skill profile. We run a three-component PCA, weighted by the NLSY ASVAB sampling weight, and then linearly recombine the first three components so that the resulting factors have a cognitive, manual, and interpersonal interpretation. The cognitive dimension is anchored by ASVAB mathematics knowledge, the manual dimension by ASVAB auto/shop information, and the interpersonal dimension by the Rosenberg score. We normalize the resulting worker ability measures to lie between zero and one and denote them by x^{cog}, x^{man}, and x^{int}. These measures are time-invariant worker characteristics and are merged back into the annual worker panel.

3 Motivating Empirical Facts

In this section we provide three novel facts that motivate our theoretical analysis. First, there is significant heterogeneity in occupational separation rates between workers and firms. Second, a significant share of the variation in occupational separation rates is explained by

[3]We drop wages below the 0.1st and above the 99.9th percentiles.

occupation-specific skill requirements and content. Specifically, manually-intensive occupations have higher separation rates, and cognitively-intensive occupations have lower separation rates. Third, we demonstrate that workers with higher manual abilities tend to sort into cognitively intensive jobs, whereas higher cognitive abilities are associated with less manually intensive jobs. Finally, we present suggestive evidence that these sorting patterns imply empirical mismatch.

3.1 Fact 1: Occupation-Level Separation Heterogeneity is Large

It has been widely documented that occupations vary widely in terms of wages and skill requirements. We now ask: how do separation rates vary across occupations?

To answer this question, we plot the empirical distribution of occupational separation rates estimated from (1) in Figure 1. We normalize the minimum estimated rate to zero and express the remaining differences in percentage points.[4] After controlling for aggregate time variation and worker characteristics, occupation-specific separation risk remains highly dispersed, with a pronounced right tail.

Figure 1: Occupational Separation Rate Distribution



The figure plots the distribution of estimated occupation fixed effects, $\delta_{\mathcal{O}}$, from equation (1). The fixed effects are normalized by subtracting the lowest occupation fixed effect and multiplying by 100. Therefore, these values measure how many percentage points higher an occupation's conditional separation probability is relative to the occupation with the lowest separation rate.

Although many occupations have separation rates within one percentage point of the

[4]Because $\hat{\delta}_{\mathcal{O}}$ is an occupation fixed effect in (1), its level is not independently identified. We therefore report $\delta_{\mathcal{O}} = 100 \times \left(\hat{\delta}_{\mathcal{O}} - \underline{\delta}_{\mathcal{O}}\right)$, where $\underline{\delta}_{\mathcal{O}}$ is the minimum estimated occupation fixed effect.

lowest rate, the occupation with the highest separation rate exceeds the one with the lowest by 4.48 percentage points. The standard deviation of separation rates across occupations is 0.62 percentage points. The distribution has a skewness of 1.99, indicating that a meaningful set of occupations exposes workers to substantially greater separation risk. Taken together, these patterns demonstrate substantial variation in separation risk across occupations which can affect worker earnings.

3.2 Fact 2: Skill Requirements are Correlated with Separation

Given the wide dispersion in occupational separation rates, are there job-specific characteristics that predict observed occupational risk?

As demonstrated in the O*NET data on occupational skills requirements, there is extensive variation in job and task contents across occupations. Is the work content of an occupation associated with its underlying separation risk? We examine this by regressing the measured occupational separation risk, $\delta_{\mathcal{O}}$, on the vector of occupational skill requirements $\mathbf{y}$ and wage earnings. To test the robustness of these facts we also construct an analogous, alternative measure of occupational separation risk using the Survey of Income and Program Participation (SIPP).[5] Because the SIPP tracks individuals over time, we are able to use worker fixed effects in (1) to more richly control for unobserved worker heterogeneity in job separations.

We estimate variations of the regression

$$\delta_{\mathcal{O}} = \alpha + \Phi' \mathbf{y} + \gamma \text{wage}_{\mathcal{O}} + \varepsilon_{\mathcal{O}}, \tag{2}$$

to test how job characteristics and occupational wages are associated with occupational separation rates. The results are reported in Table 1. Occupational cognitive and manual content are highly correlated with separation rates. A one standard deviation increase in cognitive skill requirements lowers separation rates in the occupation by nearly .38 standard deviations. However, increasing manual skill requirements is associated with significantly higher separation rates where a standard deviation increase in manual skill requirements is associated with an increase in separation rates of between .18 and .20 standard deviations. Notably this skill-correlated separation risk is robust to measuring occupational separation rates with either the CPS or the SIPP.[6]

[5] We document in detail our data construction of both wage earnings from the CPS and our construction of the SIPP sample in Appendix A.

[6] In general, the estimates using either CPS- or SIPP-based measures are quantitatively similar. This

Table 1: Occupation Characteristics and Separation Rates

	(1) CPS: $\delta_{\mathcal{O}}$	(2) CPS: $\delta_{\mathcal{O}}$	(3) CPS: $\delta_{\mathcal{O}}$	(4) SIPP: $\delta_{\mathcal{O}}$	(5) SIPP: $\delta_{\mathcal{O}}$
Occupation wage	-0.359***		-0.104		0.027
	(-7.62)		(-1.85)		(0.43)
y^C		-0.379***	-0.334***	-0.173*	-0.185*
		(-5.84)	(-4.84)	(-2.36)	(-2.36)
y^M		0.183**	0.195***	0.192**	0.189**
		(3.12)	(3.32)	(2.89)	(2.82)
y^I		-0.159*	-0.129	-0.034	-0.042
		(-2.25)	(-1.79)	(-0.42)	(-0.51)
Observations	395	395	395	395	395
R^2	0.129	0.272	0.278	0.068	0.068

Notes: The table reports standardized beta coefficients from occupation-level regressions. Each coefficient is the standard-deviation change in the occupation separation-risk measure associated with a one-standard-deviation increase in the listed occupation characteristic. Columns 1–3 use the CPS occupation fixed effect, normalized to percentage points above the lowest-risk occupation before standardization. Columns 4–5 use the SIPP occupation fixed effect. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Comparing the R^2 of the various specifications is informative about the importance of occupational differences relative to standard explanations of worker separations. In conventional search-and-matching models with endogenous separations (Mortensen and Pissarides, 1994), wages reflect the match surplus that governs separation decisions. However, occupational skill requirements explain substantially more variation in occupational separation rates than wages alone (columns 1 and 2), while adding wages to the occupational skill requirements produces little additional explanatory power (column 3). Moreover, wages become statistically insignificant when occupational skill requirements are controlled for.

We also reproduce this fact visually in Appendix Figure B.1. We plot binscatters of the occupational skill requirements against occupational separation rates. Unconditionally, the patterns of Table 1 are visually present and notable.

finding is reassuring given potential measurement noise in occupational memberships. The similarity is also notable considering that the SIPP-based estimates of occupational separation rates include worker fixed effects which absorb permanent unobserved heterogeneity in worker-labor market attachment.

3.3 Fact 3: Worker Ability and Occupational Skill Cross-Sorting Patterns

We now examine whether the skill-correlated separation risk leads to different empirical sorting patterns between workers and occupations along different skill dimensions. A large literature has demonstrated that separations are persistently costly for workers (Huckfeldt, 2022; Jarosch, 2023), inducing long-term scarring on earnings potential. Given the scarring effects of unemployment, workers may optimally sort into occupations which feature lower unemployment risk. We now document that there are indeed such empirical sorting patterns between worker abilities and occupational skill requirements,[7] with interesting cross-sorting patterns. We will also provide additional evidence which suggests that such sorting patterns are indicative of skill mismatch.

Empirical Sorting Patterns. To study labor market sorting, we use our constructed annual panel of worker abilities and occupational skill requirements from the NLSY79 discussed in Section 2. We use Census 1990 occupation codes across all results in order to harmonize occupations over time.

We begin by estimating whether the occupational skill requirements of a worker are associated with worker abilities, conditional on a rich set of worker characteristics and aggregate time variation. We estimate

$$y_{j,t}^{\mathcal{S}} = \alpha_0 + \alpha_t + \beta' x_j^{\mathcal{S}} + \Pi' X_{j,t} + \varepsilon_{j,t} \ , \tag{3}$$

where $y_{j,t}^{\mathcal{S}}$ is a worker's occupational skill requirement percentile rank, and $x_j^{\mathcal{S}}$ is a worker's measured ability percentile rank in a given skill following Guvenen et al. (2020). The superscript $\mathcal{S}$ indicates one of manual, cognitive, or interpersonal worker abilities or occupational skill requirements. The NLSY79 data has the necessary requirement that we observe worker abilities from the set of psychological exams and ASVAB tests. Furthermore, it has the distinct advantage that it contains detailed labor force and demographic information on individuals allowing us to control for worker log wages, occupational tenure, job tenure, work experience, family composition, race, and education.[8] We additionally include year effects to flexibly absorb time series variation in aggregate changes in the distribution of skill

[7] That there should be equilibrium sorting of workers and firms is not new. This concept is reviewed in Sanders and Taber (2012), Guvenen et al. (2020) provide empirical evidence of the effects of mismatch on earnings, and Lise and Postel-Vinay (2020) estimate a structural model of worker-occupation mismatch.

[8] Log wages are an equilibrium outcome. We control for them to absorb additional variation that explains worker skill requirements. However, results are robust to not controlling for worker wages.

requirements.[9] We weight the regressions by cross-sectional sampling weights.

Table 2: Worker Abilities and Occupational Skill Content

	y^C	y^M	y^I
x^C	0.289***	-0.337***	0.272***
	(0.059)	(0.063)	(0.057)
x^M	0.156***	0.368***	-0.183***
	(0.042)	(0.045)	(0.038)
x^I	-0.239**	-0.276**	0.203**
	(0.108)	(0.117)	(0.101)
Individual controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.269	0.157	0.283
Observations	29,820	29,820	29,820

Notes: Standard errors are reported in parentheses and clustered by individual. Regressions use NLSY cross-sectional sampling weights.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We report the baseline specification results of estimating (3) in Table 2. Worker abilities are highly correlated with the skill requirements of their occupations. As expected, the diagonal of Table 2 shows that there is strong positive sorting between worker abilities in a given category and their skill requirements. For example, higher cognitive abilities for a worker are associated with that worker being in an occupation with higher cognitive skill requirements.

The conditional off-diagonal sorting patterns deliver more interesting and novel findings. In particular, we compare estimates of (x^C, y^M) and (x^M, y^C), the two dimensions where the skill-correlated separation risk is more salient. Workers with higher cognitive abilities tend to hold jobs in occupations with *lower* manual skill requirements. The converse does not hold for workers with higher manual abilities, which exhibit a positive sorting pattern with jobs with higher cognitive skill requirements when conditioned on a worker's cognitive ability and worker characteristics.

We include wage earnings in the worker controls, so this sorting pattern is not mechanically due to the fact that manually intensive occupations may be associated with lower earnings. The estimates in Table 2 suggest that workers with manual abilities may sort into jobs with higher cognitive requirements. This finding is consistent with workers internalizing higher

[9]Because worker abilities are measured in the 1979 wave of the NLSY79, we do not include worker fixed effects as they would be collinear with worker abilities, the key variables of interest.

levels of occupational risk for manual occupations and optimally sorting into cognitive jobs with lower separation rates. We now examine whether such sorting patterns induce mismatch between workers and occupations as measured empirically.

Empirical Mismatch. We follow a similar measurement strategy of occupational mismatch as detailed in Guvenen et al. (2020). We first rank workers on their cognitive and manual abilities based on their percentile in the distribution of $x^{\mathcal{S}}$. Then we compute percentile ranks of occupational skill requirements $y^{\mathcal{S}}$ using the pooled worker-year distribution. Empirical mismatch for a worker and occupational pairing for a skill is then estimated as

$$mm^{\mathcal{S}}_{j,\mathcal{O},t} = \hat{F}^{\mathcal{S}}_{j,x}(x^{\mathcal{S}}) - \hat{F}^{\mathcal{S}}_{\mathcal{O},y}(y^{\mathcal{S}}_{j,t}), \tag{4}$$

where $\hat{F}^{\mathcal{S}}_{j,x}(x^{\mathcal{S}})$ is the empirical CDF of a worker skill bundle and $\hat{F}^{\mathcal{S}}_{\mathcal{O},y}(y^{\mathcal{S}}_{j,t})$ is the empirical CDF in time t of occupational skill requirement $\mathcal{S}$ where $\mathcal{S} \in \{\text{cognitive,manual,interpersonal}\}$.

We further construct an alternative measure of empirical mismatch, which we term *overqualified*. The overqualified measure is an indicator function which takes a value of 1 when a worker's ability percentile rank is higher than their occupational skill requirement percentile rank in a given year. We regress both measures of empirical mismatch on the underlying worker abilities and examine whether there are systematic differences along different skill dimensions.

Table 3: Worker Abilities and Occupational Mismatch

	$mm^{C}_{j,\mathcal{O},t}$	$overqualified^{C}_{j,\mathcal{O},t}$	$mm^{M}_{j,\mathcal{O},t}$	$overqualified^{M}_{j,\mathcal{O},t}$
x^C	0.711***	0.816***	0.337***	0.458***
	(0.059)	(0.105)	(0.063)	(0.090)
x^M	-0.156***	-0.257***	0.632***	0.526***
	(0.042)	(0.074)	(0.045)	(0.068)
x^I	0.239**	0.410**	0.276**	0.335**
	(0.108)	(0.189)	(0.117)	(0.164)
Individual controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.347	0.211	0.568	0.408
Observations	29,820	29,820	29,820	29,820

Notes: Standard errors are reported in parentheses and clustered by individual. Regressions use NLSY cross-sectional sampling weights.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We report the results in Table 3. The estimates show that higher-ability workers are more likely to be overqualified in the corresponding skill dimension. For instance, workers with

higher cognitive ability have higher cognitive mismatch and are more likely to be cognitively overqualified. The case for the manual skill is analogous.

The most informative results are the cross-dimensional mismatch coefficients. Conditional on cognitive ability, workers with higher manual ability have significantly lower cognitive mismatch, implying that manual ability is associated with sorting into occupations with higher cognitive requirements. In contrast, conditional on manual ability, workers with higher cognitive ability have significantly higher manual mismatch and are more likely to be manually overqualified, implying that cognitive ability is associated with sorting away from manual-intensive occupations. Taken together, these estimates reveal asymmetric sorting patterns across skill types.

Robustness. In Appendix B we explore robustness to the facts on worker ability and occupational skill sorting patterns. We demonstrate that the cross-sorting pattern and mismatch results are not specifically driven by new job spells or job-to-job transitions, nor are they concentrated among experienced workers. Across a variety of alternative samples, the sorting patterns remain highly significant and very similar in magnitude to the point estimates presented in this section.

3.4 Empirical Results Discussion

In this section we have documented empirically novel facts regarding occupational separation risk and patterns of sorting between workers and occupations. First, worker separation rates contain a significant occupational component, which is widely dispersed across occupations. Second, we have shown that occupational separation rates are highly correlated with the occupational skill requirements. Manually-intensive jobs are associated with substantially higher separation risk, while cognitively-intensive jobs with lower separation risk. These rates are not driven mechanically by wage differences across occupations, but reflect a separate source of occupational heterogeneity. Finally, we provide suggestive evidence that this skill-correlated separation risk may affect worker sorting patterns and occupational mismatch.[10] Conditional on worker abilities, workers with higher cognitive abilities work in occupations with lower manual requirements, generating more overqualification on the manual dimension. Workers with higher manual abilities tend to work in occupations with higher cognitive requirements, generating more underqualification on the cognitive dimension.

[10]To be clear, we do not claim that the results of Section 3.3 are causal. We only seek to characterize empirical worker-occupation sorting patterns.

4 Model

To rationalize the empirical facts, we develop a structural model featuring workers and occupations (jobs) with multidimensional skills and on-the-job search (OJS). The model is related to the theory of multidimensional sorting developed in Lindenlaub and Postel-Vinay (2023), as well as Lise and Postel-Vinay (2020). Relative to this prior work, we allow occupational separation rates to depend explicitly on skill requirements $\mathbf{y}$.

4.1 Model Setup

Agents. The model is set in continuous time. There are two classes of heterogeneous agents: workers and firms. Both sets of agents have linear preferences.

Workers discount the future at rate ρ. Workers are endowed with a two-dimensional skill vector $\mathbf{x} = (x_m, x_c) \in \mathcal{X} \subset [0,1]^2$, where x_m denotes manual skill and x_c denotes cognitive skill.[11] Throughout, we denote vectors by bold symbols. Workers are either unemployed or matched to a job. An unemployed worker with skill vector $\mathbf{x}$ receives flow home production value b.

Firms are characterized by a two-dimensional skill requirement vector $\mathbf{y} = (y_m, y_c) \in \mathcal{Y} \subset [0,1]^2$. A match between worker $\mathbf{x}$ and firm $\mathbf{y}$ produces flow output $f(\mathbf{x}, \mathbf{y})$. We assume that matches are one-to-one between workers and firms, so the matched job is the firm. We interpret each skill requirement y as an occupation. We use the terms "job" and "occupation" interchangeably throughout the analysis given this correspondence.

Job Finding and Separation Rates. Search in the model is random. Unemployed workers receive job offers at Poisson rate λ_0 and employed workers receive outside offers at Poisson rate λ_1. Offers are drawn from a fixed distribution of job requirements, denoted by $G(y)$. Assume job finding rates and the distribution of jobs are fixed over time, so the model can be considered to be partial equilibrium.

Our key departure from prior search-and-match models with multi-dimensional skill is that we allow for job separation rates to explicitly vary by occupational skill requirements. Specifically, motivated by the empirical evidence of occupation-specific separation rates in Section 3, we assume exogenous and occupation-specific separation rates $\delta(\mathbf{y})$.[12]

[11] We focus on manual and cognitive skills because these dimensions exhibit robust associations with occupational separation risk in Table 1. This two-dimensional specification isolates the tradeoff between match quality and job security that motivates our analysis.

[12] We focus on separation rate heterogeneity at the occupation level and abstract from firm-level hetero-

Match Values and Worker Mobility. Wage contracts are determined through the sequential-auction protocol à la Postel-Vinay and Robin (2002). When an employed worker receives an outside offer, the current and prospective employers Bertrand-compete for the worker's services. This protocol governs worker mobility and the division of match surplus. We also assume firms have full bargaining power for analytical convenience, and normalize the value of a vacant job to zero.

Denote by $U(\mathbf{x})$ the private value of unemployment for a worker with skill vector $\mathbf{x}$. Under the sequential-auction protocol and full firm bargaining power, unemployed workers do not capture the surplus generated by future job offers. Thus, the value of unemployment satisfies

$$\rho U(\mathbf{x}) = b \tag{5}$$

Denote by $P(\mathbf{x}, \mathbf{y})$ the total private value of a match between worker $\mathbf{x}$ and job $\mathbf{y}$. As standard, outside offers affect worker mobility and the division of match surplus between firms and workers, but not the total private value of the current match. Hence, the match value satisfies

$$\rho P(\mathbf{x}, \mathbf{y}) = f(\mathbf{x}, \mathbf{y}) + \delta(\mathbf{y}) \left[U(\mathbf{x}) - P(\mathbf{x}, \mathbf{y}) \right] \tag{6}$$

The private surplus generated by the match is then given by

$$S(\mathbf{x}, \mathbf{y}) = P(\mathbf{x}, \mathbf{y}) - U(\mathbf{x}) = \frac{f(\mathbf{x}, \mathbf{y}) - b}{\rho + \delta(\mathbf{y})} \tag{7}$$

Thus, conditional on flow output, occupations with higher separation rates generate lower match surplus. Following Postel-Vinay and Robin (2002), an unemployed worker accepts an offer from job $\mathbf{y}'$ if and only if $P(\mathbf{x}, \mathbf{y}') \geq U(\mathbf{x})$, and upon accepting, the worker receives a contract value of $U(\mathbf{x})$.

Let $W(\mathbf{x}, \mathbf{y}, \widehat{\mathbf{y}})$ denote the value of the worker's current contract in match $(\mathbf{x}, \mathbf{y})$, where the variable $\widehat{\mathbf{y}}$ denotes the worker's current bargaining position, interpreted as the best credible outside option supporting the current contract. If the worker entered the match from unemployment and has not subsequently received a competing offer, the bargaining position is unemployment, with the convention $P(\mathbf{x}, \widehat{\mathbf{y}}) = U(\mathbf{x})$.

geneity within an occupation. One can add a random component in $\delta(\mathbf{y})$ to model firm-level heterogeneity. We intentionally make a minimal departure from a standard model like Lindenlaub and Postel-Vinay (2023) to highlight the new margin.

Following Lise and Postel-Vinay (2020), under full firm bargaining power, a worker's value in a match is exactly the match value between the worker and their bargaining position, namely,

$$W(\mathbf{x}, \mathbf{y}, \hat{\mathbf{y}}) = P(\mathbf{x}, \hat{\mathbf{y}})$$

This leads to a very simple criterion to determine job mobility. Suppose that a worker employed in job $\mathbf{y}$ with bargaining position $\widehat{\mathbf{y}}$ receives an outside offer from job $\mathbf{y}'$. Bertrand competition implies that the worker chooses the match with the higher total private value. Specifically, the worker's contract value following the auction is

$$W' = \min\left\{P(\mathbf{x}, \mathbf{y}), \max\left\{P(\mathbf{x}, \mathbf{y}'), W(\mathbf{x}, \mathbf{y}, \widehat{\mathbf{y}})\right\}\right\} \tag{8}$$

As usual, there are three potential outcomes after an outside offer. In the scenario that $P(\mathbf{x}, \mathbf{y}') \leq W(\mathbf{x}, \mathbf{y}, \widehat{\mathbf{y}})$, the prospective employer cannot profitably improve upon the worker's current contract. The offer is simply dismissed, and the bargaining position remains $\widehat{\mathbf{y}}$. If the prospective employer has a match value greater than the current worker value but less than the total value of the existing match, $P(\mathbf{x}, \mathbf{y}) \geq P(\mathbf{x}, \mathbf{y}') > W(\mathbf{x}, \mathbf{y}, \widehat{\mathbf{y}})$, the worker stays in job $\mathbf{y}$, but the current employer raises the contract value to match the outside offer. In this case, the outside offer becomes the worker's new bargaining position, so $\widehat{\mathbf{y}}$ is updated to $\mathbf{y}'$. Finally, if a strictly superior employer contacts the worker, $P(\mathbf{x}, \mathbf{y}') > P(\mathbf{x}, \mathbf{y})$, the worker moves to job $\mathbf{y}'$, with a new contract value $W' = P(\mathbf{x}, \mathbf{y})$. The former job $\mathbf{y}$ becomes the worker's bargaining position in the new match. Thus, the worker's new contract is $W(\mathbf{x}, \mathbf{y}', \mathbf{y})$.

Wages. Between successful outside offers, the bargaining position and the associated split of the match surplus stay unchanged. Combining worker values for employment, unemployment and the definition of the match surplus, we can write equilibrium wages in closed form, which we define in Appendix C.1.

4.2 The Planner's Problem

The preceding value functions characterize occupational rankings and worker mobility in the decentralized economy. To assess whether these rankings are productively efficient, we now formulate the problem of the planner. Following Acemoglu and Shimer (1999), we consider a planner who faces the same search technology as workers but controls which offers are accepted. The planner takes the offer arrival rates, the distribution of job requirements, and occupational separation rates as given. It cannot redirect an offer to a different worker

or create additional jobs. Hence, its only choice is the ranking of occupations along each worker's job ladder.

Let $\mu_{E,t}(\mathbf{x}, \mathbf{y})$ and $\mu_{U,t}(\mathbf{x})$ denote the distributions of employed and unemployed workers. The planner maximizes the present value of match output and home production,

$$\mathcal{W}^P = \int_0^\infty e^{-\rho t} \left\{ \int f(\mathbf{x}, \mathbf{y}) d\mu_{E,t}(\mathbf{x}, \mathbf{y}) + \int b d\mu_{U,t}(\mathbf{x}) \right\} dt$$

Because the offer arrival rates and the offer distribution are exogenous, the planner's timeless allocation can be represented by marginal social values. Let $U^P(\mathbf{x})$ denote the social value of an unemployed worker and $V^P(\mathbf{x}, \mathbf{y})$ the social value of a worker employed in occupation $\mathbf{y}$. They satisfy

$$\rho U^P(\mathbf{x}) = b + \lambda_0 \int_Y \max \left\{ V^P(\mathbf{x}, \mathbf{y}') - U^P(\mathbf{x}), 0 \right\} dG(\mathbf{y}') \tag{9}$$

$$\begin{aligned} \rho V^P(\mathbf{x}, \mathbf{y}) = f(\mathbf{x}, \mathbf{y}) &+ \delta(\mathbf{y}) \left[U^P(\mathbf{x}) - V^P(\mathbf{x}, \mathbf{y}) \right] \\ &+ \lambda_1 \int_Y \max \left\{ V^P(\mathbf{x}, \mathbf{y}') - V^P(\mathbf{x}, \mathbf{y}), 0 \right\} dG(\mathbf{y}') \end{aligned} \tag{10}$$

The planner accepts an offer whenever it raises the relevant social value. These equations are the social counterparts to the private match values in equations (5)–(6).

We now present a useful benchmark which shows that under homogeneous separation risk, private workers and the planner would rank jobs in the same way.

Lemma 1 (Homogeneous-risk benchmark)**.** *Suppose separation risk is homogeneous, $\delta(\mathbf{y}) = \bar{\delta}$. For every worker type $\mathbf{x}$, the decentralized and planner rankings of occupations coincide. In particular,*

$$P(\mathbf{x}, \mathbf{y}') \geq P(\mathbf{x}, \mathbf{y}) \iff f(\mathbf{x}, \mathbf{y}') \geq f(\mathbf{x}, \mathbf{y}) \iff V^P(\mathbf{x}, \mathbf{y}') \geq V^P(\mathbf{x}, \mathbf{y})$$

Proof. See Appendix C.1 □

The first equivalence follows immediately because common separation risk makes the private match value an affine transformation of flow output. The second follows because the planner's Bellman operator preserves the ordering of occupations by flow output when all occupations have the same separation risk. This implies multidimensional skills alone do not create a ranking wedge. Both a private worker and the planner compress the two-dimensional

vector of occupational requirements into the same scalar index $f(\mathbf{x}, \mathbf{y})$.[13]

4.3 Separation Risk and Local Complementarity

The sequential auction protocol makes match surplus the central object that determines equilibrium sorting. Before comparing private and social rankings, we first characterize how the skill-correlated separation risk changes the ordering of private match surplus that governs worker mobility. In standard models of labor market sorting, the sorting direction depends crucially on complementarities between worker skills and job requirements (Lindenlaub and Postel-Vinay, 2023). Because the skill-correlated separation risk generates non-monotonicity in match surplus (7), global complementarities cannot be easily established in general in this environment. Instead, we characterize how the skill-correlated separation risk affects worker-occupation complementarity locally.

Proposition 1 (Separation Risk and Local Complementarity)**.** *Suppose $f_{x_k} > 0, k \in \{m, c\}$. Under some regularity conditions, the cross-partial effect of increasing occupational skill requirement j on the change in match surplus from increasing worker ability k is characterized as*

$$S_{x_k, y_j} = \frac{f_{x_k y_j}(\mathbf{x}, \mathbf{y})}{\rho + \delta(\mathbf{y})} - \frac{f_{x_k}(\mathbf{x}, \mathbf{y}) \delta_{y_j}}{(\rho + \delta(\mathbf{y}))^2} \tag{11}$$

Thus, if $\delta_{y_j} > 0$, a higher skill requirement y_j reduces the local complementarity of the match surplus.

Proof. See Appendix C.1 □

The first term on the right-hand side of equation (11) captures the standard complementarity from the production function $f(\mathbf{x}, \mathbf{y})$. Proposition 1 demonstrates that if an increase in skill requirement y_j raises the separation risk, then this reduces the complementarity of the worker-occupation match on that dimension. Concretely, in Section 3 we demonstrated that manually intensive jobs are characterized by higher separation risk. Through the lens of the model, $\delta_{y_m} > 0$, so manual job content increases risk and therefore reduces how complementary that occupation is with worker abilities. In contrast, $\delta_{y_c} < 0$ raises the complementarity

[13] The proposition concerns the ranking of occupations, which governs job-to-job mobility. Unless workers have all the bargaining power, the unemployment-to-employment (UE) margin may still retain a wedge between the decentralized economy and the planner's economy. We leave that standard UE margin in the background and focus on the occupational ranking margin created by the heterogeneous separation risk. One can also assume $\lambda_0 = \lambda_1$ to eliminate that wedge.

on the cognitive margin.

4.4 Comparing the Top of the Job Ladder

Proposition 1 shows that the skill-correlated separation risk changes local complementarity. Because of that, it makes a complete analytical characterization of the assignment problem difficult. Before quantifying the model, to obtain more economic intuition regarding how skill-correlated separation risk changes occupational choice, and whether it retains productive efficiency, we compare the top of the job ladders in different economies. This simplifies the analysis because at the top of the job ladder, there are no more valuable on-the-job offers.[14] The analysis abstracts from the full assignment problem but translates risk-adjusted match surplus into a sorting prediction that can be taken to the quantitative model.

We show in Appendix C.1 that, for a worker with skill vector $\mathbf{x}$, the occupation at the top of the job ladder is the job preferred by the worker in the decentralized economy or by the planner. Namely, denote by $\mathbf{y}^D(\mathbf{x})$ and $\mathbf{y}^P(\mathbf{x})$ the jobs preferred by workers with skill $\mathbf{x}$ and by the planner, respectively. We have

$$\mathbf{y}^D(\mathbf{x}) = \arg\max_{\mathbf{y}} S(\mathbf{x}, \mathbf{y}) \qquad \mathbf{y}^P(\mathbf{x}) = \arg\max_{\mathbf{y}} V^P(\mathbf{x}, \mathbf{y}) \tag{12}$$

Denote by $\mathbf{y}^0(\mathbf{x}) = \mathbf{y}^D(\mathbf{x})|_{\delta(\mathbf{y})=\bar{\delta}}$ the homogeneous-risk benchmark.[15] Throughout this subsection, we make the following assumptions.

Assumption 1. *For each* $\mathbf{x}$*, the favorite job* $\mathbf{y}^0(\mathbf{x})$ *in the homogeneous risk benchmark is an interior and strict local maximum and yields strictly positive match surplus. In a neighborhood of* $\mathbf{y}^0(\mathbf{x})$*,* f *is locally separable, i.e.,*

$$f(\mathbf{x}, \mathbf{y}) = a(\mathbf{x}) + f_m(x_m, y_m) + f_c(x_c, y_c)$$

Moreover, $\delta_{y_m} > 0, \delta_{y_c} < 0$*.*

The requirement of an interior maximizer rules out bilinear production functions, but a quadratic form, common in parametrizations used in structural models, often suffices. Notice that under multi-dimensional skills, each worker $\mathbf{x}$ has their own job ladder. We first compare $\mathbf{y}^D(\mathbf{x}), \mathbf{y}^P(\mathbf{x}), \mathbf{y}^0(\mathbf{x})$ for a given worker $\mathbf{x}$, and then compare their slopes that inform the sorting direction.

[14] By continuity arguments, the analysis extends to regions high up in the job ladder.

[15] According to Lemma 1, this is also $\mathbf{y}^P(\mathbf{x})|_{\delta(\mathbf{y})=\bar{\delta}}$.

4.4.1 The Level of the Choice

Compare $\mathbf{y}^D$ and $\mathbf{y}^0$. We first look at the decentralized economy with and without skill-correlated separation risk to see its effect on occupational choice. Applying the implicit function theorem to the first-order conditions from (12), we can easily show that

$$\frac{\partial y_j^D}{\partial \delta_{y_j}} < 0 \tag{13}$$

Given that $\delta_{y_m} > 0, \delta_{y_c} < 0$, we have $y_m^D < y_m^0, y_c^D > y_c^0$. Intuitively, for the same worker, given that higher manual skill requirements imply higher separation risks and therefore, lower match values, the worker would optimally reduce the preferred manual requirements. It is the converse for cognitive requirements.

Compare $\mathbf{y}^D$ and $\mathbf{y}^P$. Recall that Lemma 1 shows the decentralized ordering of jobs coincides with the planner's ordering in the homogeneous-risk benchmark. Heterogeneous separation risk can break this ordering. Notice that sequential auctions are pairwise efficient. With a new on-the-job offer, the worker moves to the match with the larger total private value. Pairwise efficiency, however, does not necessarily lead to dynamic efficiency. The current auction does not include employers the worker may meet in the future. Under any positive employer bargaining power, part of the surplus from those future matches accrues to future employers and is absent from the value governing the worker's current mobility decision. Only in the knife-edge case where the worker is the residual claimant of the entire sequence of match surpluses would the private value functions coincide with the planner equations.[16]

The ranking wedge is particularly transparent at the top of the job ladder. Notice from equation (9) that except for the uninteresting case where the planner wants all workers to remain unemployed, $U^P(\mathbf{x}) > U(\mathbf{x}) = b/\rho$ for all $\mathbf{x}$. Private and social job values in this case are

$$P(\mathbf{x},\mathbf{y}) = \frac{f(\mathbf{x},\mathbf{y}) + \delta(\mathbf{y})U(\mathbf{x})}{\rho + \delta(\mathbf{y})}, \qquad V^P(\mathbf{x},\mathbf{y}) = \frac{f(\mathbf{x},\mathbf{y}) + \delta(\mathbf{y})U^P(\mathbf{x})}{\rho + \delta(\mathbf{y})}. \tag{14}$$

This implies

$$V^P(\mathbf{x},\mathbf{y}) - P(\mathbf{x},\mathbf{y}) = \delta(\mathbf{y})\frac{U^P(\mathbf{x}) - U(\mathbf{x})}{\rho + \delta(\mathbf{y})} \tag{15}$$

[16] This source of inefficiency is similar to the inefficiency documented in Jarosch (2023).

is strictly increasing in $\delta(\mathbf{y})$. Thus, for two occupations $\mathbf{y}, \mathbf{y}'$ such that $\delta(\mathbf{y}) < \delta(\mathbf{y}')$, if the planner is indifferent between the two, the private worker would strictly prefer the safer occupation $\mathbf{y}$, i.e.,

$$V^P(\mathbf{x}, \mathbf{y}) = V^P(\mathbf{x}, \mathbf{y}') \quad \Longrightarrow \quad P(\mathbf{x}, \mathbf{y}) > P(\mathbf{x}, \mathbf{y}') \tag{16}$$

In other words, workers high on the job ladder may place too much weight on job security, because falling into unemployment destroys the difference between the current match value and $U(\mathbf{x})$. The planner sees a smaller loss because $U^P(\mathbf{x})$ also includes the output produced in future matches.

To see how this security wedge maps into the model's multidimensional occupation space, we show that

$$\nabla_y V^P - \nabla_y P = \rho \frac{U^P(\mathbf{x}) - U(\mathbf{x})}{[\rho + \delta(\mathbf{y})]^2} \nabla_y \delta(\mathbf{y}) \tag{17}$$

where ∇_y denotes the gradient with respect to $\mathbf{y}$. Given the assumption that $\delta_{y_m} > 0 > \delta_{y_c}$, evaluating at an interior planner favorite job, which satisfies $V^P_{y_m} = V^P_{y_c} = 0$, we have $P_{y_m} < 0 < P_{y_c}$. In other words, starting from the planner's choice, the worker can raise private value by moving locally toward lower manual and higher cognitive requirements, implying $y^D_m < y^P_m, y^D_c > y^P_c$.

Compare $\mathbf{y}^P$ and $\mathbf{y}^0$. As we show in Appendix C.1, the planner, like workers in the decentralized economy, also has an incentive to reduce y^P_m and raise y^P_c relative to the homogeneous-risk benchmark $\mathbf{y}^0(\mathbf{x})$. That is, the planner would also sacrifice some current match quality to keep a productive match intact for longer.

This means a worker's reaction to the skill-correlated risk is not entirely counterproductive compared to the homogeneous-risk benchmark. We can decompose a worker's total reaction relative to the benchmark as

$$\mathbf{y}^D(\mathbf{x}) - \mathbf{y}^0(\mathbf{x}) = \left[\mathbf{y}^P(\mathbf{x}) - \mathbf{y}^0(\mathbf{x})\right] + \left[\mathbf{y}^D(\mathbf{x}) - \mathbf{y}^P(\mathbf{x})\right] \tag{18}$$

The first term on the right-hand side is an efficient response to the heterogeneity in match durability. The second term is the ranking distortion characterized earlier. It captures the additional movement toward safety in the decentralized economy, as workers are more eager to avoid unemployment than the planner. The resulting productivity loss can be large, for example, for high-x_m workers, if manual skill and manual requirements are strong complements

in production.

The next proposition summarizes the above discussion.

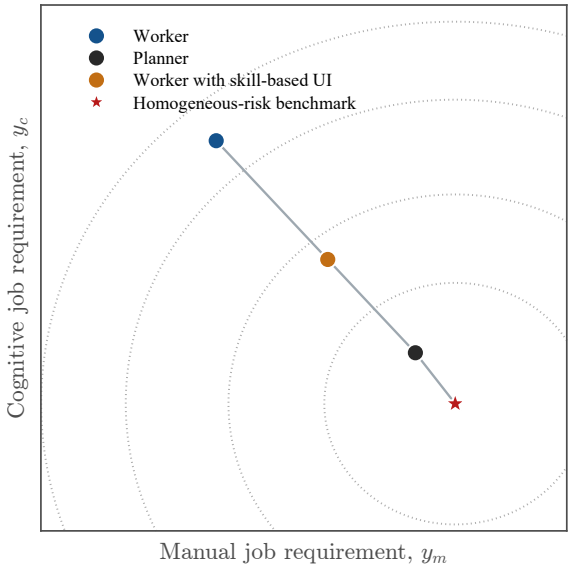
Proposition 2. *Suppose Assumption 1 holds. For small perturbations of* $\delta(\mathbf{y})$ *around the homogeneous-risk benchmark such that* $\delta_{y_m} > 0, \delta_{y_c} < 0$ *and any given* $\mathbf{x}$*,*

$$y_m^D(\mathbf{x}) < y_m^P(\mathbf{x}) < y_m^0(\mathbf{x}), \qquad y_c^D(\mathbf{x}) > y_c^P(\mathbf{x}) > y_c^0(\mathbf{x});$$

Proof. See Appendix C.1 □

Figure 2 illustrates the implication for multidimensional occupational choice.

Figure 2: The security wedge in occupation-requirement space



Notes: The figure maps the security wedge into job-requirement space for a high-manual-skill worker. Dotted curves are flow-output contours around the common homogeneous-risk benchmark (red star), which is also the productivity-maximizing occupation in this illustration. Relative to the planner's choice, the private choice has a lower manual and a higher cognitive requirement; skill-based UI moves the private choice partway toward the planner's allocation.

4.4.2 The Slope of the Choice

The last section compares the top of the job ladders for a given skill $\mathbf{x}$. We now compare how a worker's favorite job changes with skill $\mathbf{x}$ in different economies. The next proposition states the results. Although the results are intuitive, some additional regularity conditions are required to control for the curvature of the match surplus and to ensure the problem is well-behaved. These conditions are not demanding in general. A quadratic production

function with reasonable parameter values would satisfy the conditions.

Proposition 3. *Suppose Assumption 1 holds. Under additional regularity conditions defined in the Appendix, for small perturbations of $\delta(\mathbf{y})$ around the homogeneous-risk benchmark such that $\delta_{y_m} > 0, \delta_{y_c} < 0$, the following results hold*

$$\frac{\partial y_m^D}{\partial x_m} < \frac{\partial y_m^P}{\partial x_m} < \frac{\partial y_m^0}{\partial x_m}, \qquad \frac{\partial y_c^D}{\partial x_c} > \frac{\partial y_c^P}{\partial x_c} > \frac{\partial y_c^0}{\partial x_c};$$

and

$$\frac{\partial y_c^D}{\partial x_m} > \frac{\partial y_c^P}{\partial x_m} > \frac{\partial y_c^0}{\partial x_m} = 0, \qquad \frac{\partial y_m^D}{\partial x_c} < \frac{\partial y_m^P}{\partial x_c} < \frac{\partial y_m^0}{\partial x_c} = 0$$

Proof. See Appendix C.1. □

The first part of Proposition 3 describes the slope on the same-skill margin. When separation risk increases with manual skill requirements, $\delta_{y_m} > 0$, the tendency of positive sorting along the manual dimension is weakened, because the productivity return to manual match quality is partly offset by higher separation risk. When separation risk declines with cognitive skill requirements, $\delta_{y_c} < 0$, workers respond in the opposite direction. Cognitive match quality and job security point in the same direction, strengthening the tendency of positive sorting along the cognitive dimension. Thus, the top-of-ladder comparison makes the economic content of Proposition 1 explicit. Similar to the level comparison in Proposition 2, the planner's reaction lies in between.

The second part of the proposition describes the slope on the cross-skill margin. Both cross-skill slopes are zero in the homogeneous-risk benchmark. Under skill-correlated risk, manual skill makes workers productive in manual jobs, but they are also the jobs with higher separation risk. Hence, a worker with high manual skill has a reason to move toward cognitively intensive jobs, because they provide job security that partly hedges the risk attached to manual requirements. Conversely, a worker with high cognitive skill can reduce exposure to manual requirements while preserving match quality on the cognitive dimension. Again, private workers respond more strongly than the planner.

Although the above analysis does not characterize the complete equilibrium sorting pattern, it illustrates the forces that can shape it, and whether these forces are productively efficient. The quantitative model in the next section will exhibit similar patterns under the global solution.

4.4.3 Skill-Based Unemployment Insurance.

Workers in the decentralized economy have stronger incentives to search for job security by sacrificing match qualities than the planner. We now show that skill-based unemployment insurance can narrow this gap. Let the benefit received in unemployment be $B(\mathbf{x}) = b_m x_m$ and momentarily abstract from how this benefit is financed. The private unemployment value then becomes $U(\mathbf{x}; B) = [b + B(\mathbf{x})]/\rho$. The gap between the private and planner value becomes

$$V^P(\mathbf{x}, \mathbf{y}) - P(\mathbf{x}, \mathbf{y}; B) = \delta(\mathbf{y}) \frac{U^P(\mathbf{x}) - U(\mathbf{x}; B)}{\rho + \delta(\mathbf{y})} \,. \tag{19}$$

As long as the policy does not overshoot $U^P(\mathbf{x})$, raising benefit value b_m moves the valuations of the workers and planner closer. Locally, workers become more willing to select occupations with higher manual and lower cognitive requirements. Moreover, this also narrows the gap of the slopes between the decentralized and the planner economy in Proposition 3.[17] In a quantitative exercise using worker skill-based unemployment insurance, the benefit schedule is financed by a budget-balancing lump-sum tax from all employed workers, so the net output effect also reflects the endogenous change of the employment distribution.[18]

As a remark, allowing for unemployment insurance to be determined by worker abilities, while natural in this environment, may appear to be a strong assumption at first glance. In principle, the government agencies that design UI benefits cannot observe worker abilities directly. However, through UI tax receipts, government agencies can typically observe worker job transitions. We show in Appendix C.1 that under the production technology used in the quantitative exercises, worker skill vectors $\mathbf{x}$ are recoverable from observing at least two worker job transitions. Thus, there is a close correspondence between indexing unemployment benefits to worker abilities and allowing for benefits to depend on previous wages.

4.5 Away from the Top of the Ladder

Away from the top of the ladder, on-the-job search introduces a second force that complicates the analysis. Combining the planner's HJB equation with the private match value,

[17] A uniform benefit can reduce the gap in levels but not in slopes. It targets the correction toward high-manual-skill workers, for whom moving away from manual requirements destroys the most output, while limiting incentives for low-manual-skill workers to enter risky manual jobs, as they get less benefits compared to high-x_m workers.

[18] The lump-sum tax does not change the ranking of occupations but only affects UE margin.

we obtain the full version of equation (15) at any point along the job ladder

$$V^P(\mathbf{x},\mathbf{y}) - P(\mathbf{x},\mathbf{y}) = \frac{\delta(\mathbf{y})}{\rho+\delta(\mathbf{y})}\left[U^P(\mathbf{x}) - U(\mathbf{x})\right] + \frac{\lambda_1}{\rho+\delta(\mathbf{y})}\int_Y \left[V^P(\mathbf{x},\mathbf{y}') - V^P(\mathbf{x},\mathbf{y})\right]_+ dG(\mathbf{y}') \tag{20}$$

The first term, which is what we have previously studied, makes separation less costly to the planner because unemployment carries the social option value of future matches. The second term captures the social value of on-the-job search. Within a match, on-the-job search does not raise the current match value but only affects the split of the surplus. However, on-the-job search is socially valuable because it sends workers to better firms higher up the job ladder. This gives the planner an incentive to keep a worker in a safer job in order to take advantage of the opportunity of on-the-job search, especially when on-the-job search delivers a higher offer-arrival rate than search off the job (i.e., $\lambda_1 > \lambda_0$). The relative strength of the two forces depends on the worker's location on the job ladder and on the efficiency of search in and out of employment.

Taking Stock. The theory we have developed so far yields a progression from private occupational choice to productive efficiency. Heterogeneous risk first changes the worker's acceptance set, which can be different from that of a social planner. This tilts equilibrium sorting away from the efficient allocation. Targeted unemployment insurance can then partially undo workers' overreaction to job security and restore efficiency. We next calibrate the model and ask quantitatively how large these forces are.

5 Quantitative Analysis

This section takes the theory to data and asks whether the skill-correlated separation risk is quantitatively important for occupational choice, equilibrium sorting, and aggregate output. We also explore the scope for targeted unemployment insurance to mitigate the potential inefficiency. We discipline the production technology, the distribution of job requirements, and the search frictions using empirical moments from our sample regarding transition rates, sorting patterns, and wage regressions.

5.1 Calibration Strategy

We estimate the model by the simulated method of moments. The procedure follows the indirect-inference logic in Lise and Postel-Vinay (2020). For each candidate parameter

vector, we solve the model and simulate a long worker panel as implied by the model. Using this simulated panel we compute transition rates, skill correlations, moments of the realized occupational requirements, and wage-regression coefficients that can be calculated in our data described in Section 3. The calibrated parameter vector minimizes the distance between these simulated moments and their empirical counterparts.

The quantitative model is solved on a two-dimensional grid for worker skills and job requirements. The worker skill distribution, $G(\mathbf{x})$, is externally calibrated from the NLSY skill distribution. The distribution of job requirements, $G(\mathbf{y})$, is estimated internally using a flexible Gaussian copula with Beta marginals.

For the quantitative model, we parameterize the skill-correlated separation risk $\delta(\mathbf{y})$ to be

$$\delta(y) = \bar{\delta} + \bar{\delta}\delta_m y_m + \bar{\delta}\delta_c y_c \ .$$

We discipline the relative slopes using the empirical regression of separation risk on job requirements. In particular, we set $\delta_m = 0.2, \delta_c = -0.33$. Thus, manual requirements raise risk, while cognitive requirements lower it. The average level $\bar{\delta}$ is estimated internally to target the average separation rate.

The production function is a two-skill version of the multidimensional skill technology in Lise and Postel-Vinay (2020):

$$f(x,y) = \alpha_0 x_m y_m + \alpha_1 x_c y_c + \alpha_2 y_m + \alpha_3 y_c + \alpha_4 \min\{x_m - y_m, 0\}^2 + \alpha_5 \min\{x_c - y_c, 0\}^2 \ . \quad (21)$$

The first two terms capture worker-job complementarities. The next two terms allow jobs with different requirements to have different baseline productivity. The last two terms capture output losses from being underqualified relative to job requirements.

Table 4 reports the calibrated parameters. Panel A collects parameters taken directly from the data or fixed outside the SMM routine. Panel B reports the internally calibrated parameters. The offer arrival rates inform the transition rates. The parameters in the production function are primarily disciplined by coefficients from a Mincer-type wage regression and sorting patterns. The marginal distribution of job requirements among employed workers informs the latent distribution of job requirements $G(\mathbf{y})$. That said, all the parameters in Panel B are jointly estimated.

Table 4: Calibrated parameters

Panel A: Externally calibrated parameters						
	ρ	N_g	μ_{x_m}	μ_{x_c}	σ_{x_m}	σ_{x_c}
	0.0041	15	0.4998	0.5082	0.2899	0.2941
	ρ_x	η_m	η_c			
	0.6470	0.1950	-0.3350			
Panel B: Internally calibrated parameters						
Search and risk	λ_0	λ_1	$\bar{\delta}$			
	2.1674	1.6187	0.0237			
Production function	α_0	α_1	α_2	α_3	α_4	α_5
	0.1900	365.0000	292.0000	95.4717	-641.5000	-356.4478
Job distribution	ρ_G	a_m	b_m^G	a_c	b_c^G	
	0.2985	2.5278	3.9546	0.1516	1.6399	
Home production	b_0					
	104.9306					

Notes: Panel A reports parameters calibrated outside the SMM routine. Panel B reports parameters chosen internally to match the moments in Table 5.

5.2 Model Fit

Table 5 reports the targeted moments. The first block contains labor-market transition rates, including job-to-job (EE), unemployment-to-employment (UE), and employment-to-unemployment (EU) transitions. The second block summarizes the marginal distribution of job requirements among employed workers. The third block summarizes worker-job sorting by regressing job requirements on worker skills. The last block contains coefficients from a Mincer-style wage regression.

The model matches the main moments used in the quantitative exercises. In particular, it reproduces positive same-skill sorting in both manual and cognitive dimensions, and it captures the cross-sorting pattern: cognitively-skilled workers sort strongly away from manual requirements, while manually-skilled workers sort only slightly away from cognitive jobs. Panel C targets unconditional sorting coefficients, which are slightly different from the conditional regression coefficients reported in Table 2, where we partial out worker and labor market factors. In particular, manual ability is slightly negatively associated with cognitive requirements unconditionally, despite the positive conditional association documented in Table 2.[19] That said, the asymmetry in the cross-skill sorting along the two dimensions—the key pattern that we highlight—still remains. We choose unconditional sorting moments because these describe the equilibrium allocation reproduced by the model.

[19]The positive cross-sorting coefficient reported in Table 2 is largely an artifact of controlling for worker education, a notion that is absent in our model.

The fit of the wage moments is less exact, especially for the level effect of manual skill and tenure, but the model matches the key cognitive complementarity and the cognitive interaction term. For the purpose of this paper, the relevant success of the calibration is that the model can reproduce the sorting patterns through which job security interacts with multidimensional skills.

Table 5: Targeted moments

Targeted moments	Data values	Model values
Panel A: Transition rates		
Job-to-job transition rate	0.0400	0.0504
Unemployment-to-employment transition rate	0.2000	0.1955
Employment-to-unemployment transition rate	0.0200	0.0206
Panel B: Distribution of occupational requirements		
Mean manual requirement	0.5069	0.4283
Mean cognitive requirement	0.5063	0.6300
Std. dev. manual requirement	0.2882	0.2635
Std. dev. cognitive requirement	0.2929	0.1640
Corr. manual and cognitive requirements	0.0251	−0.0642
Panel C: Worker-job sorting coefficients		
y_m on x_m	0.3440	0.3300
y_c on x_c	0.3020	0.3316
y_c on x_m	−0.0160	−0.0513
y_m on x_c	−0.3350	−0.3307
Panel D: Mincer wage regression coefficients		
x_m	0.0063	−0.0252
x_c	0.7540	0.6535
y_m	0.2010	0.3529
y_c	0.2465	0.2978
Employment tenure	0.0222	0.0040
$x_m \times y_m$	0.0632	0.1544
$x_c \times y_c$	0.2955	0.2901

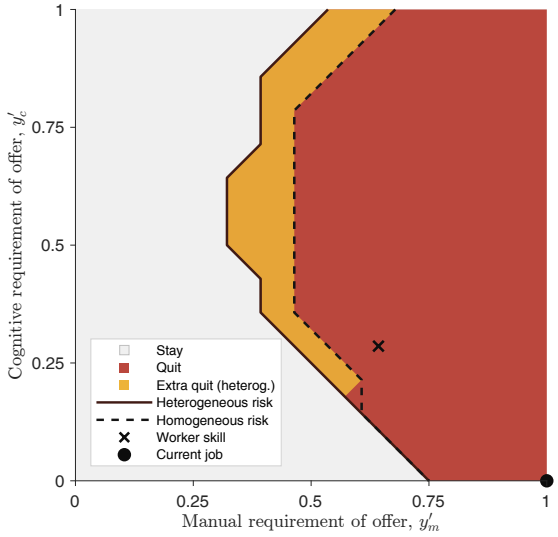
Notes: Model values are computed from a simulated worker panel under the calibrated heterogeneous-risk economy. Sorting coefficients come from regressions of job requirements on worker skills in the simulated panel.

5.3 Acceptance Sets and the Search for Job Security

The quantitative analysis follows the mechanism of the skill-correlated separation risk from individual decision rules to equilibrium sorting, aggregate output, and policy. The analysis begins with worker policy functions, specifically how the skill-correlated separation risk changes the set of outside offers that a worker is willing to accept. We then compare the calibrated economy to a homogeneous-risk benchmark. In the benchmark, we set $\delta(\mathbf{y}) \equiv \delta_0$

and choose δ_0 so that the average EU rate is the same as in the calibrated economy. This keeps the overall separation risk as well as all other parameters fixed in order to make a meaningful comparison. In other words, any difference in behavior across these model economies comes from the covariance of separation risk and job requirements.

Figure 3: Acceptance sets under heterogeneous and homogeneous separation risk



Notes: The background regions correspond to the calibrated heterogeneous-risk economy, with non-quitting outcomes grouped as stay. The dashed boundary overlays the homogeneous-risk benchmark. The yellow region highlights offers that are in the heterogeneous-risk quitting set but not in the homogeneous-risk quitting set.

Figure 3 plots the acceptance set for a worker with relatively high manual skill and lower cognitive skill, currently employed in a high-manual, low-cognitive job. We combine all non-quitting decisions into a stay region, including declining the offer directly and using the offer to bargain for a higher value. Therefore, the figure isolates the quitting set that matters for labor allocation. The solid line in the skill requirement space is the quit boundary in the economy with the skill-correlated separation risk, and the dashed line overlays the corresponding boundary in the homogeneous-risk benchmark. Therefore, the yellow region highlights offers that are accepted only when separation risk comoves with skill requirements.

The main implication of the acceptance set is that separation risk meaningfully changes the ranking of jobs. In the homogeneous-risk benchmark, the worker mainly compares jobs by match productivity. This implies that all jobs to the left of the red region yield a smaller flow output than the current match. In the economy with the skill-correlated separation risk, manually intensive jobs are discounted because they carry higher risk of job loss. The quitting set expands leftwards to include the yellow region. Thus, holding cognitive requirements fixed, the worker is willing to accept offers with lower manual requirements than in the

homogeneous-risk benchmark for more job security, at the cost of some flow output.

In Appendix C.2, we also plot the acceptance set from a planner facing the same skill-correlated separation risk. Consistent with the theoretical intuition in Proposition 2, the planner would also sacrifice some match quality along the manual dimension in exchange for matches with longer duration, but less so than the same worker in the decentralized economy. In other words, the quitting boundary the planner sets lies between the solid and the dashed line.

5.4 From Acceptance Sets to Equilibrium Sorting

The difference in the acceptance sets shows the effects of the skill-correlated separation risk on the decisions of one worker. We next examine how individual choices affect the equilibrium allocation of workers across occupations. This implication relates to Proposition 3 that the equilibrium may feature weaker manual sorting, stronger cognitive sorting, and asymmetric cross-skill responses once separation risk is tied to job requirements, especially for workers high up in the job ladder.

Table 6 compares the sorting regression coefficients under homogeneous and skill-correlated separation risk from the simulated worker panels, as well as those in the planner's allocation. The coefficients are computed by regressing simulated job requirements on worker skills, the same procedure that we use to compute the calibration moments.

Table 6: Sorting coefficients under homogeneous and heterogeneous separation risk

Sorting coefficient	y^{hom}	y^{het}	y^{P}	$y^{het} - y^{hom}$	$y^{P} - y^{hom}$
y_m on x_m	0.362	0.350	0.377	−0.012	0.016
y_c on x_c	0.334	0.358	0.346	0.024	0.012
y_c on x_m	−0.081	−0.068	−0.079	0.013	0.001
y_m on x_c	−0.239	−0.327	−0.275	−0.088	−0.037

Notes: The table reports coefficients from regressions of job requirements on worker skills in the simulated panel. The final two columns report level differences relative to the decentralized economy with homogeneous separation risk. Percent change is computed as the difference between the heterogeneous-risk and homogeneous-risk coefficients divided by the absolute value of the homogeneous-risk coefficient. For negative coefficients, a positive percent change means that the coefficient becomes less negative, while a negative percent change means that it becomes more negative.

The $y^{het} - y^{hom}$ column compares the economy with the skill-correlated separation risk (y^{het}) and the homogeneous-risk benchmark (y^{hom}). This column demonstrates that the signs of the sorting coefficients follow the predictions from the theory. The skill-correlated separation risk weakens sorting along the manual dimension and strengthens sorting along the cognitive dimension. For cross-skill sorting, under the skill-correlated separation risk,

higher manual skill becomes associated with relatively more cognitive requirements, while higher cognitive skill becomes associated with relatively fewer manual requirements.

The $y^P - y^{hom}$ column compares the homogeneous-risk benchmark with the planner's allocation. Compared to the economy with the skill-correlated separation risk, the directions of the changes in the sorting pattern are broadly similar, but the decentralized economy has changes of larger magnitude. This is consistent with the theoretical prediction that the skill-correlated separation risk has a stronger impact on skill sorting in the decentralized economy. The only exception is in the manual-to-manual sorting dimension. In the planner's allocation, manual-to-manual sorting strengthens rather than worsens. This reflects more of a selection force on the UE margin. Because $\lambda_0 > \lambda_1$ in the calibrated model, searching in unemployment is more efficient than searching on the job. Unemployed workers in the decentralized economy will accept any job whose match value is higher than that from unemployment. In contrast, the planner wishes for workers to sample better jobs during unemployment because that is more efficient in generating better matches. Thus, in the planner's economy, realized match quality becomes selectively better.[20] If we compare manual-to-manual sorting in the planner's allocation under homogeneous and skill-correlated separation risk (both have already fixed the UE selection margin), manual-to-manual sorting indeed worsens because of the channel we highlight in this paper.

5.5 Aggregate Output

Having shown that the change in acceptance sets affects equilibrium sorting and creates a wedge between the decentralized and the planner's economies, we next ask how costly it is in the aggregate. Table 7 compares the aggregate outcomes of the calibrated decentralized economy to the homogeneous-risk benchmark and the planner's allocation with and without skill-correlated separation risks. The table reports the employment rate and aggregate output (including home production) under the stationary worker distribution.

Table 7: Aggregate implications of heterogeneous separation risk

	Decentralized heterog. risk	Decentralized homog. risk	Planner heterog. risk	Planner homog. risk
Employment rate (%)	94.23	94.38	92.45	92.68
Total output	301.32	303.36	303.02	303.83

Notes: The homogeneous-risk benchmark sets the skill slopes of separation risk to zero and chooses the separation-risk level to match the baseline employment-to-unemployment transition rate. The gap is the percent difference relative to the homogeneous-risk benchmark.

[20] See Appendix C.1 for more details.

We first analyze our calibrated decentralized economy relative to the homogeneous-risk benchmark. The employment rates in the two economies are similar, but the economy with the skill-correlated separation risk has a lower total output. In other words, the average match quality under the skill-correlated separation risk is worse than that in the homogeneous-risk benchmark. This exactly reflects the tradeoff between job security and match quality. Quantitatively, the skill-correlated separation risk reduces total output by 0.67%. This magnitude of efficiency losses is not enormous, but it is economically meaningful given the narrow counterfactual.

Although the above comparison highlights the negative output effect from the skill-correlated separation risk, we need to evaluate whether it is socially desirable by comparing the calibrated economy with the planner's allocation. At the aggregate level, total output in the decentralized economy is 0.56% lower than that under the planner's allocation, close to the output loss relative to the decentralized homogeneous-risk economy.

We can further decompose the 0.56% output loss into two components: the UE selection margin and workers' excess responses to the skill-correlated separation risk relative to the planner's economy. The first component has been discussed in the last subsection: the planner wants workers to wait and sample better jobs in unemployment because that is more efficient given the calibrated job-finding rates $\lambda_0 > \lambda_1$. This channel is isolated by comparing columns 2 and 4 in Table 7 under homogeneous separation risk for workers and for the planner. It accounts for 0.47 units of output loss. The remaining loss comes from the excess response of searching for job security by private workers relative to the planner. This channel accounts for 1.23 units of output loss.[21] Thus, about 70% of the output loss is attributed to the skill-correlated separation risk.

5.6 Skill-Based Unemployment Insurance

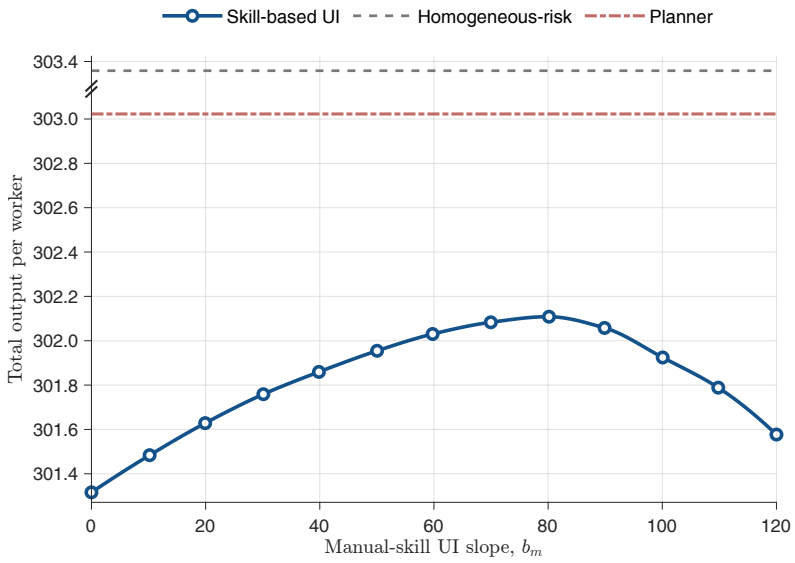
The majority of the output loss in the decentralized economy derives from the stronger response of worker job acceptances to skill-correlated risk, which generates the wedge in ranking different occupations. We show in Section 4.4.3 that skill-based unemployment insurance can partially eliminate that wedge. We now quantify the effect in this section.

We consider a policy exercise with a simple skill-based unemployment insurance $B(\mathbf{x}) = b_m x_m$, where $b_m > 0$. This means that unemployed workers with larger x_m receive higher

[21] Total loss is about 303.02-301.32=1.7 units of output. The UE margin accounts for 0.47 units, and this channel accounts for 1.7-0.47=1.23 units.

UI.[22] All employed workers pay a lump-sum tax τ. The idea is that workers with higher manual skills are productive in manual jobs, but those jobs are also riskier. By raising their fallback value after job loss, UI reduces the private compensation they require for accepting risky manual matches and can thus improve total match efficiency.

Figure 4: Aggregate output under skill-based unemployment insurance



Notes: The solid line plots aggregate output per worker under different slopes of unemployment benefits with respect to manual skill. The dashed line is aggregate output per worker in the homogeneous-risk benchmark. Benefits are financed by a budget-balancing tax in each policy experiment.

For each value of b_m, we solve the model and choose τ so that the government runs a balanced budget in the resulting equilibrium. Figure 4 plots the aggregate output per worker as b_m changes. The gray dashed line is the homogeneous-risk benchmark, and the red dashed line is the planner's allocation.

Figure 4 shows that the relationship between output and UI benefits is nonmonotonic. Moderate increases in b_m improve the aggregate output relative to the baseline economy with skill-correlated separation risk, consistent with the idea that social insurance can reduce the excessive private demand for job security. However, when the UI becomes sufficiently large, it reduces output. This is because the distortions on the UE margin induced by more generous benefits dominate the gains from improved match quality. In the current calibration, the optimal slope of the skill-based UI is $b_m = 80$, which raises aggregate output per worker from 301.32 to 302.11, or by about 0.26%. This is still below the planner's allocation but

[22] One could also study more general forms of UI, e.g., a UI schedule that depends both on manual and cognitive skill. We take a first step and assume a very simple schedule, which is linear in manual skills and does not respond to cognitive skills. We discuss that this can be implemented and can correspond to a UI schedule that relates to previous wage levels in Appendix C.

already restores almost half of the output loss. The outcome of this simple policy reveals that partially compensating workers for taking riskier manually-intensive jobs is effective in improving the allocative efficiency of the labor market.

6 Conclusion

This paper is motivated by the central insight that occupations differ not just in their compensation, but also their propensity for job loss. We find that job loss is fundamentally associated with occupational skill content: manually intensive occupations have higher separation rates, while cognitively intensive occupations have the converse. This finding is robust, and present even conditional on wages, the standard indicator for job loss in the search-and-match literature. In the NLSY, we find that workers with higher cognitive ability tend to sort away from manually intensive occupations, while workers with higher manual ability are conditionally associated with occupations with higher cognitive skill requirements.

We build a dynamic model with two-sided multidimensional heterogeneity between workers and occupations, where separation risk depends on skill attributes to rationalize the empirical evidence. We also characterize how this decentralized economy features allocative inefficiencies relative to a social planner, who would optimally cause more workers to accept riskier manually-intensive occupations. After calibrating the model to the data, we find that the skill-correlated separation risk changes workers' job acceptance sets, as workers seek more job security. This generates output losses in the economy relative to both a homogeneous-risk benchmark and the planner's allocation. The model demonstrates that workers' failure to internalize all of the productivity losses of sorting into safer occupations generates skill mismatch and a loss in output. Most of the output losses come from this force rather than a UE margin. Finally, we demonstrate that unemployment insurance which depends on worker abilities has the capability to meaningfully reduce some of these output losses.

The key assumption in our theoretical and quantitative analysis is that occupational requirements determine separation risk. We take both separation and the heterogeneous separation risk as exogenous, and we provide direct empirical evidence for the latter. A natural extension is to investigate the sources of this heterogeneity in a framework with endogenous separation. For example, different sectors may differ in their demand conditions. Demand for goods produced in manually intensive jobs may be very volatile, and manual workers are thus more likely to be laid off when separation is endogenous. In contrast, demand for goods (or services) produced in cognitively intensive jobs can be relatively stable, making layoffs less likely. We leave a formal analysis of this mechanism to future research.

References

Acemoglu, Daron and Robert Shimer (1999). "Efficient Unemployment Insurance". *Journal of political Economy*. 107(5), pp. 893–928.

Baley, Isaac, Ana Figueiredo, and Robert Ulbricht (2022). "Mismatch Cycles". *Journal of Political Economy*. 130(11), pp. 2943–2984.

Clymo, Alex, Piotr Denderski, Yusuf Mercan, and Benjamin Schoefer (2026). "Cautious Careers: Job Mobility under Incomplete Markets". *NBER Working Paper No. 35580*.

Dillon, Eleanor W (2018). "Risk and Return Trade-Offs in Lifetime Earnings". *Journal of Labor Economics*. 36(4), pp. 981–1021.

Farber, Henry S and Robert Gibbons (1996). "Learning and wage dynamics". *The Quarterly Journal of Economics*. 111(4), pp. 1007–1047.

Guvenen, Fatih, Burhan Kuruscu, Satoshi Tanaka, and David Wiczer (2020). "Multidimensional skill mismatch". *American Economic Journal: Macroeconomics*. 12(1), pp. 210–244.

Huang, Jincheng and Xincheng Qiu (2026). "Precautionary Mismatch". *Working Paper*.

Huckfeldt, Christopher (2022). "Understanding the Scarring Effect of Recessions". *American Economic Review*. 112(4), pp. 1273–1310.

Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan (1993). "Earnings Losses of Displaced Workers". *American Economic Review*. 83 (4), pp. 685–709.

Jarosch, Gregor (2023). "Searching for job security and the consequences of job loss". *Econometrica*. 91(3), pp. 903–942.

Lehner, Lukas, Ishaana Talesara, and Arthur Wickard (2026). "Worker Beliefs about Layoff Risk". *Working Paper*.

Lindenlaub, Ilse (2017). "Sorting Multidimensional Types: Theory and Application". *The Review of Economic Studies*. 84(2), pp. 718–789.

Lindenlaub, Ilse and Fabien Postel-Vinay (2023). "Multidimensional sorting under random search". *Journal of political Economy*. 131(12), pp. 3497–3539.

Lise, Jeremy and Fabien Postel-Vinay (2020). "Multidimensional skills, sorting, and human capital accumulation". *American Economic Review*. 110(8), pp. 2328–2376.

Maestas, Nicole, Kathleen J Mullen, David Powell, Till Von Wachter, and Jeffrey B Wenger (2023). "The Value of Working Conditions in the United States and Implications for the Structure of Wages". *American Economic Review*. 113(7), pp. 2007–2047.

Mortensen, Dale T and Christopher A Pissarides (1994). "Job creation and job destruction in the theory of unemployment". *The Review of Economic Studies*. 61(3), pp. 397–415.

Nekoei, Arash and Andrea Weber (2017). "Does Extending Unemployment Benefits Improve Job Quality?" *American Economic Review*. 107(2), pp. 527–561.

Papageorgiou, Theodore (2014). "Learning your Comparative Advantages". *Review of Economic Studies*. 81(3), pp. 1263–1295.

Postel-Vinay, Fabien and Jean-Marc Robin (2002). "Equilibrium wage dispersion with worker and employer heterogeneity". *Econometrica*. 70(6), pp. 2295–2350.

Rosen, Sherwin (1986). "The Theory of Equalizing Differences". *Handbook of Labor Economics*. 1, pp. 641–692.

Sanders, Carl and Christopher Taber (2012). "Life-cycle wage growth and heterogeneous human capital". *Annual Review of Economics*. 4(1), pp. 399–425.

Schmieder, Johannes F, Till Von Wachter, and Jörg Heining (2023). "The Costs of Job Displacement over the Business Cycle and its Sources: Evidence from Germany". *American Economic Review*. 113(5), pp. 1208–1254.

Shimer, Robert and Iván Werning (2008). "Liquidity and Insurance for the Unemployed". *American Economic Review*. 98(5), pp. 1922–1942.

Sorkin, Isaac (2018). "Ranking Firms using Revealed Preference". *The Quarterly Journal of Economics*. 133(3), pp. 1331–1393.

A Data Description

This appendix describes the construction and cleaning of the data sources used for the empirical facts of Section 3.

A.1 CPS: Occupation-Level Separation Risk

Monthly CPS sample. We construct the baseline occupation-specific separation measure from an IPUMS Current Population Survey (CPS) monthly extract covering 1994–2019. We exclude ASEC records, restrict the sample to respondents in the labor force who are age 60 or younger, and remove records without a valid longitudinal person identifier. Employment and unemployment are defined by CPS employment-status codes. We use occupations harmonized to 2010 Census codes.

For an individual employed in month t, we define a separation ($EU_{i,t}$) as when the same individual is observed as unemployed in month $t+1$. We estimate the following weighted linear probability model among employed respondents:

$$EU_{i,t} = \alpha + \delta_{o(i,t)} + \lambda_{q(t)} + \Gamma' X_{it} + \varepsilon_{it}, \tag{A.1}$$

where EU_{it} denotes an employment-to-unemployment transition, $\delta_{o(i,t)}$ is a 2010-Census-occupation fixed effect, $\lambda_{q(t)}$ is a calendar-quarter fixed effect, and X_{it} contains categorical controls for sex, race, marital status, education, and age. The regression uses the CPS monthly final person weight. Our baseline measure of occupation-specific separation risk is the estimated occupation fixed effect $\widehat{\delta}_o$.

For Figure 1, we normalize this effect by subtracting the smallest occupation effect and multiplying by 100:

$$\widetilde{\delta}_o = 100 \left(\widehat{\delta}_o - \min_{o'} \widehat{\delta}_{o'} \right). \tag{A.2}$$

The resulting measure is the estimated monthly separation probability, in percentage points, relative to the lowest-risk occupation. The normalization changes the level but not the cross-occupation ranking or the standardized coefficients reported in Table 1.

CPS ASEC Occupational Wages. We construct the occupation-wage control in Table 1 from the Annual Social and Economic Supplement (ASEC) to the CPS. We retain observations with positive annual wage and salary income and exclude agriculture and related

industries. We define potential experience as $\max\{\text{age} - 20, 0\}$ and regress wage and salary income in levels on potential experience and its square. The regression uses the ASEC person weight and absorbs fixed effects for education, sex, race, marital status, calendar year, and 2010 Census occupation. The estimated occupation fixed effect is the occupation-wage measure used in Table 1.

A.2 Survey of Income and Program Participation

The alternative separation-risk measure in columns 4–5 of Table 1 is constructed from the 1996, 2001, 2004, and 2008 panels of the Survey of Income and Program Participation (SIPP). We combine the four panels into a monthly worker panel and harmonize reported occupations to 2010 Census occupation codes. We restrict the sample to respondents ages 16–64 and remove self-employment, agricultural employment, and military employment. Employment-to-unemployment transitions are constructed from the monthly labor-force histories using the worker's employment status in the second reference week of each month. We exclude terminal months for which a forward transition cannot be measured and account for the seam between SIPP reference periods when constructing the monthly histories.

We estimate a weighted linear probability model of the employment-to-unemployment transition on age, age squared, sex, race, marital status, and education. The regression absorbs calendar-month, individual, and occupation fixed effects and uses the SIPP final person weight. The estimated occupation fixed effects form the SIPP measure of occupation-specific separation risk used in Table 1. These effects are multiplied by 1,000 before the occupation-level regressions; because Table 1 reports standardized beta coefficients, this rescaling does not affect the reported coefficients.

A.3 O*NET Occupational Skill Requirements

O*NET provides occupation-level measures of the skills, knowledge, abilities, work activities, and work context associated with an occupation. We use these descriptors to construct three occupation requirements: cognitive, manual, and interpersonal. For each application, we retain the first three principal components of the relevant O*NET descriptor matrix and rotate those components using interpretable descriptors for mathematics, mechanical knowledge, and social perceptiveness. The rotated factors are subsequently normalized to be in the range of $[0, 1]$.

To construct our occupational skill requirements O*NET descriptor matrix containing work activities, work context, skills, knowledge, and abilities. We remove importance-scale

responses and detailed work-context categories, rescale the remaining descriptors to comparable units, and omit descriptors that cannot be classified as cognitive, manual, or interpersonal content. For the occupational separation rate heterogeneity, we map O*NET-SOC scores to Census 2000 occupations using the Sanders occupational crosswalk and harmonize the measures to 2010 Census occupations. In the cases where the occupational crosswalks are not one-to-one we retain the mapping with the largest conversion rate. For the NLSY79 analysis, to make the sample of occupations harmonized, we follow the same procedure to map to 1990 Census occupation codes. In the actual construction of the principal components, we rotate the principal components such that the mathematics skill from O*NET loads only on the first principal component, the mechanical knowledge skill loads on the second principal component, and the social perceptiveness skill loads only on the third principal component.

A.4 NLSY79 Sample Construction

Data sources and analysis population. We use the National Longitudinal Survey of Youth 1979 to construct an annual panel of workers, jobs, and occupational skill requirements. The analysis combines the NLSY79 individual, employment, weekly work-history, health, social, and earnings records. Our baseline population is the cross-sectional male sample: White men, low-income White men, Black men, and Hispanic men. Our sample runs from 1979-2018. We follow closely the data cleaning process of Guvenen et al. (2020) to construct a similar sample.

Weekly histories and annual main jobs. We use the weekly work histories to link workers to employers and to measure usual weekly hours. If a respondent holds multiple jobs during a week, we define the main job as the job with the greatest usual weekly hours. We then select the annual main job as the job accumulating the greatest number of main-job hours within the person-year. Annual full-time hours are calculated from weeks in which usual hours are at least 30.

Labor-market entry. We restrict the sample to workers whose entry into sustained full-time employment is observed in the NLSY79. Sustained full-time employment is defined as at least 1,200 annual hours in two consecutive annual observations. We exclude respondents who are already attached to full-time employment at the beginning of the observed panel. If a respondent returns to school early in the career, we treat the subsequent labor-market re-entry as the start of the career and remove the earlier observations.

Employment-history restrictions. We drop the 1977 summary record for individuals and retain usable job histories through 2018; the 2019 observations do not contain usable jobs for this construction. We exclude respondents with more than two years of military service and remove military-employment observations for the remaining respondents. We remove observations after the final reported job and exclude repeated or extended spells of nonemployment that indicate weak labor-force attachment. When multiple observations remain for the same person-year, we use employer linkages, hours, interview timing, and the availability of occupation, industry, and wage information to select a single annual observation.

Occupation and industry coding. We combine employer-specific occupation and industry responses with the CPS-informed current-job, last-employer, and all-employer fields. Occupations reported under the 1970, 1980, and 2000 Census coding systems are mapped to 1990 Census occupations using crosswalks. Remaining unmatched occupation codes are assigned to the closest substantive 1990 occupation when an economically comparable match is available, and military occupation codes are excluded. Industries are harmonized to 12 broad categories. Within a continuous employer spell, we treat occupation and industry as constant and assign the modal occupation and industry observed during the spell. We exclude observations without valid occupation and industry codes and occupations that cannot be matched to the O*NET requirement measures.

Demographics, schooling, and ASVAB information. We clean age and completed-schooling histories within individuals, smooth isolated reversals or spikes in reported grade, and impose a nondecreasing schooling history when adjacent reports identify a reporting inconsistency. We carry age, race, schooling, and ASVAB information across adjacent observations when it is otherwise unavailable. We exclude observations before age 16, records with missing age or completed schooling, and respondents without a valid ASVAB assessment. The final schooling screen flags records satisfying $\text{age} - \text{grade} - 6 < 0$ and carries that flag backward within the worker, thereby removing observations that precede the worker's completed-schooling history.

Wages and labor-market controls. We require valid wage information, deflate nominal wages using the Personal Consumption Expenditures price index, and define log real wages as the logarithm of $100 \times \text{wage}_{it}/\text{PCE}_t$. We remove negative wages and trim nominal wages at the 0.1st and 99.9th percentiles within interview wave. Employer tenure, occupation tenure, and industry tenure are constructed from successive observations with the same employer, occupation, or industry. Experience counts the worker's successive retained labor-market

observations. Consequently, after the NLSY79 changes to a biennial interview schedule, these measures count retained observations rather than elapsed calendar years.

A.5 NLSY79 Worker Abilities and Empirical Measures

Education-implied O*NET requirements. O*NET reports the distribution of required education within each occupation. We harmonize the O*NET education categories to the schooling categories available in the NLSY79, merge those requirements with the cognitive, manual, and interpersonal occupation factors, and calculate the requirement vector for each education category using the O*NET education-response shares as weights. Each NLSY79 respondent is assigned the corresponding education-implied O*NET profile based on completed schooling. This education-implied profile enters the construction of worker abilities; the occupation requirement assigned to a worker-year continues to be determined by the worker's observed occupation.

Worker ability factors. We construct worker abilities using one observation per individual. The inputs are the ten ASVAB subtests, the Rosenberg self-esteem score, the Rotter locus-of-control score, body mass index, and the education-implied cognitive, manual, and interpersonal O*NET profile. We estimate three principal components using the NLSY ASVAB sampling weight and rotate the components using ASVAB Mathematics Knowledge, ASVAB Auto/Shop Information, and the Rosenberg score as the cognitive, manual, and interpersonal anchors. The resulting cognitive, manual, and interpersonal worker factors are standardized to the interval $[0, 1]$ and merged back to the annual worker panel as time-invariant characteristics.

Worker and occupation ranks. The x and y variables used in Tables 2 and 3 are percentile ranks. For skill dimension $S \in \{C, M, I\}$, x_i^S is the percentile rank of worker i's time-invariant ability factor, calculated across one observation per worker. The variable y_{it}^S is the percentile rank of the O*NET requirement of worker i's current occupation. The y rank is calculated from the pooled worker-year distribution over all years. Both x_i^S and y_{it}^S range from zero to one, and the rank calculations do not use sampling weights.

Mismatch. For each skill dimension, signed mismatch is defined as

$$mm_{it}^S = x_i^S - y_{it}^S. \tag{A.3}$$

A positive value indicates that the worker's ability rank exceeds the requirement rank of the current occupation. We define overqualification as $\mathbf{1}\{x_i^S > y_{it}^S\}$. The continuous mismatch outcomes in Table 3 therefore express the Table 2 sorting relationships as gaps between worker and occupation ranks, while the overqualification outcomes indicate whether the worker rank exceeds the occupation rank.

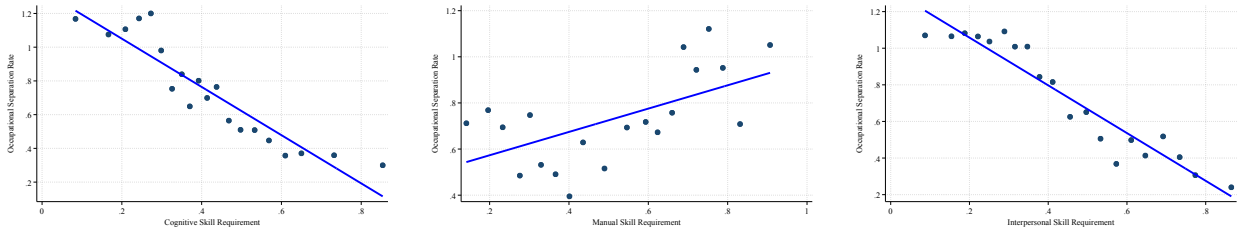
Regression sample and weighting. The common complete-case estimation sample for Tables 2 and 3 contains 29,820 worker-year observations for 1,599 workers and ends in 2017. The regressions weight observations using the contemporaneous NLSY cross-sectional sampling weight, include year fixed effects, and cluster standard errors by individual. The individual controls are log real wage; employer and occupation tenure and their quadratic and cubic terms; experience and its quadratic and cubic terms; family size; race; and education.

B Additional Empirical Results

In this appendix we present additional empirical results and robustness to the estimates reported in Section 3.

B.1 Occupational Separations and Skill Requirements

In Figure B.1, we display the unconditional correlations of occupational separation risk with skill requirements in binscatter plots. We use the occupation-level $\delta_{\mathcal{O}}$ estimates discussed in Section 3 and show their correlations against the empirical $\mathbf{y}$. These unconditional correlations confirm that the regression results in Table 1 are not driven by conditioning on the entire occupational skill vector, and further motivate the modeling of heterogeneous occupational separation rates.



(a) y^C **(b)** y^M **(c)** y^I

Figure B.1: Occupational Separation Rates and Skill Requirements

Notes. Binscatters of occupational separation rates, $\delta_{\mathcal{O}}$ and occupational skill requirements. The skill requirements are constructed from the principal component analysis of O*NET data, described in the main text.

B.2 Empirical Robustness

In Section 3, for Fact 3, we leverage the NLSY79 panel to study equilibrium worker-and-occupation matches following standard approaches in the literature (Guvenen et al., 2020). In this subsection, we replicate these results by conditioning on various data slices. In particular, we test that the worker-occupation sorting and mismatch patterns hold for new job spells, older-tenured job spells, and upon job switches.

Early Spells. Tables B.1 and B.2 report worker-occupation sorting and mismatch patterns for young job spells. These we define to be job spells where the worker has been at their current job for less than or equal to five years. Comparing the estimated coefficients for early spells to the pooled sample used in the main text, very little is changed. All coefficients on cognitive and manual abilities remain highly significant and within a close range of those

reported in Tables 2 and 3. We therefore conclude that the reported sorting and mismatch patterns exist early within job spells.

Table B.1: Worker Abilities and Occupational Skill Content: Early Spells

	y^C	y^M	y^I
x^C	0.308***	-0.311***	0.258***
	(0.067)	(0.070)	(0.061)
x^M	0.147***	0.366***	-0.210***
	(0.048)	(0.050)	(0.042)
x^I	-0.242*	-0.272**	0.245**
	(0.124)	(0.129)	(0.114)
Individual controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.271	0.160	0.302
Observations	20,089	20,089	20,089

Notes: Standard errors are reported in parentheses and clustered by individual. Regressions use NLSY cross-sectional sampling weights. Observations are for annual job spells where the worker has been at current job for less than or equal to five years.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Later Career. Tables B.3 and B.4 report worker-occupation sorting and mismatch patterns for experienced workers. We define a worker as experienced if they have been in the labor force for more than five consecutive years. Again, the estimated coefficients for experienced workers are highly similar to the coefficients estimated from the pooled sample used in the main text. We find that, while close in magnitude, interpersonal worker skills become marginally consistent. However, the primary worker and occupational characteristics we focus on, cognitive and manual, remain very similar and significant to the estimates reported in the main text. These results indicate that the empirical sorting and mismatch patterns are not driven by early career workers climbing the job ladder and accumulating human capital. When conditioning only on experienced worker observations, such conditional cross-sorting patterns remain potent.

Job Switches. Finally, we examine whether the facts presented in Section 3 are driven by matched employee-firm dynamics. To test this, we only use observations where the worker has changed their primary job within a given year. Tables B.5 and B.6 report worker-occupation sorting and mismatch patterns for workers who changed their primary job within a given year. Even in this more restrictive sample, workers with higher manual skills are matched conditionally to occupations with higher manual requirements, and workers with greater cognitive abilities are matched to occupations with lower manual skill requirements. For

Table B.2: Worker Abilities and Occupational Mismatch: Early Spells

	$mm^{C}_{j,\mathcal{O},t}$	$overqualified^{C}_{j,\mathcal{O},t}$	$mm^{M}_{j,\mathcal{O},t}$	$overqualified^{M}_{j,\mathcal{O},t}$
x^C	0.692***	0.744***	0.311***	0.428***
	(0.067)	(0.120)	(0.070)	(0.105)
x^M	-0.147***	-0.254***	0.634***	0.560***
	(0.048)	(0.082)	(0.050)	(0.077)
x^I	0.242*	0.477**	0.272**	0.275
	(0.124)	(0.212)	(0.129)	(0.190)
Individual controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.339	0.203	0.562	0.401
Observations	20,089	20,089	20,820	20,089

Notes: Standard errors are reported in parentheses and clustered by individual. Regressions use NLSY cross-sectional sampling weights. Observations are for annual job spells where the worker has been at current job for less than or equal to five years.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Worker Abilities and Occupational Skill Content: Later Career

	y^C	y^M	y^I
x^C	0.285***	-0.363***	0.288***
	(0.064)	(0.071)	(0.065)
x^M	0.162***	0.359***	-0.182***
	(0.046)	(0.049)	(0.042)
x^I	-0.224*	-0.234*	0.191*
	(0.117)	(0.128)	(0.113)
Individual controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.262	0.163	0.272
Observations	22,326	22,326	22,326

Notes: Standard errors are reported in parentheses and clustered by individual. Regressions use NLSY cross-sectional sampling weights. Observations are for annual job spells where the worker has been in the labor force for greater than five years.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Worker Abilities and Occupational Mismatch: Later Career

	$mm^{C}_{j,\mathcal{O},t}$	$overqualified^{C}_{j,\mathcal{O},t}$	$mm^{M}_{j,\mathcal{O},t}$	$overqualified^{M}_{j,\mathcal{O},t}$
x^C	0.715***	0.858***	0.363***	0.513***
	(0.064)	(0.117)	(0.071)	(0.098)
x^M	-0.162***	-0.243***	0.641***	0.531***
	(0.046)	(0.081)	(0.049)	(0.074)
x^I	0.224*	0.318	0.234*	0.264
	(0.117)	(0.208)	(0.128)	(0.178)
Individual controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.336	0.208	0.573	0.413
Observations	22,326	22,326	22,326	22,326

Notes: Standard errors are reported in parentheses and clustered by individual. Regressions use NLSY cross-sectional sampling weights. Observations are for annual job spells where the worker has been in the labor force for greater than five years.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

mismatch, the coefficients are again highly similar. Being overqualified cognitively is less associated with worker cognitive abilities upon job switches, but interpersonal skills are more associated with mismatch patterns. Regardless, the conditional cross-sorting and mismatch patterns exist for workers that switch jobs.

Table B.5: Worker Abilities and Occupational Skill Content: Job Switches

	y^C	y^M	y^I
x^C	0.321***	-0.319***	0.287***
	(0.058)	(0.060)	(0.057)
x^M	0.136***	0.378***	-0.174***
	(0.040)	(0.043)	(0.038)
x^I	-0.275***	-0.338***	0.159
	(0.103)	(0.113)	(0.099)
Individual controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.281	0.165	0.294
Observations	9,934	9,934	9,934

Notes: Standard errors are reported in parentheses and clustered by individual. Regressions use NLSY cross-sectional sampling weights. Observations are for annual job spells where the worker has changed principal job within the year.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Worker Abilities and Occupational Mismatch: Job Switches

	$mm^C_{j,\mathcal{O},t}$	$overqualified^C_{j,\mathcal{O},t}$	$mm^M_{j,\mathcal{O},t}$	$overqualified^M_{j,\mathcal{O},t}$
x^C	0.679***	0.753***	0.319***	0.431***
	(0.058)	(0.103)	(0.060)	(0.089)
x^M	-0.136***	-0.249***	0.622***	0.478***
	(0.040)	(0.072)	(0.043)	(0.065)
x^I	0.275***	0.518***	0.338***	0.449***
	(0.103)	(0.181)	(0.113)	(0.155)
Individual controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.380	0.240	0.578	0.414
Observations	9,934	9,934	9,934	9,934

Notes: Standard errors are reported in parentheses and clustered by individual. Regressions use NLSY cross-sectional sampling weights. Observations are for annual job spells where the worker has changed principal job within the year.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Model Appendix

C.1 Proofs

This appendix collects the proofs of the theoretical results and the derivations used in the main text. The private unemployment value is $U(\mathbf{x}) = b/\rho$. The total private value of a match and the private match surplus are

$$P(\mathbf{x},\mathbf{y}) = \frac{f(\mathbf{x},\mathbf{y}) + \delta(\mathbf{y})U(\mathbf{x})}{\rho + \delta(\mathbf{y})}, \qquad S(\mathbf{x},\mathbf{y}) = P(\mathbf{x},\mathbf{y}) - U(\mathbf{x}) = \frac{f(\mathbf{x},\mathbf{y}) - b}{\rho + \delta(\mathbf{y})}.$$

The planner values satisfy

$$\rho U^P(\mathbf{x}) = b + \lambda_0 \int_Y \left[V^P(\mathbf{x},\mathbf{y}') - U^P(\mathbf{x})\right]_+ dG(\mathbf{y}')$$

and

$$\rho V^P(\mathbf{x},\mathbf{y}) = f(\mathbf{x},\mathbf{y}) + \delta(\mathbf{y})\left[U^P(\mathbf{x}) - V^P(\mathbf{x},\mathbf{y})\right] + \lambda_1 \int_Y \left[V^P(\mathbf{x},\mathbf{y}') - V^P(\mathbf{x},\mathbf{y})\right]_+ dG(\mathbf{y}').$$

Proof of Lemma 1

Proof. Fix a worker type $\mathbf{x}$. When separation risk is homogeneous, $\delta(\mathbf{y}) = \bar{\delta}$, the private match value is

$$P(\mathbf{x},\mathbf{y}) = \frac{f(\mathbf{x},\mathbf{y}) + \bar{\delta}U(\mathbf{x})}{\rho + \bar{\delta}}.$$

Since $U(\mathbf{x})$ does not depend on $\mathbf{y}$ and $\rho + \bar{\delta} > 0$,

$$P(\mathbf{x},\mathbf{y}') \geq P(\mathbf{x},\mathbf{y}) \quad \Longleftrightarrow \quad f(\mathbf{x},\mathbf{y}') \geq f(\mathbf{x},\mathbf{y}).$$

It remains to show that the planner has the same ranking. Suppose $f(\mathbf{x},\mathbf{y}') \geq f(\mathbf{x},\mathbf{y})$. If, toward a contradiction, $V^P(\mathbf{x},\mathbf{y}') < V^P(\mathbf{x},\mathbf{y})$, then subtracting the planner equation for $\mathbf{y}$ from the planner equation for $\mathbf{y}'$ gives

$$\begin{aligned}(\rho + \bar{\delta})\left[V^P(\mathbf{x},\mathbf{y}') - V^P(\mathbf{x},\mathbf{y})\right] = f(\mathbf{x},\mathbf{y}') - f(\mathbf{x},\mathbf{y}) \\ + \lambda_1 \int_Y \Big(\left[V^P(\mathbf{x},\widetilde{\mathbf{y}}) - V^P(\mathbf{x},\mathbf{y}')\right]_+ \\ - \left[V^P(\mathbf{x},\widetilde{\mathbf{y}}) - V^P(\mathbf{x},\mathbf{y})\right]_+ \Big) dG(\widetilde{\mathbf{y}}).\end{aligned}$$

The left-hand side is strictly negative under the contradiction. The first term on the right-hand side is weakly positive. The integrand is also weakly positive for every $\widetilde{\mathbf{y}}$, because $V^P(\mathbf{x}, \mathbf{y}') < V^P(\mathbf{x}, \mathbf{y})$ lowers the threshold inside the positive part. This is impossible. Hence

$$f(\mathbf{x}, \mathbf{y}') \geq f(\mathbf{x}, \mathbf{y}) \quad \Longrightarrow \quad V^P(\mathbf{x}, \mathbf{y}') \geq V^P(\mathbf{x}, \mathbf{y}).$$

Applying the same argument with $\mathbf{y}$ and $\mathbf{y}'$ reversed gives the reverse weak-order implication. Therefore

$$f(\mathbf{x}, \mathbf{y}') \geq f(\mathbf{x}, \mathbf{y}) \quad \Longleftrightarrow \quad V^P(\mathbf{x}, \mathbf{y}') \geq V^P(\mathbf{x}, \mathbf{y}),$$

which proves the lemma. □

Proof of Proposition 1

Proof. The private match surplus is

$$S(\mathbf{x}, \mathbf{y}) = \frac{f(\mathbf{x}, \mathbf{y}) - b}{\rho + \delta(\mathbf{y})}.$$

Differentiating with respect to worker skill x_k gives

$$S_{x_k}(\mathbf{x}, \mathbf{y}) = \frac{f_{x_k}(\mathbf{x}, \mathbf{y})}{\rho + \delta(\mathbf{y})}.$$

Differentiating this expression with respect to occupational requirement y_j gives

$$S_{x_k, y_j}(\mathbf{x}, \mathbf{y}) = \frac{f_{x_k y_j}(\mathbf{x}, \mathbf{y})}{\rho + \delta(\mathbf{y})} - \frac{f_{x_k}(\mathbf{x}, \mathbf{y}) \delta_{y_j}(\mathbf{y})}{[\rho + \delta(\mathbf{y})]^2}.$$

Since $f_{x_k}(\mathbf{x}, \mathbf{y}) > 0$, a requirement with $\delta_{y_j}(\mathbf{y}) > 0$ subtracts a positive term from the productivity complementarity $f_{x_k y_j}(\mathbf{x}, \mathbf{y})/[\rho + \delta(\mathbf{y})]$. Thus higher separation risk along dimension j reduces the local complementarity of private match surplus along the (x_k, y_j) margin. □

Top of the Job Ladder

Proof. In the decentralized economy, job-to-job mobility is governed by comparisons of $P(\mathbf{x}, \mathbf{y})$. Because

$$S(\mathbf{x}, \mathbf{y}) = P(\mathbf{x}, \mathbf{y}) - U(\mathbf{x})$$

and $U(\mathbf{x})$ does not depend on $\mathbf{y}$, maximizing $P(\mathbf{x}, \mathbf{y})$ over jobs is equivalent to maximizing $S(\mathbf{x}, \mathbf{y})$ over jobs. Therefore the top of the decentralized job ladder is

$$\mathbf{y}^D(\mathbf{x}) = \arg\max_{\mathbf{y}} S(\mathbf{x}, \mathbf{y}).$$

For the planner, the job ladder is ranked by the social value $V^P(\mathbf{x}, \mathbf{y})$. Therefore the top of the planner's job ladder is

$$\mathbf{y}^P(\mathbf{x}) = \arg\max_{\mathbf{y}} V^P(\mathbf{x}, \mathbf{y}).$$

At $\mathbf{y}^P(\mathbf{x})$, no offered job has a strictly higher social value. Hence

$$\int_Y \left[V^P(\mathbf{x}, \mathbf{y}') - V^P(\mathbf{x}, \mathbf{y}^P(\mathbf{x}))\right]_+ dG(\mathbf{y}') = 0.$$

In the local top-rung comparisons below, we use the regular case in which the top job is unique and the offer distribution places no mass on jobs tied with the top value. The search term then has no first-order effect at the top. The planner value at the top of the ladder is therefore characterized by

$$V^P(\mathbf{x}, \mathbf{y}^P(\mathbf{x})) = \frac{f(\mathbf{x}, \mathbf{y}^P(\mathbf{x})) + \delta(\mathbf{y}^P(\mathbf{x}))U^P(\mathbf{x})}{\rho + \delta(\mathbf{y}^P(\mathbf{x}))}.$$

□

Proof of Proposition 2

Proof. Fix $\mathbf{x}$. Write the heterogeneous-risk perturbation as

$$\delta(\mathbf{y}; \epsilon) = \bar{\delta} + \epsilon h(\mathbf{y}),$$

where $\epsilon > 0$ is small and, at the homogeneous-risk top job $\mathbf{y}^0(\mathbf{x})$,

$$h_{y_m}(\mathbf{y}^0(\mathbf{x})) > 0, \qquad h_{y_c}(\mathbf{y}^0(\mathbf{x})) < 0.$$

We work in the regular interior case studied in the text: $\mathbf{y}^0(\mathbf{x})$ is a strict local maximum, f is locally separable near $\mathbf{y}^0(\mathbf{x})$, and

$$f_{y_m y_m}(\mathbf{x}, \mathbf{y}^0(\mathbf{x})) < 0, \qquad f_{y_c y_c}(\mathbf{x}, \mathbf{y}^0(\mathbf{x})) < 0.$$

We also focus on the economically relevant case in which the benchmark top job is socially accepted, so

$$f(\mathbf{x}, \mathbf{y}^0(\mathbf{x})) > \rho U^P(\mathbf{x}).$$

For $r \in \{D, P\}$, let $J^D = P$, $J^P = V^P$, $U^D = U$, and let U^P denote the planner unemployment value. At the top of the ladder,

$$J^r(\mathbf{x}, \mathbf{y}; \epsilon) = \frac{f(\mathbf{x}, \mathbf{y}) + \delta(\mathbf{y}; \epsilon) U^r(\mathbf{x}; \epsilon)}{\rho + \delta(\mathbf{y}; \epsilon)}.$$

Thus, with

$$\kappa^r(\mathbf{x}, \mathbf{y}; \epsilon) = J^r(\mathbf{x}, \mathbf{y}; \epsilon) - U^r(\mathbf{x}; \epsilon),$$

the derivative with respect to job requirements is

$$\nabla_y J^r(\mathbf{x}, \mathbf{y}; \epsilon) = \frac{\nabla_y f(\mathbf{x}, \mathbf{y}) - \kappa^r(\mathbf{x}, \mathbf{y}; \epsilon) \nabla_y \delta(\mathbf{y}; \epsilon)}{\rho + \delta(\mathbf{y}; \epsilon)}.$$

The top job therefore satisfies

$$\nabla_y f(\mathbf{x}, \mathbf{y}^r(\mathbf{x}; \epsilon)) - \kappa^r(\mathbf{x}, \mathbf{y}^r(\mathbf{x}; \epsilon); \epsilon) \nabla_y \delta(\mathbf{y}^r(\mathbf{x}; \epsilon); \epsilon) = 0.$$

At $\epsilon = 0$, separation risk is homogeneous. Then $\nabla_y \delta(\mathbf{y}; 0) = 0$, and both the decentralized economy and the planner choose $\mathbf{y}^0(\mathbf{x})$, which solves

$$\nabla_y f(\mathbf{x}, \mathbf{y}^0(\mathbf{x})) = 0.$$

Let

$$\kappa_0^r(\mathbf{x}) = J^r(\mathbf{x}, \mathbf{y}^0(\mathbf{x}); 0) - U^r(\mathbf{x}; 0).$$

The implicit function theorem gives

$$\left. \frac{d\mathbf{y}^r(\mathbf{x}; \epsilon)}{d\epsilon} \right|_{\epsilon=0} = \kappa_0^r(\mathbf{x}) \left[f_{yy}(\mathbf{x}, \mathbf{y}^0(\mathbf{x})) \right]^{-1} \nabla_y h(\mathbf{y}^0(\mathbf{x})).$$

Since f is locally separable, the Hessian is diagonal at $\mathbf{y}^0(\mathbf{x})$. Therefore

$$\left. \frac{dy_m^r(\mathbf{x}; \epsilon)}{d\epsilon} \right|_{\epsilon=0} = \kappa_0^r(\mathbf{x}) \frac{h_{y_m}(\mathbf{y}^0(\mathbf{x}))}{f_{y_m y_m}(\mathbf{x}, \mathbf{y}^0(\mathbf{x}))} < 0$$

and

$$\left.\frac{dy_c^r(\mathbf{x};\epsilon)}{d\epsilon}\right|_{\epsilon=0} = \kappa_0^r(\mathbf{x})\frac{h_{y_c}(\mathbf{y}^0(\mathbf{x}))}{f_{y_cy_c}(\mathbf{x},\mathbf{y}^0(\mathbf{x}))} > 0,$$

provided $\kappa_0^r(\mathbf{x}) > 0$.

It remains to compare the size of the decentralized and planner responses. At the homogeneous-risk benchmark,

$$\kappa_0^D(\mathbf{x}) = \frac{f(\mathbf{x},\mathbf{y}^0(\mathbf{x})) - b}{\rho + \bar{\delta}}, \qquad \kappa_0^P(\mathbf{x}) = \frac{f(\mathbf{x},\mathbf{y}^0(\mathbf{x})) - \rho U^P(\mathbf{x})}{\rho + \bar{\delta}}.$$

Because $U^P(\mathbf{x}) > U(\mathbf{x}) = b/\rho$,

$$\kappa_0^D(\mathbf{x}) - \kappa_0^P(\mathbf{x}) = \frac{\rho\left[U^P(\mathbf{x}) - U(\mathbf{x})\right]}{\rho + \bar{\delta}} > 0.$$

The maintained social-acceptance condition gives $\kappa_0^P(\mathbf{x}) > 0$. Hence

$$\kappa_0^D(\mathbf{x}) > \kappa_0^P(\mathbf{x}) > 0.$$

The manual response is negative, so the larger decentralized surplus implies a stronger downward movement in y_m:

$$\left.\frac{dy_m^D}{d\epsilon}\right|_{\epsilon=0} < \left.\frac{dy_m^P}{d\epsilon}\right|_{\epsilon=0} < 0.$$

The cognitive response is positive, so the larger decentralized surplus implies a stronger upward movement in y_c:

$$\left.\frac{dy_c^D}{d\epsilon}\right|_{\epsilon=0} > \left.\frac{dy_c^P}{d\epsilon}\right|_{\epsilon=0} > 0.$$

For all sufficiently small $\epsilon > 0$, these derivative inequalities imply

$$y_m^D(\mathbf{x}) < y_m^P(\mathbf{x}) < y_m^0(\mathbf{x}), \qquad y_c^D(\mathbf{x}) > y_c^P(\mathbf{x}) > y_c^0(\mathbf{x}).$$

□

Proof of Proposition 3

Proof. We first spell out the additional regularity condition used for the slope comparison. In the same local neighborhood as in Proposition 2, write

$$\delta(\mathbf{y};\epsilon) = \bar{\delta} + \epsilon h(\mathbf{y}).$$

The risk perturbation is locally affine in job requirements, so h_{y_m} and h_{y_c} are locally constant, with

$$h_{y_m} > 0, \qquad h_{y_c} < 0.$$

The local curvature terms $f_{y_m y_m}$ and $f_{y_c y_c}$ are also locally constant and strictly negative. Finally, at the homogeneous-risk benchmark, the planner unemployment value is increasing in each worker skill but less than one-for-one with the flow-output value of that skill at the benchmark top job:

$$0 < \rho U^P_{x_k}(\mathbf{x}) < f_{x_k}(\mathbf{x}, \mathbf{y}^0(\mathbf{x})), \qquad k \in \{m, c\}.$$

From the proof of Proposition 2, for $i \in \{m, c\}$ and $r \in \{D, P\}$,

$$y^r_i(\mathbf{x}; \epsilon) = y^0_i(\mathbf{x}) + \epsilon \kappa^r_0(\mathbf{x}) \frac{h_{y_i}}{f_{y_i y_i}} + o(\epsilon).$$

The local constancy assumptions imply that $h_{y_i}/f_{y_i y_i}$ does not vary with $\mathbf{x}$ in this neighborhood. Differentiating the expansion with respect to x_ℓ, for $\ell \in \{m, c\}$, gives

$$\frac{\partial y^r_i(\mathbf{x}; \epsilon)}{\partial x_\ell} = \frac{\partial y^0_i(\mathbf{x})}{\partial x_\ell} + \epsilon \frac{h_{y_i}}{f_{y_i y_i}} \frac{\partial \kappa^r_0(\mathbf{x})}{\partial x_\ell} + o(\epsilon).$$

Because b is constant and $\mathbf{y}^0(\mathbf{x})$ solves $\nabla_y f(\mathbf{x}, \mathbf{y}^0(\mathbf{x})) = 0$, the envelope theorem gives

$$\frac{\partial \kappa^D_0(\mathbf{x})}{\partial x_\ell} = \frac{f_{x_\ell}(\mathbf{x}, \mathbf{y}^0(\mathbf{x}))}{\rho + \bar{\delta}}, \qquad \frac{\partial \kappa^P_0(\mathbf{x})}{\partial x_\ell} = \frac{f_{x_\ell}(\mathbf{x}, \mathbf{y}^0(\mathbf{x})) - \rho U^P_{x_\ell}(\mathbf{x})}{\rho + \bar{\delta}}.$$

The additional regularity condition therefore implies

$$\frac{\partial \kappa^D_0(\mathbf{x})}{\partial x_\ell} > \frac{\partial \kappa^P_0(\mathbf{x})}{\partial x_\ell} > 0.$$

For the manual requirement, $h_{y_m} > 0$ and $f_{y_m y_m} < 0$, so

$$\frac{h_{y_m}}{f_{y_m y_m}} < 0.$$

Combining this sign with the surplus-gradient ordering yields, for sufficiently small $\epsilon > 0$,

$$\frac{\partial y^D_m}{\partial x_\ell} < \frac{\partial y^P_m}{\partial x_\ell} < \frac{\partial y^0_m}{\partial x_\ell}.$$

For the cognitive requirement, $h_{y_c} < 0$ and $f_{y_c y_c} < 0$, so

$$\frac{h_{y_c}}{f_{y_c y_c}} > 0.$$

The same surplus-gradient ordering then yields

$$\frac{\partial y_c^D}{\partial x_\ell} > \frac{\partial y_c^P}{\partial x_\ell} > \frac{\partial y_c^0}{\partial x_\ell}.$$

Setting $\ell = m$ gives

$$\frac{\partial y_m^D}{\partial x_m} < \frac{\partial y_m^P}{\partial x_m} < \frac{\partial y_m^0}{\partial x_m}, \qquad \frac{\partial y_c^D}{\partial x_m} > \frac{\partial y_c^P}{\partial x_m} > \frac{\partial y_c^0}{\partial x_m}.$$

Setting $\ell = c$ gives

$$\frac{\partial y_c^D}{\partial x_c} > \frac{\partial y_c^P}{\partial x_c} > \frac{\partial y_c^0}{\partial x_c}, \qquad \frac{\partial y_m^D}{\partial x_c} < \frac{\partial y_m^P}{\partial x_c} < \frac{\partial y_m^0}{\partial x_c}.$$

Finally, local separability implies that the homogeneous-risk top job solves the two separate first-order conditions

$$f_{m,y_m}(x_m, y_m^0(\mathbf{x})) = 0, \qquad f_{c,y_c}(x_c, y_c^0(\mathbf{x})) = 0.$$

Thus $y_m^0(\mathbf{x})$ does not depend on x_c, and $y_c^0(\mathbf{x})$ does not depend on x_m:

$$\frac{\partial y_m^0}{\partial x_c} = 0, \qquad \frac{\partial y_c^0}{\partial x_m} = 0.$$

Substituting these equalities gives the two cross-skill inequalities stated in the proposition. □

Wages

Consider an employed worker in job $\mathbf{y}$ with bargaining position $\hat{\mathbf{y}}$. The worker's contract value is $W(\mathbf{x}, \mathbf{y}, \hat{\mathbf{y}}) = P(\mathbf{x}, \hat{\mathbf{y}})$, with the convention that $P(\mathbf{x}, \hat{\mathbf{y}}) = U(\mathbf{x})$ if the bargaining position is unemployment. After an outside offer $\mathbf{y}'$, the worker's new contract value is

$$\min\left\{P(\mathbf{x}, \mathbf{y}), \max\left\{P(\mathbf{x}, \mathbf{y}'), P(\mathbf{x}, \hat{\mathbf{y}})\right\}\right\}.$$

The worker's contract value therefore satisfies

$$\rho P(\mathbf{x},\hat{\mathbf{y}}) = w(\mathbf{x},\mathbf{y},\hat{\mathbf{y}}) + \delta(\mathbf{y})\left[U(\mathbf{x}) - P(\mathbf{x},\hat{\mathbf{y}})\right] + \lambda_1 \int_Y \left[\min\{P(\mathbf{x},\mathbf{y}), P(\mathbf{x},\mathbf{y}')\} - P(\mathbf{x},\hat{\mathbf{y}})\right]_+ dG(\mathbf{y}').$$

Solving for wages and using $S(\mathbf{x},\mathbf{y}) = P(\mathbf{x},\mathbf{y}) - U(\mathbf{x})$ gives

$$w(\mathbf{x},\mathbf{y},\hat{\mathbf{y}}) = b + \left[\rho + \delta(\mathbf{y})\right] S(\mathbf{x},\hat{\mathbf{y}}) - \lambda_1 \int_Y \left[\min\{S(\mathbf{x},\mathbf{y}), S(\mathbf{x},\mathbf{y}')\} - S(\mathbf{x},\hat{\mathbf{y}})\right]_+ dG(\mathbf{y}').$$

For an employment bargaining position $\hat{\mathbf{y}}$, this can be written entirely in primitives as

$$\begin{aligned} w(\mathbf{x},\mathbf{y},\hat{\mathbf{y}}) = b + \frac{\rho + \delta(\mathbf{y})}{\rho + \delta(\hat{\mathbf{y}})}\left[f(\mathbf{x},\hat{\mathbf{y}}) - b\right] \\ - \lambda_1 \int_Y \left[\min\left\{\frac{f(\mathbf{x},\mathbf{y}) - b}{\rho + \delta(\mathbf{y})}, \frac{f(\mathbf{x},\mathbf{y}') - b}{\rho + \delta(\mathbf{y}')}\right\} - \frac{f(\mathbf{x},\hat{\mathbf{y}}) - b}{\rho + \delta(\hat{\mathbf{y}})}\right]_+ dG(\mathbf{y}'). \end{aligned} \tag{C.4}$$

If the bargaining position is unemployment, the same expression applies with $S(\mathbf{x},\hat{\mathbf{y}}) = 0$ in the surplus form above.

Homogeneous-Risk Unemployment Acceptance Margin

Suppose $\delta(\mathbf{y}) = \bar{\delta}$ and $\lambda_0 = \lambda_1$. Define

$$Q(\mathbf{x},\mathbf{y}) = V^P(\mathbf{x},\mathbf{y}) - U^P(\mathbf{x}).$$

Subtracting the planner unemployment equation from the planner employment equation gives

$$\begin{aligned} (\rho + \bar{\delta})Q(\mathbf{x},\mathbf{y}) = f(\mathbf{x},\mathbf{y}) - b \\ + \lambda_1 \int_Y \left[Q(\mathbf{x},\mathbf{y}') - Q(\mathbf{x},\mathbf{y})\right]_+ dG(\mathbf{y}') - \lambda_0 \int_Y \left[Q(\mathbf{x},\mathbf{y}')\right]_+ dG(\mathbf{y}'). \end{aligned}$$

At a marginal job for the planner, $Q(\mathbf{x},\mathbf{y}) = 0$. Hence

$$0 = f(\mathbf{x},\mathbf{y}) - b + (\lambda_1 - \lambda_0) \int_Y \left[Q(\mathbf{x},\mathbf{y}')\right]_+ dG(\mathbf{y}').$$

If $\lambda_0 = \lambda_1$, the planner's marginal accepted job satisfies

$$f(\mathbf{x},\mathbf{y}) = b.$$

The private worker accepts an unemployment offer if and only if

$$S(\mathbf{x}, \mathbf{y}) = \frac{f(\mathbf{x}, \mathbf{y}) - b}{\rho + \bar{\delta}} \geq 0,$$

which is also equivalent to $f(\mathbf{x}, \mathbf{y}) \geq b$. Thus, under homogeneous risk and $\lambda_0 = \lambda_1$, the planner and the decentralized economy have the same unemployment acceptance margin as well as the same job ranking.

Skill-Based Unemployment Insurance

Let the unemployment benefit be $B(\mathbf{x}) = b_m x_m$, and abstract for the moment from the financing tax. The private unemployment value becomes

$$U(\mathbf{x}; B) = \frac{b + B(\mathbf{x})}{\rho}.$$

At the top of the job ladder,

$$P(\mathbf{x}, \mathbf{y}; B) = \frac{f(\mathbf{x}, \mathbf{y}) + \delta(\mathbf{y}) U(\mathbf{x}; B)}{\rho + \delta(\mathbf{y})}.$$

Subtracting this value from the planner value gives

$$V^P(\mathbf{x}, \mathbf{y}) - P(\mathbf{x}, \mathbf{y}; B) = \delta(\mathbf{y}) \frac{U^P(\mathbf{x}) - U(\mathbf{x}; B)}{\rho + \delta(\mathbf{y})}.$$

As long as the policy does not make $U(\mathbf{x}; B)$ exceed $U^P(\mathbf{x})$, raising b_m reduces the gap between private and planner values for workers with higher x_m.

The same force appears in the local top-rung surplus:

$$\kappa^D(\mathbf{x}, \mathbf{y}; B) = P(\mathbf{x}, \mathbf{y}; B) - U(\mathbf{x}; B) = \frac{f(\mathbf{x}, \mathbf{y}) - b - B(\mathbf{x})}{\rho + \delta(\mathbf{y})}.$$

By lowering κ^D, the policy weakens the private movement toward lower manual requirements and higher cognitive requirements. This moves the private top job toward the planner top job as long as the policy does not overshoot the social outside value.

For the slope comparison, $B(\mathbf{x}) = b_m x_m$ directly changes the derivative of private top-rung

surplus with respect to x_m:

$$\frac{\partial \kappa^D(\mathbf{x}, \mathbf{y}^0(\mathbf{x}); B)}{\partial x_m} = \frac{f_{x_m}(\mathbf{x}, \mathbf{y}^0(\mathbf{x})) - b_m}{\rho + \bar{\delta}}.$$

It does not directly change the derivative with respect to x_c. Therefore this policy directly narrows the slope gaps that involve x_m. A benefit schedule depending on both skills would directly target both the x_m- and x_c-slope gaps in the local calculation.

We now provide a result that demonstrates that skill-based unemployment insurance can be implemented by the government if the government observes at least two job transitions of a worker.

Proposition C.1 (Identification from job-switch wage histories)**.** *Assume that the occupational skill-requirement distribution, $G(\boldsymbol{y})$ is absolutely continuous with two-dimensional support, $\rho + \delta(\boldsymbol{y}) > 0$, and the production technology is given by (21). Furthermore, suppose the production parameters are generic and nondegenerate, in particular*

$$\alpha_0 \neq 0, \qquad \alpha_1 \neq 0, \qquad \alpha_0 - 2\alpha_4 \neq 0, \qquad \alpha_1 - 2\alpha_5 \neq 0.$$

Suppose the government observes a worker's wages and occupational requirements at two successive job-to-job transitions,

$$\boldsymbol{y}_0 \to \boldsymbol{y}_1 \to \boldsymbol{y}_2.$$

For almost every $\lambda_1 > 0$, the Jacobian

$$\frac{\partial(w_1, w_2)}{\partial(x_m, x_c)}$$

has rank two with probability one over observed two-switch histories. Hence $\boldsymbol{x} = (x_m, x_c)$ is locally identified from the worker's observed job-switch wage history.

Proof. The private match surplus is

$$S(\boldsymbol{x}, \boldsymbol{y}) = \frac{f(\boldsymbol{x}, \boldsymbol{y}) - b}{\rho + \delta(\boldsymbol{y})}.$$

For the production function above,

$$S_{x_m}(\boldsymbol{x}, \boldsymbol{y}) = \frac{\alpha_0 y_m + 2\alpha_4 (x_m - y_m)\mathbf{1}\{x_m < y_m\}}{\rho + \delta(\boldsymbol{y})},$$

and

$$S_{x_c}(\boldsymbol{x}, \boldsymbol{y}) = \frac{\alpha_1 y_c + 2\alpha_5 (x_c - y_c)\mathbf{1}\{x_c < y_c\}}{\rho + \delta(\boldsymbol{y})}.$$

When a worker switches from $\boldsymbol{y}_{t-1}$ to $\boldsymbol{y}_t$, the previous job becomes the bargaining position in the new match. Thus, immediately following the switch,

$$w_t = b + [\rho + \delta(\boldsymbol{y}_t)] S(\boldsymbol{x}, \boldsymbol{y}_{t-1}) - \lambda_1 \int_{\mathcal{Y}} \left[\min\{S(\boldsymbol{x}, \boldsymbol{y}_t), S(\boldsymbol{x}, \boldsymbol{y}')\} - S(\boldsymbol{x}, \boldsymbol{y}_{t-1})\right]^+ dG(\boldsymbol{y}').$$

Because G is absolutely continuous, ties in match surplus occur with probability zero. Differentiating with respect to $\boldsymbol{x}$ gives

$$\begin{aligned}
\nabla_{\boldsymbol{x}} w_t = {} & [\rho + \delta(\boldsymbol{y}_t)] \nabla_{\boldsymbol{x}} S(\boldsymbol{x}, \boldsymbol{y}_{t-1}) \\
& - \lambda_1 \int_{S(\boldsymbol{x}, \boldsymbol{y}_{t-1}) < S(\boldsymbol{x}, \boldsymbol{y}') < S(\boldsymbol{x}, \boldsymbol{y}_t)} \left[\nabla_{\boldsymbol{x}} S(\boldsymbol{x}, \boldsymbol{y}') - \nabla_{\boldsymbol{x}} S(\boldsymbol{x}, \boldsymbol{y}_{t-1})\right] dG(\boldsymbol{y}') \\
& - \lambda_1 \int_{S(\boldsymbol{x}, \boldsymbol{y}') \geq S(\boldsymbol{x}, \boldsymbol{y}_t)} \left[\nabla_{\boldsymbol{x}} S(\boldsymbol{x}, \boldsymbol{y}_t) - \nabla_{\boldsymbol{x}} S(\boldsymbol{x}, \boldsymbol{y}_{t-1})\right] dG(\boldsymbol{y}').
\end{aligned}$$

Neither S nor the integration regions depend on λ_1. Therefore each row of the two-switch wage Jacobian is affine in λ_1, and its determinant is a polynomial of degree at most two in λ_1.

The constant coefficient of this polynomial is

$$[\rho + \delta(\boldsymbol{y}_1)][\rho + \delta(\boldsymbol{y}_2)] \det \begin{pmatrix} S_{x_m}(\boldsymbol{x}, \boldsymbol{y}_0) & S_{x_c}(\boldsymbol{x}, \boldsymbol{y}_0) \\ S_{x_m}(\boldsymbol{x}, \boldsymbol{y}_1) & S_{x_c}(\boldsymbol{x}, \boldsymbol{y}_1) \end{pmatrix}.$$

Up to the strictly positive factor $(\rho + \delta(\boldsymbol{y}_2))/(\rho + \delta(\boldsymbol{y}_0))$, this equals

$$\begin{aligned}
& \left[\alpha_0 y_{0m} + 2\alpha_4 (x_m - y_{0m})\mathbf{1}\{x_m < y_{0m}\}\right] \left[\alpha_1 y_{1c} + 2\alpha_5 (x_c - y_{1c})\mathbf{1}\{x_c < y_{1c}\}\right] \\
& \quad - \left[\alpha_1 y_{0c} + 2\alpha_5 (x_c - y_{0c})\mathbf{1}\{x_c < y_{0c}\}\right] \left[\alpha_0 y_{1m} + 2\alpha_4 (x_m - y_{1m})\mathbf{1}\{x_m < y_{1m}\}\right].
\end{aligned}$$

Conditional on $\boldsymbol{y}_0$, within each of the four regions defined by $y_{1m} \lessgtr x_m$ and $y_{1c} \lessgtr x_c$, this expression is affine in (y_{1m}, y_{1c}). Under the generic parameter restrictions above, it is not identically zero except for a measure-zero set of $\boldsymbol{y}_0$. Its zero set is therefore at most a finite union of one-dimensional curves in the two-dimensional support of G. Absolute continuity

of G implies

$$\Pr\left(\det\begin{pmatrix} S_{x_m}(\boldsymbol{x},\boldsymbol{y}_0) & S_{x_c}(\boldsymbol{x},\boldsymbol{y}_0) \\ S_{x_m}(\boldsymbol{x},\boldsymbol{y}_1) & S_{x_c}(\boldsymbol{x},\boldsymbol{y}_1)\end{pmatrix}=0\right)=0.$$

Hence, for almost every two-switch history, the determinant of the wage Jacobian is a nonzero polynomial in λ_1. A nonzero quadratic polynomial has at most two roots. By Fubini's theorem, for almost every $\lambda_1 > 0$, the set of two-switch histories for which the determinant is zero has probability zero.

Therefore

$$\operatorname{rank}\frac{\partial(w_1,w_2)}{\partial(x_m,x_c)}=2$$

almost surely, and the inverse function theorem implies that $\boldsymbol{x}$ is locally identified from the two observed switch wages and occupational requirements. □

Away from the Top of the Ladder

The planner employment equation can be written as

$$[\rho+\delta(\mathbf{y})]\,V^P(\mathbf{x},\mathbf{y})=f(\mathbf{x},\mathbf{y})+\delta(\mathbf{y})U^P(\mathbf{x})+\lambda_1\int_Y\left[V^P(\mathbf{x},\mathbf{y}')-V^P(\mathbf{x},\mathbf{y})\right]_+dG(\mathbf{y}').$$

The private match value can be written as

$$[\rho+\delta(\mathbf{y})]\,P(\mathbf{x},\mathbf{y})=f(\mathbf{x},\mathbf{y})+\delta(\mathbf{y})U(\mathbf{x}).$$

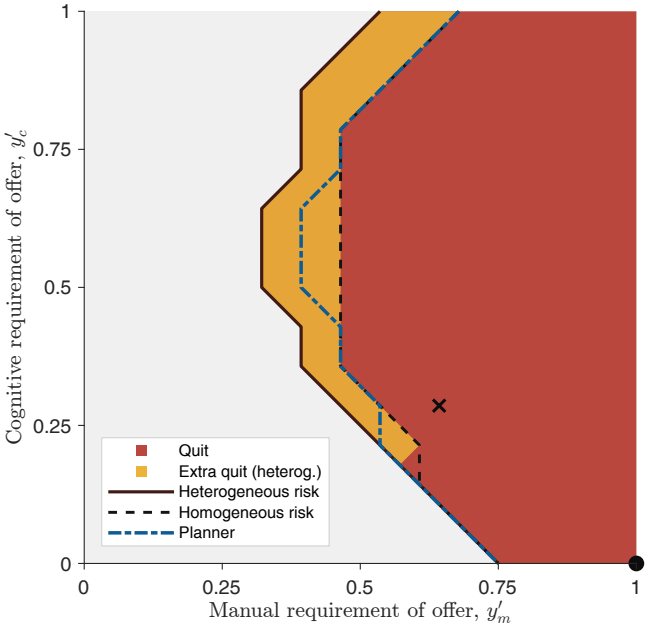
Subtracting the private value from the planner value gives

$$V^P(\mathbf{x},\mathbf{y})-P(\mathbf{x},\mathbf{y})=\frac{\delta(\mathbf{y})}{\rho+\delta(\mathbf{y})}\left[U^P(\mathbf{x})-U(\mathbf{x})\right]+\frac{\lambda_1}{\rho+\delta(\mathbf{y})}\int_Y\left[V^P(\mathbf{x},\mathbf{y}')-V^P(\mathbf{x},\mathbf{y})\right]_+dG(\mathbf{y}').$$

This is the decomposition used in the text.

C.2 Additional Quantitative Results

Figure C.2: Acceptance sets under heterogeneous and homogeneous separation risk



Notes: The background regions correspond to the calibrated heterogeneous-risk economy, with non-quitting outcomes grouped as stay. The dashed boundary overlays the homogeneous-risk benchmark. The yellow region highlights offers that are in the heterogeneous-risk quitting set but not in the homogeneous-risk quitting set.