

THE UNIVERSITY OF CHICAGO

SKILL REMOTENESS AND THE ECONOMICS OF LOCAL LABOR MARKETS

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

DEPARTMENT OF ECONOMICS

BY
CLAUDIA MACALUSO

CHICAGO, ILLINOIS

JUNE 2017

Copyright © 2017 by Claudia Macaluso

All Rights Reserved

To my parents, my sisters and my soon-to-be husband,
for their unfailing support.

As you set out for Ithaka
hope the voyage is a long one,
full of adventure, full of discovery.
Laistrygonians and Cyclops,
angry Poseidon — don't be afraid of them:
you'll never find things like that on your way
as long as you keep your thoughts raised high,
as long as a rare excitement
stirs your spirit and your body.
Laistrygonians and Cyclops,
wild Poseidon — you won't encounter them
unless you bring them along inside your soul,
unless your soul sets them up in front of you.

C.P. Cavafy, *Ithaka*

Table of Contents

List of Figures	vii
List of Tables	vii
Acknowledgments	xii
Abstract	xiii
1 Introduction	1
1.1 Skill remoteness and post-layoff labor market outcomes	1
1.2 Literature review	3
2 Local skill remoteness: concept and measurement	7
2.1 Skill mismatch and skill remoteness	7
2.2 Skill data	7
2.3 Heterogeneous occupations	11
2.4 Local labor markets	12
2.5 Skill remoteness as average distance	13
2.6 Skill remoteness in action	15
3 Skill remoteness and post-layoff labor market outcomes	20
3.1 Empirical findings from individual labor market longitudinal data	20
3.2 Earnings and wages	21

3.3	Re-employment rates and wages	27
3.4	Occupational mobility	32
3.5	Geographic mobility	36
3.6	Summary of empirical evidence	37
4	Skill remoteness in a stylized model of mismatch	40
4.1	Set-up	40
4.2	Match surplus, skill proximity and skill remoteness	44
4.3	Steady state equilibrium	47
4.4	Calibrating the cost of mismatch	50
4.5	Subsidized on-the-job training	54
4.6	Summary and concluding remarks	61
	References	64
	A Data Appendix	69
A.1	Major occupational groups	69
A.2	Skills	70
A.3	O*NET: brief description of the data	71
A.4	Skills versus tasks	72
A.5	Vacancy and employment shares data sources	73
A.6	Wage trimming procedure	76
	B Descriptive Appendix	78
B.1	Summary statistics	78
B.2	Matching	80
B.3	Augmented CPS	82
B.4	Selection on unobservables concerns	82

B.5 NLSY79: brief description of the data	85
C Theory Appendix	86
C.1 Algorithm	86

List of Figures

2.1	Panel structure of the CPS: 4 months in the sample, 8 out of the sample and 4 months in again. In this example, 2 unemployment spells are depicted. . . .	9
2.2	The distance rank between occupations predicts the magnitude of gross flows between them: the closer the two occupations' skill profiles, the larger the number of workers who became went from one to the other.	10
2.3	Each occupation displays different local skill remoteness values depending on its location.	16
2.4	Skill remoteness for laid-off workers in the South West.	17
2.5	Average skill remoteness of laid-off workers, by city. CPS-O*NET 2000.	18
3.1	Predicted earnings from regression (3.1). Standard errors clustered at the city-year level. Source: NLSY79 1994-2012.	26
3.2	Monthly re-employment rate for skill-remote and skill-central laid-off workers. SE clustered at MSA-year level. Top: CPS, 2000-2015. Bottom: NLSY79 1994-2012.	30
3.3	Wages at re-employment for laid-off workers at the 25th and at the 75thremoteness percentile. SE clustered at the MSA-year level. Source: NLSY79, 1994-2012.	31

3.4	The predicted occupational mobility rate is 8-14% higher for workers who lost their job at the 75th skill remoteness percentile than those at 25th skill remoteness percentile. Source: CPS, 2000-2015. SE clustered at MSA-year level.	33
3.5	laid-off workers whose occupation at layoff was skill-remote are more likely to be re-employed in an occupation that has a large skill distance with respect to the lost job. Source: CPS, 2000-2015.	35
3.6	The predicted probability of migration for laid-off workers at the 25th and at the 75th remoteness percentile.	37
3.7	Migration is directed towards cities where the movers' original occupation is less skill-remote. Source: NLSY79 1994-2012.	38
4.1	Evaluating the approximation of the theoretical proximity index with the empirical remoteness measure for several levels of training cost α . Source: HWOL and O*NET data in 2006.	47
4.2	Median and 75th pctile of skill remoteness, as a function of the cost of the training. The latter increases more than the former.	57
4.3	The aggregate unemployment rate increases when the cost of training increases, in a markedly non-linear fashion.	57
4.4	Average earnings and wages decrease when the cost of training increases.	58
4.5	As the cost of mismatch increases, the set of productive matches decreases.	60
4.6	As the cost of mismatch increases, sectoral dispersion in mkt tightness increases.	60
A.1	Example of the O*NET Skills questionnaire. Highlighted in orange, the level score which is the basis of the skill distances used in constructing the local skill remoteness measure.	71

A.2	Employment and vacancy shares for 51 metropolitan statistical areas and 6 occupational groups, HWOL and OES monthly data 2005-2015.	76
B.1	Skill remoteness values across U.S. MSAs for distinct occupational groups. . .	79
B.2	The CPS 4-8-4 panel scheme: example with an initial unemployment spell. Green dots denote interview months; blue “w” letters denote interview months in which wage information is collected.	81
B.3	Residual wage level and skill remoteness. NLSY79 1994-2012.	84
B.4	Residual wage growth and skill remoteness. NLSY79 1994-2012.	84

List of Tables

2.1	The elasticity of gross inter-occupational flows to skill distance between occupations is 77%.	10
2.2	Summary statistics, skill remoteness. CPS-O*NET 2000-2015.	15
3.1	Earnings regression (3.1). SE clustered at the city-year level (953 clusters). Source: NLSY79 1994-2012.	25
3.2	Employment rate regression (3.2): coefficient on local skill remoteness and implied losses. Source: CPS 2000-15.	28
3.3	Employment rate regression (3.2): predicted re-employment rate after 12 months from layoff. Source: NLSY79 1994-2012.	29
3.4	Skill remoteness at layoff increases occupational change rates up to 48 months. Source: NLSY79 1994-2012.	34
3.5	Occupational change accounts for approximately half of the effect of skill remoteness at layoff during the first quarter after layoff, but has no impact afterwards. Source: NLSY79 1994-2012.	34
4.1	Calibrated parameters and respective data sources. Monthly frequency, data at May 2006.	52
4.2	Model fit, aggregate moments, calibration at May 2006. Data: CPS and OES.	53
4.3	Aggregate effects of varying the cost of mismatch.	56
B.1	Average skill remoteness by demographics and city size groups. CPS 2000-2015.	78

ACKNOWLEDGMENTS

I thank my advisors Steven J. Davis, Robert Shimer, Loukas Karabarbounis and Jonathan Dingel for their valuable comments and encouragement. In addition, this work greatly benefited from conversations with many brilliant economists, among which Gadi Barlevy, Stephane Bonhomme, Jeff Campbell, Mariacristina De Nardi, Thibaut Lamadon, Jeremy Lise, Derek Neal, Aaron Pancost, Alessandra Voena, Chen Yeh and many others at the University of Chicago, the University of Minnesota and the Federal Reserve Bank of Chicago. Friends and family have contributed greatly to this dissertation by their continuous support: without them, I would have never neither started nor finished my Ph.D. Therefore, a special thought of gratitude goes to Allison, Carla, David, Holly, Marcello, Niena, Winnie, my parents Maria and Giovanni, and my sisters Silvia and Giulia. Finally, I dedicate this dissertation to the memory of my grandparents, Grazia and Francesco: through their quiet, simple lives in the mountains of my native Sicily, they have taught me the values any scholarly work is predicated upon: perseverance, honesty and a genuine passion for knowledge. *Grazie di tutto, nonni.*

ABSTRACT

This work quantifies the effects of discrepancies between local supply and demand for skills on wages, employment, and mobility rates of laid-off workers. I propose the concept of *local skill remoteness* to capture the degree of dissimilarity between the skill profiles of workers and jobs in a local labor market. I implement a measure of local skill remoteness at the occupation-city level, and find that higher skill remoteness at layoff is associated with lower re-employment rates and lower wages upon re-employment. Earnings differences between the top and bottom skill remoteness quartiles amount to a loss of 15% of the median worker's annual income and persist for at least two years. Skill-remote workers also have a higher probability of changing occupation, a lower probability of being re-employed at jobs with similar skill profiles, a higher propensity to migrate to another city and, conditional on migration, a higher likelihood of becoming less skill-remote. Motivated by this evidence, I develop a search-and-matching model with two-sided heterogeneity that provides a natural framework to interpret my skill remoteness measure. I use a calibrated version of the model to show that subsidies to on-the-job training lower the average skill remoteness of unemployed workers, thus the aggregate unemployment rate. The marginal benefit of such a policy is increasing in the level of unemployment.

CHAPTER 1

INTRODUCTION

1.1 Skill remoteness and post-layoff labor market outcomes

This work studies how labor market outcomes for laid-off workers are affected by disparities between skills that workers supply and skills that employers demand. In the presence of search frictions in the labor market, such differences potentially determine both individual economic outcomes — such as employment status and wages — and aggregate allocative efficiency. To investigate these effects, I develop the concept of *local skill remoteness* and quantify the extent to which workers' skill profiles differ from jobs' skill profiles in a local labor market. I propose a measure of skill remoteness that is consistent with a search-and-matching model with two-sided heterogeneity, and implement it using U.S. micro-data on the skill content of occupations and employment composition of cities. Using individual labor market histories, I show that skill remoteness at layoff is associated with lower earnings for at least two years after layoff. Furthermore, most losses are attributable to lower wages upon re-employment, not longer non-employment spells. Skill remoteness at layoff also affects occupational change and geographic mobility: skill-remote workers have a higher propensity to change occupation or migrate to another city after layoff.

Skill remoteness differs from skill mismatch. Skill mismatch characterizes the difference between a worker's and a job's skill profiles in a specific employment relationship. Skill remoteness, instead, refers to how similar the worker's skills are to those required by *other* jobs in a specific location. Therefore, I define skill-remote workers as individuals in areas with few occupations similar to theirs (where similarity is assessed on the basis of jobs' skill profiles). These workers have a harder time finding a suitable job than workers in areas with many similar jobs, increasing the likelihood that they are poorly matched upon

re-employment.

I construct a measure of skill remoteness that varies for the same occupation across locations, and also across occupations in the same city. To allow for variation along both dimensions, I first use detailed data on the skill content of occupations to characterize them as vectors of skills and compute distances between them. Then, to consider how plentiful various jobs are in different locations, I use data on the occupational composition of city-level employment.

Studying U.S. workers' re-employment histories, I provide evidence that unemployed individuals with greater local skill remoteness earn substantially lower wages, become re-employed more slowly and are more likely to change their occupation or location upon re-employment. Specifically, I use the longitudinally-linked Current Population Survey (CPS) and the National Longitudinal Survey of Youth 1979 (NLSY79) to show how recovery paths for workers at the 75th skill remoteness percentile differ from those of workers at the 25th. Earning differences are large and persistent: the inter-quartile range amounts to a loss of more than \$14,000 over two years. I find limited support in the data for substantially longer non-employment spells for skill-remote workers: in fact, most losses are attributable to lower wages upon re-employment, not persistent joblessness.

Skill-remote laid-off workers are also more prone to both occupational change and geographic mobility, even four years after the original layoff episode. Skill remoteness at job loss is a good predictor of the direction of such changes; skill-remote laid-off workers are, on average, re-employed in an occupation whose skill content is half a standard deviation further from the previous job's skill profile than skill-central ones. Migration rates across cities are also directed: laid-off workers who leave their city of residence after layoff tend to reduce their occupation's skill remoteness in the new location.

Motivated by these empirical patterns, I develop a search-and-matching model with two-sided heterogeneity to illustrate the effect of changes in skill remoteness when occupational

choices are endogenous. The model features a natural role for skill remoteness in the job-finding rate; since skill-remote workers have skills that are less suitable for the jobs available in their labor market, they are less likely to become re-employed. Skill-remote workers are also more likely to be poorly matched upon re-employment, lowering their productivity and wages. In a calibration exercise, I use the model to show a positive, non-linear relationship between subsidies to on-the-job training and the average skill remoteness of unemployed workers. A drop in training costs lowers both the average skill remoteness of unemployed workers and the aggregate unemployment rate. In addition, the marginal benefit of such a policy is increasing in the level of unemployment.

1.2 Literature review

This work primarily contributes to two strands of literature: the effects of mismatch on the labor market and the role of specific human capital in the consequences of job loss.

A well-cited example of the former literature is Şahin, Song, Topa and Violante (2014). Using a “misallocation” approach, the authors draw inference on the contribution of mismatch to aggregate unemployment by comparing the planner’s preferred allocation and the empirical distribution of job seekers. They find that, during the Great Recession, mismatch accounts for at most a loss of three percentage points in the monthly job-finding rate. In contrast to Şahin, Song, Topa and Violante (2014), I use a random search framework in which workers search in a single market, meet with many randomly assigned jobs but match with only a subset of them. This framework yields a natural index of skill remoteness that describes the extent to which unemployed workers are exposed to mismatch as they search for a job in their city. I find a modest impact of skill remoteness on re-employment rates, as in Şahin, Song, Topa and Violante (2014); unlike them, however, I also document a large,

persistent effect of skill remoteness on wages and mobility rates.¹

My approach expands existing empirical studies on the effect of mismatch on wages, by documenting spatial heterogeneity in the exposure to mismatch and focusing on local skill remoteness. Gathmann and Schoenberg (2010) and Guvenen, Kuruscu, Tanaka and Wiczer (2015), for example, use a mismatch index also based on occupation-level skill data. They conclude that mismatch affects returns to tenure, wage growth over the lifecycle, and cross-occupational mobility patterns. In this work, I extend Gathmann and Schoenberg’s (2010) results to a multi-city environment in the U.S. context. Furthermore, building upon their and Guvenen, Kuruscu, Tanaka and Wiczer’s (2015) findings on labor mobility, I provide evidence on the pronounced spatial disparities in workers’ reallocation opportunities after layoff.²

I find that spatial differences in skill remoteness also lead to widespread geographic relocation among laid-off workers, and even more so among skill-remote ones. On average, migration results in a drop in workers’ skill remoteness, in accordance with the large relocation costs and income benefits put forth by the migration and labor market outcomes literature (Kennan and Walker, 2011; Notowidigdo, 2013; Yagan, 2016).

My work explicitly considers variation in skill remoteness across cities and occupations, and shows how the interaction between these two dimensions affects individual and aggregate labor market adjustments. Andersson, Haltiwanger, Kutzbach, Pollakowski, Weinberg (2014) or Marinescu and Rathelot (2016) consider mismatch that arises from job openings not being located in the same geographic location as job seekers, but do not mention oc-

1. Using the same “misallocation” empirical strategy and data from the United Kingdom, Patterson, Şahin, Topa, and Violante (2016) show that the effect of mismatch on labor productivity growth is larger and more persistent.

2. Lindenlaub (2014), Lise and Postel-Vinay (2015), and Lindenlaub and Postel-Vinay (2016) are other examples of works that use skill-level data to provide measures of mismatch. They combine structural estimation with skill-level micro-data to explore sorting patterns across occupations and efficiency in frictionless and frictional labor markets.

cupational characteristics. Şahin, Song, Topa and Violante (2014) and Hertz and van Rens (2016) calibrate a structural framework to a system of geographically distinct markets but then compute an aggregate index of mismatch that does not vary across locations. Şahin, Song, Topa and Violante (2014) also mention a calibration in which a city and an occupation define a market, similar to the current work. However, they maintain that such a granular analysis is unfeasible in the case of the structural estimation procedure they propose because of paucity of data and computational burden. The skill remoteness approach I introduce addresses both concerns; it features variation across space because it exploits heterogeneity in cities' occupational structures, and accommodates high-dimensional heterogeneity in occupations by considering the average distance between occupational skill profiles of workers and jobs in each city.³

Lastly, my findings show that recovery after job loss is heterogeneous across job seekers that are located in different cities; these differences can be traced back to the interaction between heterogeneity in the skill content of occupations and heterogeneity in the occupational structures of local labor markets. Therefore, my work contributes to the literature that investigates earnings losses after job loss. Existing studies have focused on characteristics of the worker or of the job, including the timing of layoff (Jacobson, Lalonde and Sullivan, 1993; Farber, 1993; Davis and von Wachter, 2011; Krolikowski, 2015; Jarosch, 2015; Huckfeldt, 2016). I consider instead spatial variation in workers' local skill remoteness.

The work is organized in 3 more chapters. In chapter 2, I provide an intuitive derivation of skill remoteness and show how to implement it empirically. Chapter 3 describes the bulk of the empirical analysis, and provides evidence on how local skill remoteness influences labor market outcomes for laid-off workers. Chapter 4 develops a theoretical framework that

3. Since I summarize high-dimensional heterogeneity in skills using a one-dimensional average measure (skill remoteness), my approach emphasizes mean skill differences and leaves other, potentially relevant moments for future research.

illustrates how skill remoteness relates to individual and aggregate outcomes when the labor market is frictional.

CHAPTER 2

LOCAL SKILL REMOTENESS: CONCEPT AND MEASUREMENT

2.1 Skill mismatch and skill remoteness

In this work, I refer to “mismatch” as the extent to which a worker’s skills differ from the skills her job demands. Notice how this presumes the existence of an employment relationship. I propose the concept of “local skill remoteness” to broaden the scope of mismatch to the unemployed. I characterize skill remoteness as the extent to which a worker’s skills differ from those demanded by *other* jobs in her city. In this section, I lay out an intuitive framework that yields a measure of skill remoteness based on the skill content of occupations and city-level occupational employment shares. I implement this measure with U.S. micro-data and show empirical patterns across occupations and cities. Theoretically inclined readers are referred to section 4, in which I derive a similar skill remoteness measure in the context of a search-and-matching model with two-sided heterogeneity.

2.2 Skill data

Throughout this work, I concentrate on differences between the skills demanded by jobs and those supplied by workers. Since skills can be *taught*, focusing on skills is particularly informative when developing policies to facilitate re-employment of displaced workers.¹ Much literature also espouses human capital specificity as a determinant of individual employment outcomes and highlights how skills need not be perfectly transferable across jobs (Neal 1995, 1999; Kambourov and Manovski 2009a, 2009b; Poletaev and Robinson, 2010).

1. Training programs received considerable attention after the 2008-2009 Recession, since job losses were concentrated in declining sectors (Jaimovich and Siu, 2014), and the U.S. government greatly increased public spending on training programs for laid-off workers.

I begin my analysis by characterizing heterogeneity in the skills that jobs require for performance. I follow the literature on specific human capital — Kambourov and Manovskii (2009a, 2009b) and Gathmann and Schoenberg (2010) — when presuming that the first-order dimension of skill heterogeneity is at the occupation level.² I identify 22 occupational groups and respective skill content from the O*NET 2000-2015 occupational panels.

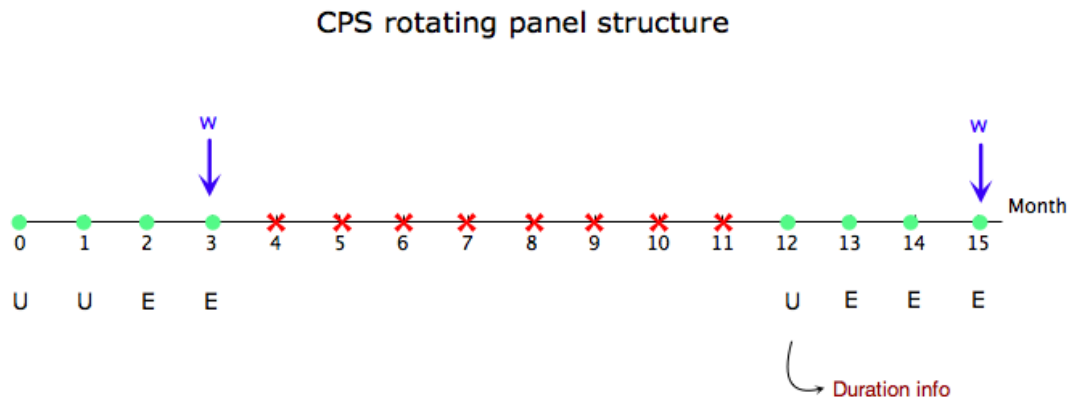
The O*NET (Occupational information Network) describes more than 900 occupations in the United States, spanning 2000-2015. Its core information is the mix of knowledge, skills, and abilities that occupations require. To conduct my analysis, I use the *Skills* descriptor. In the O*NET questionnaire, skills are defined as “the ability to perform a task well, usually developed over time through training or experience, can be used to do work in many jobs or in learning.” Workers are asked to indicate “the level [of each skill] *needed* to perform the [worker’s] current job,” on a scale from 1 to 7.³

Using skill data from O*NET offers several advantages. First, it provides clear interpretation of findings, since it mirrors human capital acquisition on the job. Second, skill data were derived from job incumbents, and unlike occupational descriptions in the DOT, they are less prone to classification and coding errors. In particular, the DOT was compiled by occupational analysts who attributed task scores based on job descriptions, resulting in a non-standardized, volatile set of tasks attributed to various jobs over time. The skill content of jobs in O*NET is instead documented richly and consistently: 7 standardized levels of 35 skills for each occupation, reported annually. I normalized these scores to be in the unit

2. The literature also recognizes the role of industry-specific knowledge and skills and consequently, although my skill mismatch measure varies at the occupation-city level, all empirical specifications include extensive industry controls.

3. The Skills descriptor in O*NET explicitly considers abilities and attitudes a worker may learn and ameliorate on the job, such as *Active Listening*, *Service orientation* and *Complex problem solving*. The literature, instead, uses either individual qualities such as *Physical strength* or *General intelligence* (Poletaev and Robinson, 2008) or things workers do such as *Setting limits and tolerances* and other task-attributes in Autor, Levy and Murnane (2003). Using skills provides characterizes the human capital that is developed on-the-job more closely and offers an exhaustive description of occupations that is standardized and consistent over time and across jobs.

Figure 2.1: Panel structure of the CPS: 4 months in the sample, 8 out of the sample and 4 months in again. In this example, 2 unemployment spells are depicted.



interval.

Finally, skill distances between occupations are highly predictive of occupational flows. To show this, I use inter-occupational flows from the Current Population Survey (CPS). The CPS is the well-used household survey that is the source of official labor market statistics. In addition to its significance as a cross-sectional dataset, the CPS also has a rotating panel structure. Individuals are interviewed for four consecutive months, then left out of the sample for eight months and interviewed again for four last consecutive months (see figure 2.1 for an illustration). It is precisely this limited panel data structure that I use in my analysis of occupational change. Though the panel dimension is limited, the CPS has the considerable strength of a large sample size.⁴

A log-log regression of inter-occupational flows on skill distances gives an coefficient of 0.77. That is, a 1% increase in the distance between occupations decreases the flows between them by 0.77%. The regression includes fixed effects for the previous and current occupations and the distance between them. The R^2 is 81%. The contribution of the distance term, on

4. See the paragraph dedicated to the month-by-month matching procedure in the Data Appendix for details on the longitudinally linked CPS.

top of the fixed effects, is 23%. A graph of worker flows by skill distances ranks shows a strong positive relationship as well (see table 2.1 and figure 2.2).

Figure 2.2: The distance rank between occupations predicts the magnitude of gross flows between them: the closer the two occupations' skill profiles, the larger the number of workers who became went from one to the other.

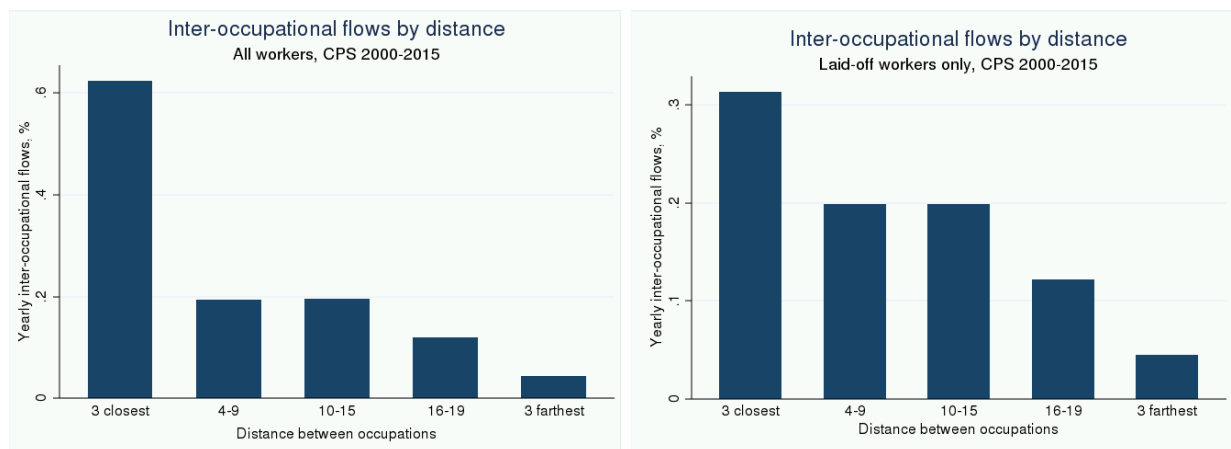


Table 2.1: The elasticity of gross inter-occupational flows to skill distance between occupations is 77%.

	Coefficient	Coefficient	Coefficient
Skill distance: $\log d_{ij}$	-0.73 (0.12)	-0.74 (0.11)	-0.77 (0.14)
R^2	0.23	0.52	0.81
i Fixed Effects	N	Y	Y
j Fixed Effects	N	N	Y
N	484	484	484

Source: longitudinally-linked CPS 2000-2015. Pooled regression for 22 occupational groups (SOC 2-digits): $\log\left(\frac{\#i,j \text{ occup. moves}}{\text{total } \# \text{ occup. moves}}\right) = \alpha + \alpha_i + \alpha_j + \beta \log(d_{ij}) + \epsilon_{ij}$.

2.3 Heterogeneous occupations

Empirically, occupations combine several, often different types of skills at varying intensity. Broad skill groups such as cognitive and manual skills are not necessarily mutually exclusive. such as Fernandez-Macias, Hurley, and Storrie (2012) document in European countries, I find that many jobs display a balanced combination of cognitive, manual and interpersonal skills.

As an example of this feature, consider two occupations, a machinist and a barista. According to O*NET, being a machinist calls for proficiency in *operation monitoring*, a manual skill that consists primarily of checking that technical equipment is working properly. Baristas instead need pronounced *service orientation* skills, an interpersonal trait, in addition to some *operation monitoring* skills. Both occupations require some degree of *complex problem solving*, a cognitive skill. Generally, many types of skills are often combined in a complex way to produce services and goods.

Even within the category of mostly cognitive, manual or interpersonal jobs, skill differences can be significant. Consider automotive engineers and magistrates. Both are high-skill, predominantly cognitive occupations, according to the method developed by Autor, Levy and Murnane (2003) and Autor, Dorn and Hanson (2013). However, data in O*NET reveal that these two cognitive occupations entail different skill portfolios. Both professions use high levels of *complex problem solving*, a cognitive skill, but judges associate complex problem solving with active listening, negotiation, and social perceptiveness skills to produce legal opinions. The skill portfolio of automotive engineers is also intensive in problem solving and active listening, but also features prominently mathematics, science, and system analysis. Although all skills described above are cognitive, it would be misleading to conclude that because of this, workers who lost an engineering job can easily apply for a legal career.⁵

5. This concern is aggravated due to widespread use of licensing for professional and non-professional occupations. Any notion of mismatch based purely on technological differences in skill profiles represents a lower bound.

Local skill remoteness reflects the extent to which a worker is a “good fit” for jobs available in her labor market. Empirically, occupations are often a mix of disparate skills; even within skills that belong to the same broad category, data display significant heterogeneity. Thus, describing occupations as being part of two or three polar categories (cognitive versus manual, routine versus non-routine, high- versus low-skill) is misleading when measuring skill remoteness. Therefore, as I implement an empirical skill remoteness measure, I considered many skills — as many as available in the data — regardless of their affinity with cognitive or manual components. The list of skills and occupational groups, and a sample questionnaire question appear in the Appendix.

2.4 Local labor markets

Migration literature suggests that labor markets are spatially segregated, and the spatial distribution of economic activity imposes additional frictions to the allocation of workers to jobs (Kennan and Walker, 2011 and Yagan, 2015). If spatial mobility is not costless, workers whose last jobs were in the same occupation will have different values of skill remoteness depending on the occupational employment composition of their local labor market. Again, consider a city in which sales and social work are the predominant occupations. These occupations use service orientation skills intensively. Consider another city, in which engineering occupations have a large employment share. Engineering occupations require little service orientation skills. If we consider the degree to which a barista’s skill profile differs from the jobs in her labor market, we conclude that a barista in the second city is more *skill-remote* than a barista in the first city. If the two baristas lose their jobs, it is natural to hypothesize that the former finds a new job faster, and with a higher wage, than the latter does.

To investigate this conjecture, I consider a measure of skill remoteness that varies across space and use metropolitan statistical areas (MSAs) as the spatial unit of analysis. This

choice is motivated by the pronounced sectoral specialization patterns documented by economic geography literature (Moretti, 2004, 2011; Hsieh and Moretti, 2015; and Davis and Dingel, 2015), and the evidence that more than 80% of job applications by unemployed workers is concentrated in the MSA of residence (Marinescu and Rathelot, 2016). The Occupational Employment Statistics (OES), an establishment-based survey of employers, reports data on the occupational composition of more than 500 metropolitan and micropolitan urban areas in the U.S. since the early 1990s. For the purposes of skill remoteness, I use yearly data on employment in each occupational group as a share of total employment in metropolitan areas.

2.5 Skill remoteness as average distance

Let me now describe exactly how to construct a measure of skill remoteness that varies at the occupation-city level and can be implemented with a combination of O*NET and OES data.

Postulate that the economy is composed by many types of workers, indexed by $i = 1, \dots, I$, and many types of jobs, indexed by $j = 1, \dots, J$. Let $s = 1, \dots, S$ denote skills, and let ℓ_{js}^R be the level of skill s required by job j , ℓ_{is}^A be the level of skill s acquired by worker i . Then, jobs and workers may be described as vector of length S :

$$job_j = [\ell_{j1}^R, \dots, \ell_{jS}^R]$$

$$worker_i = [\ell_{i1}^A, \dots, \ell_{iS}^A]$$

Following the literature on task-specific human capital (Gathmann and Schoenberg, 2010; Pavan, 2011), I assume that a worker's skill portfolio is equal to her previous job's one and

quantify mismatch between occupations by the distance between the respective skill vectors:

$$d_{ij} = \frac{1}{S} \sum_{s=1}^S |\ell_{is}^A - \ell_{js}^R| \quad (2.1)$$

Notice that, for a worker of type i and a job of type j , the above measure is invariant across locations. Equation (2.1) is therefore a good proxy for mismatch, but not for skill remoteness. In fact, to quantify the extent to which the skills possessed by a worker differ from the skills demanded by *all* jobs in a specific labor market, one has to consider the occupational composition of city-level employment.⁶

To this end, denote by ω_{jc} the share of job j in total employment in city c . Then the degree of skill remoteness of worker i 's skills in city c can be parsimoniously captured by following average distance:

$$\text{remoteness}_{ic} = \sum_{k=1}^J \omega_{kc} d_{ik} \quad (2.2)$$

Notice that (2.2) depends on how *different* are i 's skills with respect to other jobs k through d_{ik} , where each element of the sum is weighted by its employment share in city c .

To sum up, the empirical strategy for the implementation of the skill remoteness measure in (2.2) has therefore three steps: first describe occupations as vectors of skills using O*NET and compute the distance between all possible occupation pairs as in (2.1). Second, use city-level occupational shares from OES to compute the correspondent skill remoteness value for all occupations in all cities as in (2.2). Third, connect the occupation-city level skill remoteness measure to individual employment histories. To do so, I attribute to each worker a skill remoteness value according to the city (MSA) where she lives and the occupation of the last job she held. As a result, workers whose last occupation is the same but who live in different cities have different values of skill remoteness. On the other hand, it is also true that

6. Using the Euclidean distance and experimenting with different weighting procedures leave all results practically unchanged. See the Appendix for details and a discussion of the optimal weighting procedure.

Table 2.2: Summary statistics, skill remoteness. CPS-O*NET 2000-2015.

Occupation	Mean	Std. Dev.	25th Pct	75th Pct	Msa-Soc-Year cells
All, raw	0.11	0.10	0.08	0.12	68,485
All, std	3.22	1.00	2.55	3.66	68,485
Managerial	4.45	0.94	3.46 (New York, NY)	5.40 (Madera, CA)	3,507
Sales	2.47	0.42	2.01 (Laredo, TX)	2.86 (Austin, TX)	3,507
Production	3.83	0.48	3.32 (Detroit, MI)	4.21 (Youngstown, OH)	3,498

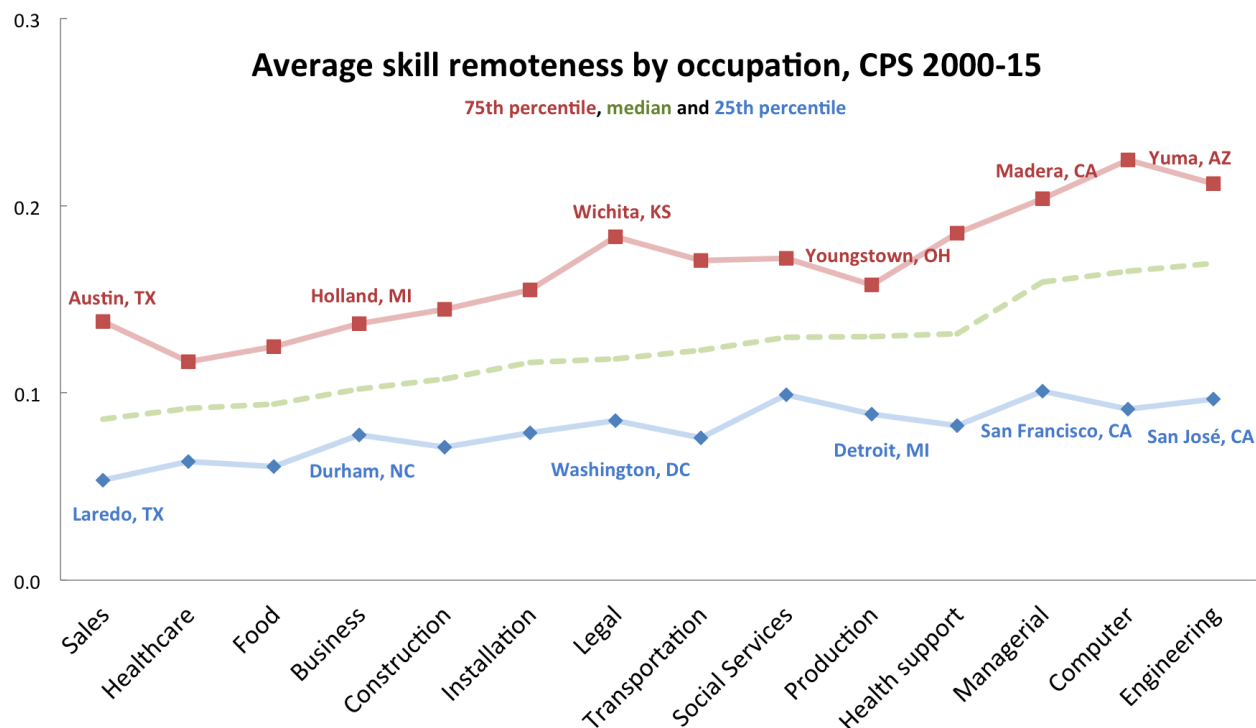
workers who live in the same city but lost their job in different occupations have different values of skill remoteness. Table 2.2 reports summary statistics for the basic version of skill remoteness and a standardized one with unit variance that I use in my empirical analysis. Notice how workers in the same occupation have different skill remoteness depending on where they reside and the share of local jobs that use *similar* skills.

2.6 Skill remoteness in action

This section contains summary statistics and graphs based on monthly Current Population Survey (CPS) data that illustrate the variation in local skill remoteness across cities and occupations. The Appendix supplements this section with graphs that correlate local skill remoteness with demographic variables, such as age and gender, and with education and city size. Though no stark correlations are detected, older and more educated workers tend to be more skill-remote and larger cities appear, on average, to have a slightly more skill-remote mix of workers.

Local skill remoteness varies significantly both between and *within* occupational groups, as figure 2.3 depicts. Transportation workers are on average less skill-remote than managerial occupations; however, this need not be true everywhere. Nor is the distinction between skill-

Figure 2.3: Each occupation displays different local skill remoteness values depending on its location.

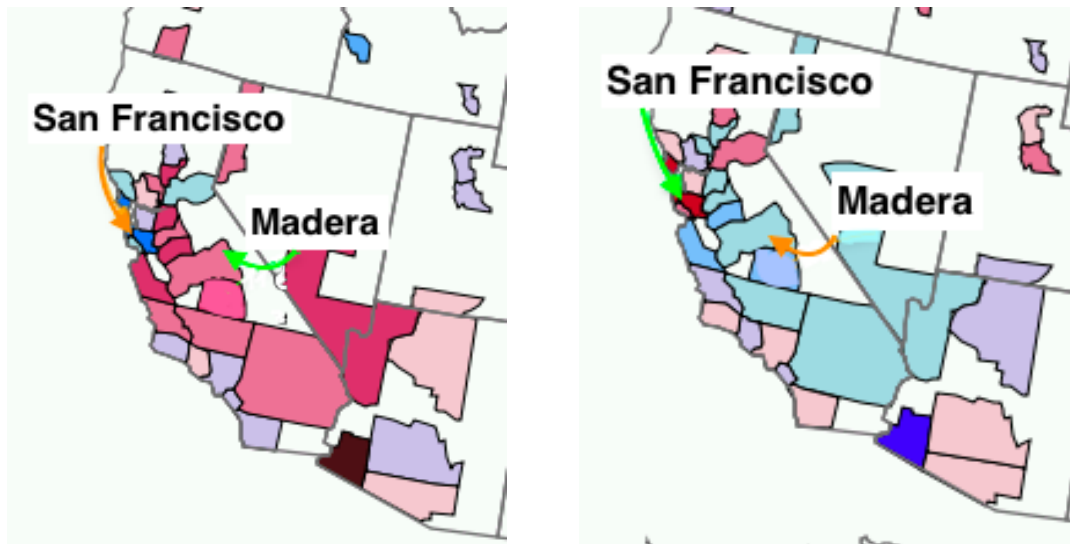


Note: the figure displays the 25th percentile (blue), median (green, dotted) and 75th percentile (red) value of local skill remoteness for 14 major occupational groups across 392 American MSAs. Source: CPS-O*NET 2000-2015.

remote and skill-central jobs purely overlapping with low- and high-skill occupations. For example, although on average a low-skill occupation such as transportation workers is less skill-remote than a high-skill one such as managers, the picture may be more pronounced or even reversed when one looks at specific local labor markets.

Indeed, the city of Madera and San Francisco in California provide an example of such reversal. Madera is the largest urban agglomeration in Madera county, one of the most intensely agricultural areas in the United States. San Francisco-Oakland-Fremont, instead, is one of the metropolitan areas with the highest concentration of high-tech firms. While the bounty of Madera’s fruit farms needs to be transported to other areas of the country to

Figure 2.4: Skill remoteness for laid-off workers in the South West.



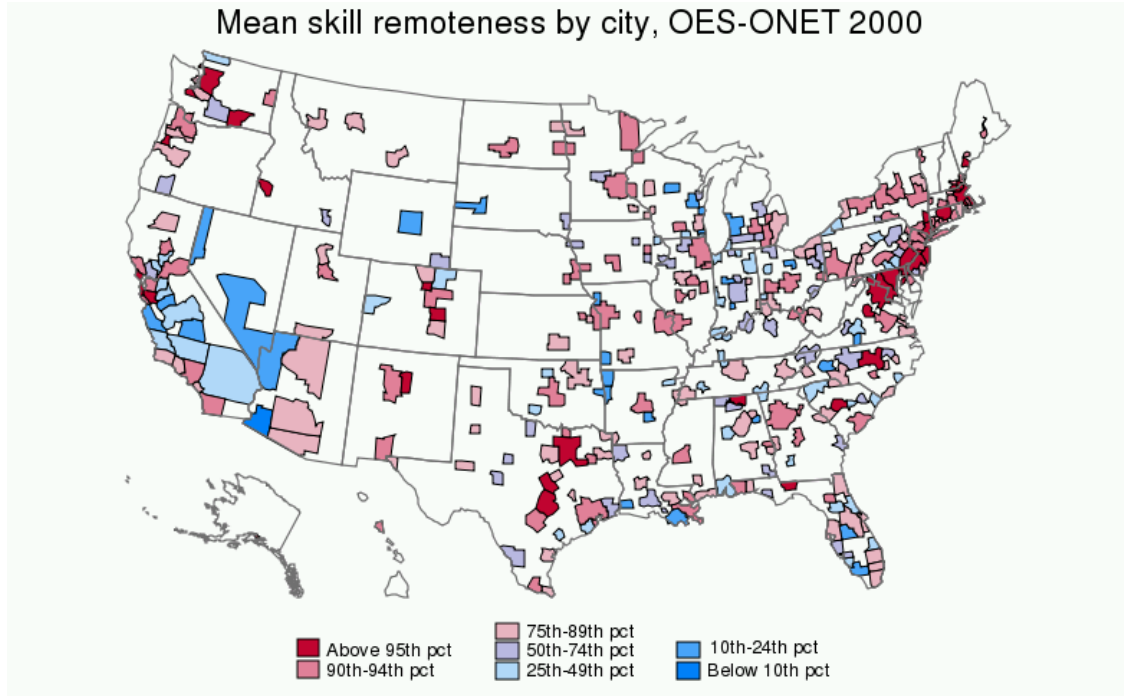
Note: on the left, managerial occupations. On the right, transportation occupations. Blue indicates low skill remoteness values (1st-25th percentile) and red high skill remoteness values (75th-99th percentiles). Source: CPS-O*NET 2005.

be sold, software products do not need to be physically shipped. Additionally, agricultural firms in Madera are not likely to have a numerous managerial board, or require consulting or marketing expertise such as high-tech companies in San Francisco. Hence the different values of skill remoteness for transportation workers and managers in the two cities, despite their geographical proximity. and the somewhat unexpected fact that transportation occupations are at an advantage over managerial ones in Madera's labor market (but, predictably, not in San Francisco's one).

The same intuitive findings are confirmed when one looks at other occupational groups: Computer and Math occupations are the least skill-remote in San José, CA, the center of Silicon Valley, while Sales occupations are at the least skill-remote in Laredo, TX, the port of entry of approximately 50% of U.S.-Mexico international trade (Federal Reserve Bank of Dallas, 2008).

In general, large cities appear to have a more skill-remote mix of occupations than smaller

Figure 2.5: Average skill remoteness of laid-off workers, by city. CPS-O*NET 2000.



ones, as shown in figure 2.5. The figure depicts a heat map of skill remoteness for laid-off workers across U.S. cities. To construct the map, I first classify each occupation by a value of remoteness and compute the percentile rank. For example, transportation workers in Madera, CA are at 25th percentile of their occupation. Transportation workers in San Francisco, CA are at the 75th. Then, I average at the city-level; cities are on average more skill-remote when a higher share of workers who live there are above the median skill remoteness. The Bay Area around St.Francisco and the North-eastern megalopolis (Baltimore-Boston-New York-Philadelphia-Washington, DC) stand out for their deep red color, signaling that these are the urban areas where unemployed workers' skill profiles are "further" from jobs' skill profiles. Cities in Southern Florida and Western Michigan, instead, appear to have smaller discrepancies between workers' and jobs' skill profiles.

In conclusion, the patterns of skill remoteness across U.S. cities are in accordance with known empirical regularities on industrial and occupational specialization, suggesting that

skill remoteness accurately captures the transferability of skills across jobs in local labor markets. The Appendix contains maps to illustrate the distribution of local skill remoteness for selected occupations across all U.S. MSAs (figure B.1).

CHAPTER 3

SKILL REMOTENESS AND POST-LAYOFF LABOR MARKET OUTCOMES

3.1 Empirical findings from individual labor market longitudinal data

Armed with values of local skill remoteness for 22 occupational groups and 392 MSA-CBSAs, I study how local skill remoteness affects individual labor market outcomes after layoff. I focus on workers who lost their job for several reasons: first of all, by concentrating on laid-off workers only, I am able to analyze separation episodes that are independent from the worker's initiative, thus reducing concerns of endogeneity bias in my estimates. Second, concentrating the attention on post-layoff outcomes allows me to document significant spatial variation in the earnings losses associated with layoff (Jacobson, Lalonde and Sullivan, 1993; Davis and von Wachter, 2011). Furthermore, I relate these losses to the prevalence and direction of occupational change and migration among laid-off workers. Finally, this approach is particularly informative for aggregate employment adjustments since recessions are precisely times of abnormally high involuntary separations rates.

I use data from the Current Population Survey (CPS) 2000-2015 and the restricted-use geo-coded National Longitudinal Survey of Youth 1979 (NLSY79) 1994-2012. Throughout the analysis, I consider workers who were laid-off at least once during the sample period and are aged between 18 and 65 years. Abstracting from sample weights, this leaves me with an average of 72 observations per occupation-city-year cell for 15 years in the CPS and 14 observations per occupation-city-year cell for 18 years in the NLSY79. Finally, because the NLSY79 follows individuals as they migrate across cities so I also observe the change in skill remoteness as individuals move across space.

Information on the last occupation before layoff and the current city of residence is available in both surveys, so I can attribute a value of skill remoteness to each individual in the sample accordingly. I strive to correctly identify the relevant occupation by excluding short-term jobs. Specifically, I consider as the “last job” the occupation in the month before layoff, unless the duration of employment in that job is less than 5 weeks. If so, I either look at the previous long-term job or, if the information is unavailable, drop the observation altogether. In addition, when using the longer panels in the NLSY79, I computed each worker’s combined skill portfolio at any point in time as the average of skill profiles in all previous jobs, weighted by employment duration. Somewhat surprisingly, computing skill remoteness on the basis of this combined skill profiles leads to no significant changes with respect to the main analysis that uses the skill profile of the last job.¹

3.2 Earnings and wages

Jacobson, Lalonde and Sullivan (1993) and Davis and von Wachter (2011) document large, persistent earnings losses for laid-off workers. For West Germany in the period 1975-2001, Gathmann and Schoenberg (2010) found that distances between the tasks performed in the previous and in the current job are successful in explaining the pace of wage growth across occupational transitions. It seems therefore natural to ask whether local skill remoteness at the time of layoff influences post-layoff earnings.

To do so, I use the NLSY79 panels. The NLSY79 has a limited sample size but a long time dimension, an impressive breadth of individual-level variables and weekly employment information. Since the survey underwent a major redesign in 1994, I use NLSY79 data starting on January 1st, 1994.

1. In addition, though the only skills explicitly attributed to workers’ are those related to their previous job, in my reduced-form exercises there will be an extensive set of individual-level demographic controls that include occupation and industry fix effects, age, education and, when possible, the previous wage.

Consider the following regression:

$$earn_{it+m} = \alpha_m + \alpha_y + \alpha_c + \alpha_o + \alpha_{ind} + \beta_m \mathbf{X}_{it} + \gamma_m \text{remote}_{oct} + \epsilon_{it+m} \quad (3.1)$$

where $earn_{it+m}$ is the monthly wage for worker i , m months after layoff, and is zero if the worker is non-employed. Notice that the regressor of interest, remote_{oct} is fixed at t , the time of layoff. Standard errors are clustered at the MSA-year level to allow for within-city within-year correlation. The coefficients of interest, γ_m , are estimated separately for every period in a series of monthly regressions.

To isolate the effect of local skill remoteness at layoff, the regression includes a large set of controls \mathbf{X}_{it} : fixed effects for city, month, year, occupation (2 digits SOC) and industry (3 digits NAICS), demographics (age, sex, race and education), a fixed effect for the month of re-employment (if different than m) and initial unemployment duration in weeks for individuals who enter the sample unemployed (15 categories). The coefficient on skill remoteness in this specification is -2.30 one month after layoff, and varies slightly over time: -1.88 six months after layoff, -2.56 twelve months after layoff, -3.18 eighteen months after layoff. The coefficient is still negative (-0.95) twenty-four months after layoff but becomes statistically insignificant (see columns 2 of table 3.1).

As a robustness check, in a second specification, I also include geographic controls in \mathbf{X}_{it} (see columns 3 in every panel of table 3.1). Specifically, I consider city size (population), city-level unemployment rate, city-level share of college-educated workers — in the spirit of Moretti (2004, 2010) — and city-level share of people younger than 25 — as per the “young workers hypothesis” in Shimer (2001). I also add controls for the city-level share of the own occupation, to account for agglomeration economies, and an interaction term between city size and occupational dummies, to control for selection of specific occupations in larger urban areas. Interestingly, the share of the worker’s own occupation appears to have

an important role early on, while it becomes statistically insignificant as time from layoff progresses. The coefficient on remoteness at different dates, instead, peaks at approximately 10-12 months after layoff. Adding the controls barely changes the magnitude of the skill remoteness coefficient; for later months, it is even larger than in the baseline specification.

Finally, I use migration information in the NLSY79 to control for whether the worker is re-employed in a different city than the one where she lost her job. I find that, after controlling for migration status, the effect of skill remoteness on post-layoff earnings is larger than in the baseline. In addition, the coefficient on skill remoteness is statistically significant until 30 months after layoff (see columns 4 in every panel of table 3.1). Unfortunately, the small sample size prevents a thorough analysis of earnings and skill remoteness changes for migrants. However, the evidence in table 3.1 is broadly consistent with a positive effect of migration on post-layoff earnings — in accordance with findings in Kennan and Walker (2011).

To better visualize the earnings effect, figure 3.1 depicts the predicted earnings for laid-off workers at the 25th and 75th skill remoteness percentile according to regression (3.1) (respectively, the blue and red line). Each point in the graph is a value for earnings, predicted according to equation (3.1). Recall that earnings are zero for the unemployed. All geographic controls and a dummy for migration status are included in the regression — that is, coefficients are as in columns 4 of table 3.1). All regressors are evaluated at the mean but for skill remoteness.

The figure displays the same V-shaped pattern featured in other studies of post-layoff earnings losses (Davis and von Wachter, 2011; Jarosch, 2015). However, the “unemployment scar” is noticeably smaller for laid-off workers at the 25th than at the 75th skill remoteness percentile. At the peak the difference in hourly wages is approximately \$5. Total average loss is more than \$14,000 over more than two years, equivalent to a yearly loss of over at least 15% of the median income in my sample.

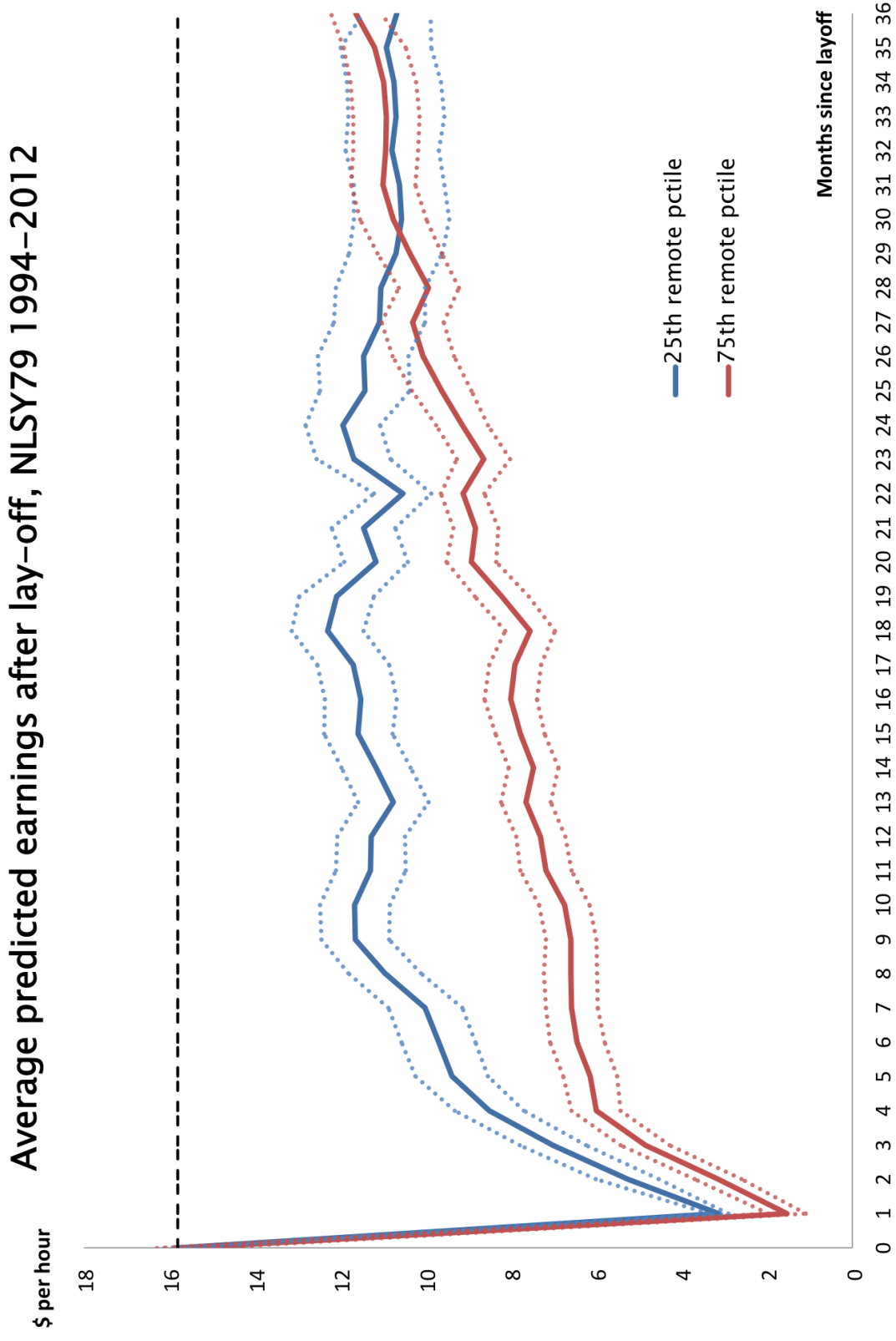
Figure 3.1 is evidence of substantial spatial heterogeneity in the individual response to layoff, an empirical regularity new to this work. In other words, laid-off workers recovery path after job displacement is affected by the share of jobs *in their city* that use skills similar to their previous occupation. When this share is small, post-layoff earnings are considerably lower for more than two years after layoff. I conclude that the geographic location of workers plays a role in determining the severity of post lay-off earnings losses. To go back to one of the many examples in table 2.2, these results highlight how, taking secular trends away from manufacturing as given, production workers laid-off in Youngstown, OH are likely to earn less than similar workers laid-off in Detroit, MI. The reason is that a large share of jobs in Detroit uses “production” skills: Detroit is a well-know center for automotive and an increasingly larger hub for high-tech manufacturing as well. Instead, the largest employers after the Chevrolet plant in Youngstown are the local university and hospital — establishments in which jobs are unlikely to use the same skills used in production occupations.

Table 3.1: Earnings regression (3.1). SE clustered at the city-year level (953 clusters). Source: NLSY79 1994-2012.

	t+1		t+6		t+12							
Skill remoteness	-2.00 (1.32)	-2.30 (1.34)	-2.62 (1.81)	-2.38 (1.91)	-2.45 (0.91)	-1.88 (0.82)	-2.39 (0.92)	-3.01 (1.06)	-2.94 (0.78)	-2.56 (0.75)	-2.58 (0.81)	-4.11 (0.82)
College	3.21 (2.32)	3.73 (2.70)	3.76 (2.71)	3.76 (2.71)	3.85 (1.31)	3.62 (1.39)	3.75 (1.35)	3.75 (1.35)	4.48 (1.13)	4.47 (1.18)	4.47 (1.17)	4.47 (1.17)
Own occup. share	5.22 (6.25)	4.81 (6.45)	4.81 (6.45)	4.81 (6.45)	2.89 (3.98)	2.81 (4.01)	2.81 (4.01)	2.81 (4.01)	1.05 (3.36)	1.05 (3.36)	1.05 (3.36)	1.17 (3.98)
City size	3.83 (1.57)	3.71 (1.60)	3.71 (1.60)	3.71 (1.60)	4.57 (1.55)	4.16 (1.61)	4.16 (1.61)	4.16 (1.61)	3.51 (1.33)	3.51 (1.33)	3.51 (1.33)	3.00 (1.56)
R^2	0.60	0.62	0.65	0.71	0.58	0.59	0.64	0.71	0.60	0.61	0.65	0.70
	t+14		t+18		t+24							
Skill remoteness	-2.56 (0.75)	-2.41 (0.74)	-2.44 (0.80)	-4.13 (1.60)	-3.51 (0.74)	-3.18 (0.70)	-3.14 (0.76)	-4.86 (1.51)	-1.19 (0.87)	-0.95 (0.75)	-1.22 (0.96)	-3.89 (1.26)
College	3.09 (1.07)	3.06 (1.12)	3.07 (1.34)	3.07 (1.34)	4.68 (1.10)	4.80 (1.16)	4.76 (1.34)	4.76 (1.34)	4.50 (1.37)	4.60 (1.32)	4.58 (1.41)	4.58 (1.41)
Own occup. share	3.03 (3.45)	2.45 (3.61)	2.45 (3.61)	2.45 (3.61)	1.34 (3.03)	1.28 (3.16)	1.28 (3.16)	1.28 (3.16)	2.53 (3.63)	2.53 (3.63)	2.53 (3.63)	1.98 (3.78)
City size	3.82 (1.41)	3.76 (1.55)	3.76 (1.55)	3.76 (1.55)	3.24 (1.30)	3.09 (1.47)	3.09 (1.47)	3.09 (1.47)	4.52 (1.48)	4.52 (1.48)	4.52 (1.48)	3.99 (1.58)
R^2	0.56	0.58	0.62	0.69	0.55	0.58	0.63	0.70	0.59	0.61	0.66	0.69
Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Demographics	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Geo-controls	N	N	Y	Y	N	Y	Y	Y	N	N	Y	Y
Migration	N	N	N	Y	N	N	N	Y	N	N	N	Y

Fixed effects: month, year, occupation, industry, city. Demographics: age, sex, race, education, month of re-employment, initial unemployment duration. Geo-controls (city-level): population \times occupational dummies, share of college-educated workers, share of people younger than 25, share of the own occupation, unemployment rate. "Migration" equals 1 if the city of residence at $t+m$ is different than at t .

Figure 3.1: Predicted earnings from regression (3.1). Standard errors clustered at the city-year level. Source: NLSY79 1994-2012.



3.3 Re-employment rates and wages

Given the large earning losses documented in the previous section, the question arises whether they are due to long-term non-employment or rather lower earnings upon re-employment. To this end, I use the longitudinally-linked CPS monthly data to compute predicted re-employment probabilities at different months after layoff as a function of local skill remoteness at layoff.² I run a logit specification of the following regression:

$$Pr\{\text{empl}_{it+m} = 1\} = \alpha_m + \alpha_y + \alpha_c + \alpha_o + \alpha_{ind} + \beta_m \mathbf{X}_{it} + \gamma_m \text{remote}_{oct} + \epsilon_{it+m} \quad (3.2)$$

where t is the month of layoff, $m = 1, 2, 3, 12, 13, 14, 15$ because of the rotating panel structure of the CPS, empl_{it} is a dummy that takes value one if worker i is employed at date t , and \mathbf{X}_{it} is the same vector of controls as in (3.1). Errors are clustered at the MSA-year level.³

The effect of skill remoteness on re-employment trajectories is limited (table 3.2). Each month in the first quarter after layoff, workers at the 75th percentile are less likely to be employed than their counterpart at the 25th remoteness percentile by approximately 6 percentage points (the coefficients γ_m are all in the vicinity of -0.05 yielding an average marginal effect of -0.035). This result echoes the findings in Şahin, Song, Topa and Violante (2014), where the authors document a 3% loss in the monthly job finding rate for unemployed workers due to mismatch frictions. In a back-of-the-envelope calculation I attribute to each worker the median duration in her “category”: workers employed at month 1 have 2 weeks of unemployment, workers unemployed at month 1 but employed at month 2 have 6 weeks of unemployment and so on, with workers still unemployed at month 3 being attributed a

2. The CPS yields an average monthly employment rate that is consistent with the aggregate level as per official BLS data. The point estimates in this section exercise are the same in the two datasets but the predicted levels differ.

3. A linear probability model or a proportional hazard specification in a model of unemployment duration yield very similar results as the logit specification presented in this section.

value of 18 weeks. According to this calculation, 6% lower monthly re-employment probability translates into ten days of non-employment. The associated predicted probabilities of re-employment for workers at the 25th and 75th skill remoteness percentiles are depicted in figure 3.2.

From the CPS, there is no conclusive evidence that the earnings losses in figure 3.1 can be explained by persistent non-employment for skill-remote workers. In fact, the difference in employment rates is significantly different from zero only during the first three months after layoff. The CPS, however, does not allow for the analysis of long-term outcomes; I therefore turn to the NLSY79 panels. The short-term results are very similar, though the point estimates for the predicted employment rate of skill-remote workers are now always lower than for skill-central ones (bottom panel of figure 3.2). When I explicitly investigate the effects of skill remoteness at layoff on employment status after 12, 16, 20, 24, 32 and 48 months after layoff, I find that the predicted re-employment rate for workers at the 25th skill remoteness percentile is not statistically different from the employment rate at the 75th percentile, though the point estimate for the latter is always smaller than the former (see table3.3).

Table 3.2: Employment rate regression (3.2): coefficient on local skill remoteness and implied losses. Source: CPS 2000-15.

	t+1	t+2	t+3	Mean effect: $\frac{\partial Y}{\partial X}$	IQR (days)	IQR (earnings)
Skill rem.	-0.047 (0.023)	-0.050 (0.027)	-0.055 (0.025)	-0.04 (0.01)	-10 (3)	-\$660 (198)
Own occ.	2.38 (0.10)	2.24 (0.14)	2.26 (0.13)	0.11 (-0.02)	22 (4)	\$1340 (243)
U-rate	-5.31 (0.57)	-6.50 (0.63)	-6.64 (0.62)	-0.24 (-0.02)	-33 (4)	-\$2178 (264)

Note: logit specification. All controls as in table 3.1. SE clustered at the city level (318 clusters).

Re-employment rates for skill-remote and skill-central workers do not appear to be persistently different, so I turn to re-employment wages to explain the earning losses in figure

Table 3.3: Employment rate regression (3.2): predicted re-employment rate after 12 months from layoff. Source: NLSY79 1994-2012.

	25th pctile	75th pctile		25th pctile	75th pctile
t+12	0.40 (0.04)	0.36 (0.03)		t+24	0.46 (0.04)
t+16	0.46 (0.04)	0.41 (0.03)		t+32	0.46 (0.04)
t+20	0.49 (0.04)	0.42 (0.04)		t+48	0.46 (0.04)

Note: logit specification. All controls as in table 3.1. SE clustered at the city-year level (5,220 clusters).

3.1. I use again the NLSY79 panels and the same specification as in (3.1) with all controls. Figure 3.3 depicts the associated predicted wage conditional on re-employment, for workers at the 25th or at the 75th skill remoteness percentile. Wages at re-employment are on average 30% lower for skill-remote workers for the first 18 months and do not reach the same level until 30 months from layoff. Conditional on re-employment, the wage profile of skill-central workers is instead practically unchanged.

Figure 3.2: Monthly re-employment rate for skill-remote and skill-central laid-off workers. SE clustered at MSA-year level. Top: CPS, 2000-2015. Bottom: NLSY79 1994-2012.

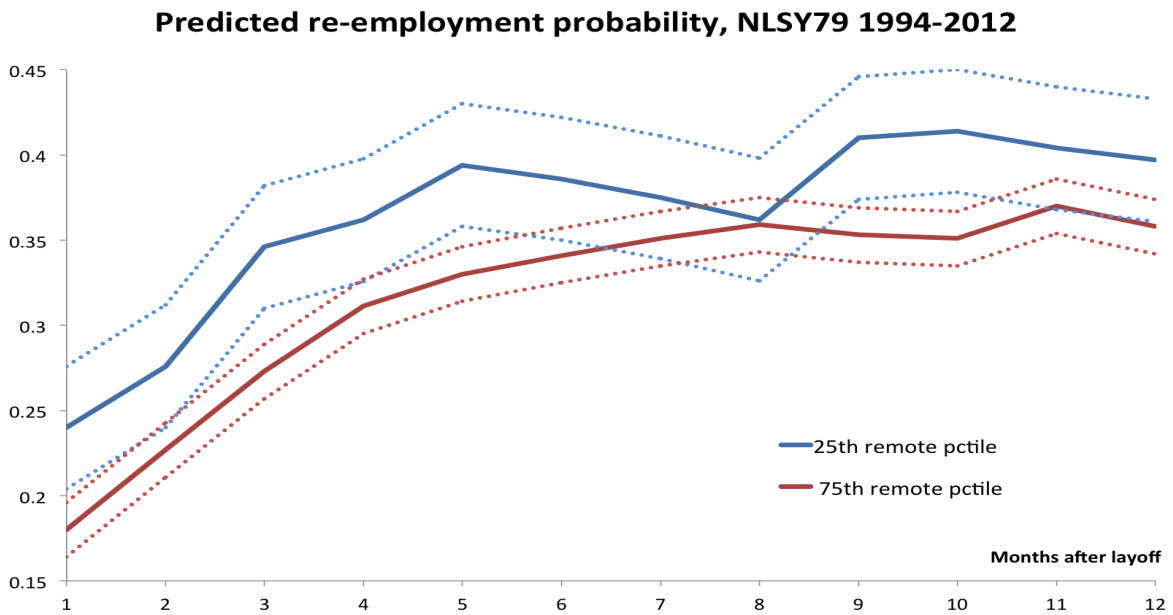
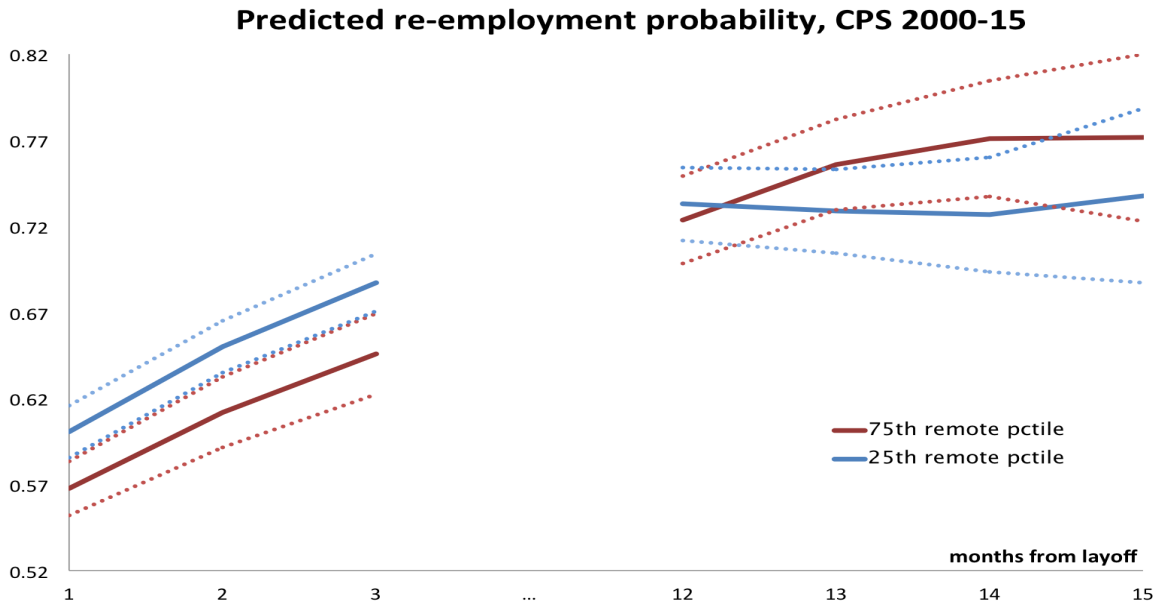
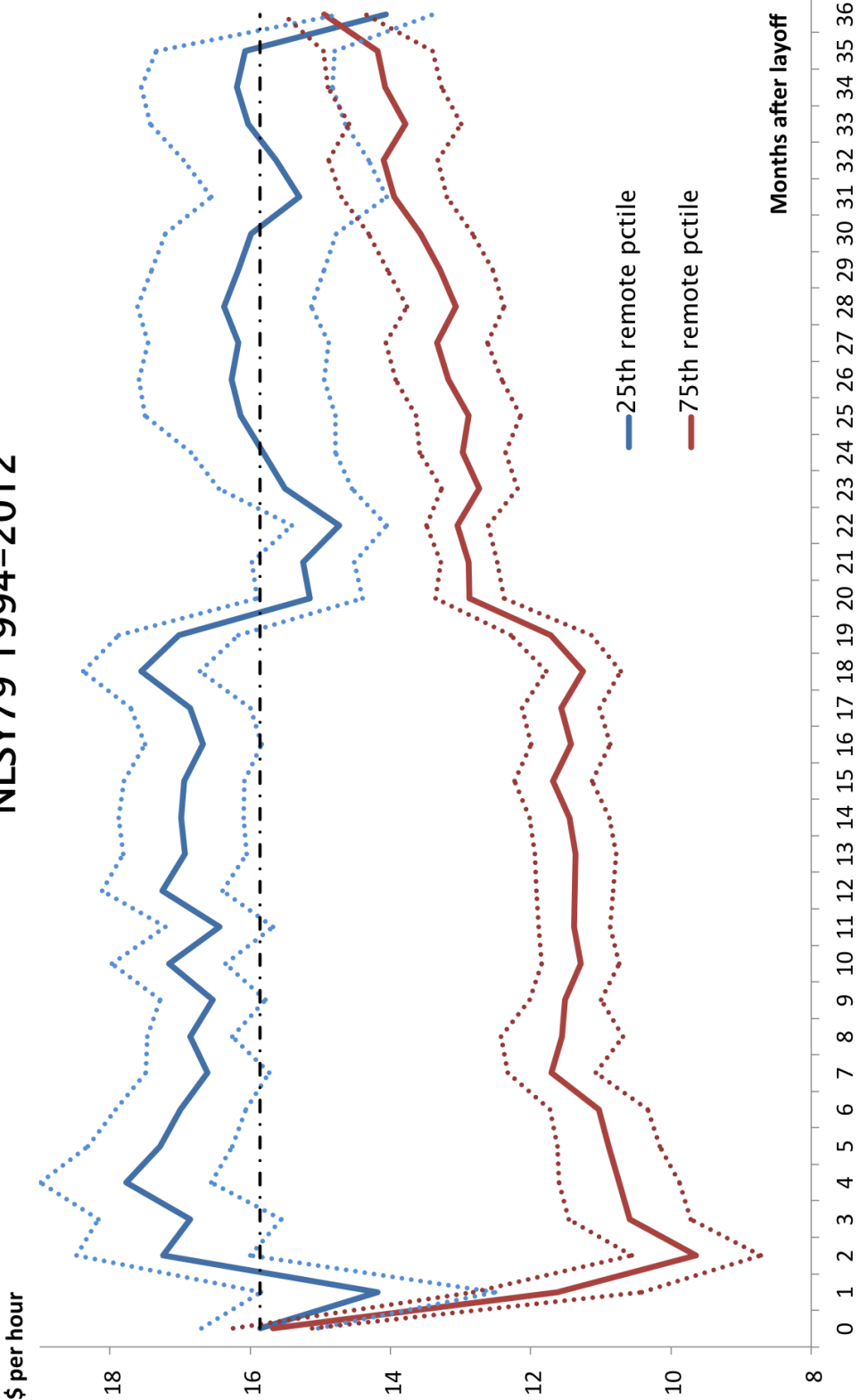


Figure 3.3: Wages at re-employment for laid-off workers at the 25th and at the 75th remoteness percentile. SE clustered at the MSA-year level. Source: NLSY79, 1994-2012.

Average predicted wages upon re-employment, NLSY79 1994-2012



3.4 Occupational mobility

Changing occupation has been shown in the literature to have adverse consequences on wage levels at re-employment and post-layoff wage growth (see, for example, Kambourov and Manovskii, 2008; Gathmann and Schoenberg, 2010 and recently Huckfeldt, 2016). Using the CPS for an auxiliary calculation, I find that occupational change after layoff leads to wage losses of approximately \$2 per hour, which translates in \$4,160 yearly loss for the median full-time worker — a significant but somewhat smaller sum than the predicted losses in the previous paragraph. Using the CPS panels, I find that laid-off workers at the 75th skill remoteness percentile are more likely to have changed occupations upon re-employment and less likely to return to the previous occupations at any date after layoff.

Specifically, I compute the predicted probability of occupational change from a logit specification of the following regression:

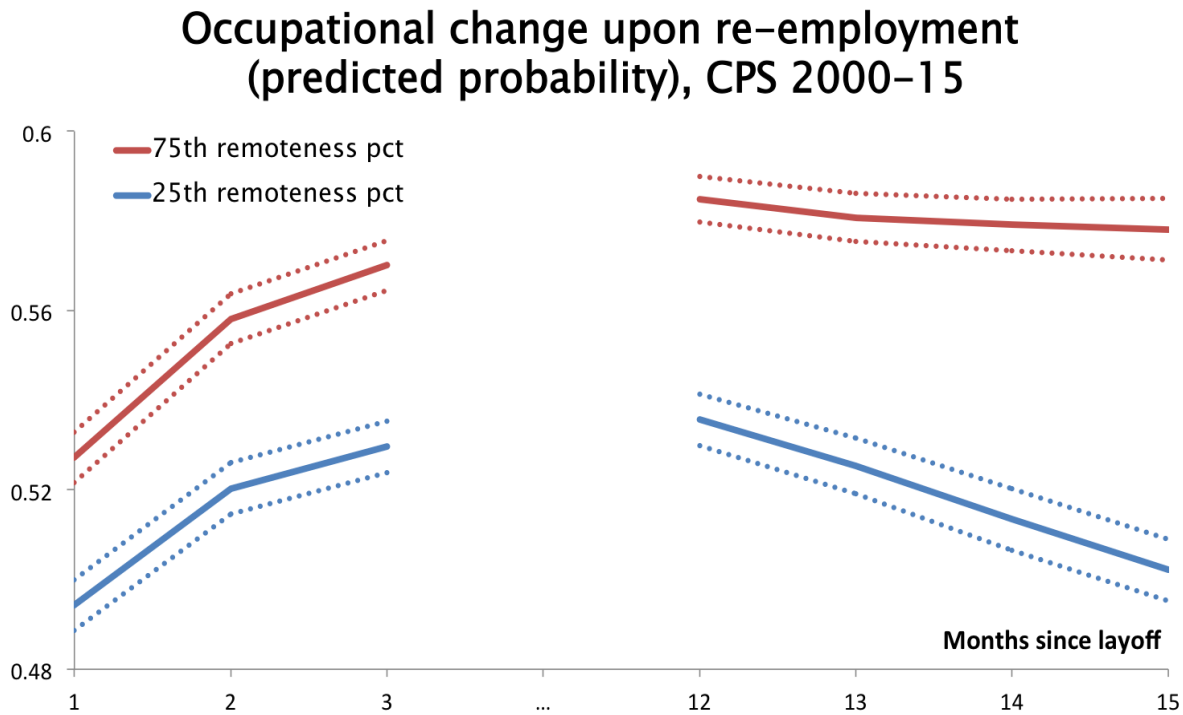
$$Pr\{o_{t+m} \neq o_t\} = \alpha_m + \alpha_y + \alpha_c + \alpha_o + \alpha_{ind} + \beta_m \mathbf{X}_{it} + \gamma_m \text{remote}_{oct} + \epsilon_{it+m} \quad (3.3)$$

where o_t denotes a worker's occupational group at time t , t is the time of layoff and controls are as in regression 3.1. Errors are clustered at the MSA-year level.

The difference in occupational mobility between skill-remote (red) and skill-central (blue) laid-off workers is significant and becomes larger over time: with respect to workers who lost their job where their occupation is skill-central, workers who lost their job where their occupation is skill-remote have a 8% larger probability of being re-employed in a different occupation in the first month. This difference becomes 14% after 15 months. Conversely, for skill-central workers, the predicted mobility rates at 1 or 15 months after layoff are virtually identical. A possible explanation is that some of these workers found employment again in the original occupation, perhaps after a (short) spell in other occupations. A similar

exercise in the NLSY79 data delivers a consistent picture, with somewhat larger and noisier estimates. On average, however, both in the CPS and in the NLSY79, skill-remote laid-off workers are more likely to be re-employed in a different occupations than skill-central ones at any date after layoff (see figure 3.4 and table 3.4).

Figure 3.4: The predicted occupational mobility rate is 8-14% higher for workers who lost their job at the 75th skill remoteness percentile than those at 25th skill remoteness percentile. Source: CPS, 2000-2015. SE clustered at MSA-year level.



The results of regressions 3.3 tie in with the dynamics of earnings losses discussed in the previous section. In particular, they suggest that one of the reasons why high skill remoteness at layoff is associated with lower wage levels at re-employment, may be the human capital loss entailed in occupational change. The magnitude of this loss may be further related to the differences in the skill profiles of the old and the new occupation, as suggested by earlier literature (Gathmann and Schoenberg, 2010; Huckfeldt, 2016).

When I directly investigate the contribution of occupational change to wage losses asso-

Table 3.4: Skill remoteness at layoff increases occupational change rates up to 48 months. Source: NLSY79 1994-2012.

	Coeff.	Average		Coeff.	Average		Coeff.	Average
t+1	+0.09 (0.04)	0.11	t+12	+0.04 (0.04)	0.31	t+24	+0.09 (0.04)	0.37
t+2	+0.11 (0.06)	0.12	t+16	+0.08 (0.04)	0.35	t+32	+0.11 (0.04)	0.37
t+3	+0.06 (0.03)	0.13	t+20	+0.07 (0.04)	0.36	t+48	+0.10 (0.04)	0.38

Note: logit specification. All controls as in table 3.1. SE clustered at the city-year level (5,220 clusters).

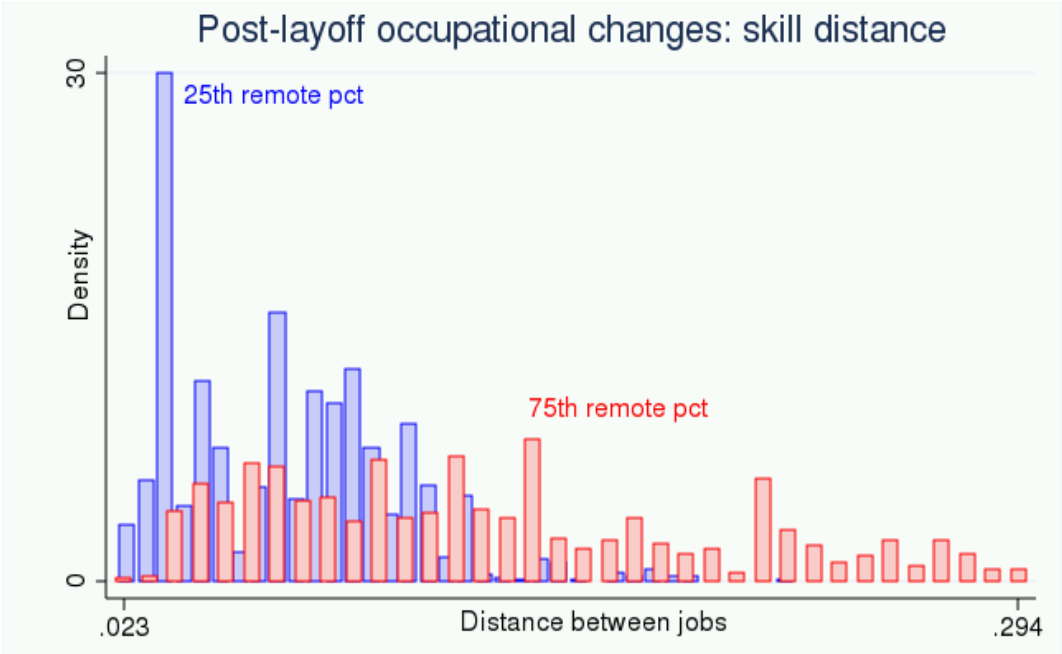
ciated to skill remoteness at layoff, I find that occupational change accounts for almost all of the losses in the first month after layoff, approximately half of them in the first quarter and almost none of them afterwards. Table 3.5 compares the coefficient on local skill remoteness at layoff for a regression of post-layoff wages, when a dummy for occupational change at re-employment is included or not. Occupational change is always a significant source of wage losses for laid-off workers, as documented in previous literature (Huckfeldt, 2016). However, controlling for occupational change significantly alters the effect of skill remoteness only in the first three months after layoff.

Table 3.5: Occupational change accounts for approximately half of the effect of skill remoteness at layoff during the first quarter after layoff, but has no impact afterwards. Source: NLSY79 1994-2012.

	t+1		t+2		t+3		t+4		t+5	
remote	-2.62 (1.81)	-1.57 (1.74)	-5.76 (1.45)	-2.47 (1.19)	-5.01 (1.57)	-2.74 (1.04)	-4.88 (0.92)	-3.11 (1.10)	-3.32 (1.07)	-2.97 (1.01)
Occ. ch.		-5.99 (1.25)		-2.57 (0.78)		-2.26 (0.70)		-1.64 (0.68)		-1.85 (0.66)
	t+6		t+12		t+14		t+18		t+24	
remote	-2.39 (0.92)	-2.63 (0.88)	-2.58 (0.81)	-2.57 (0.78)	-2.44 (0.80)	-2.42 (0.77)	-3.14 (0.76)	-3.05 (0.75)	-1.22 (0.96)	1.10 (0.91)
Occ. ch.		-2.27 (0.66)		-1.82 (0.66)		-1.72 (0.68)		-1.03 (0.56)		-2.19 (0.65)

Finally, analyzing the skill distance of occupational moves for skill-remote and skill-central workers, I find that laid-off workers in remote occupation-city pairs are more likely to find new employment in an occupation that, skill-wise, is further from the job they lost. As an illustration, figure 3.5 reports the density of the skill distance (the d_{ij} in section 2.2) for occupational changers at the 25th and at the 75th skill remoteness percentile of their (original) occupation. The distribution for the latter, in red, has a significantly longer tail. I conclude that there is evidence in favor of a higher occupational change rate for skill-remote workers than for skill-central ones. In addition, on average, the distance between the old and the new job for skill-remote workers is half a standard deviation larger (+0.05) than for skill-central ones.

Figure 3.5: laid-off workers whose occupation at layoff was skill-remote are more likely to be re-employed in an occupation that has a large skill distance with respect to the lost job. Source: CPS, 2000-2015.



3.5 Geographic mobility

Evidence from the CPS shows that skill remoteness at layoff is associated with a high rate of occupational mobility. However, their occupation is not the only margin workers may adjust: they can also change city. The previous analysis of earnings changes after lay-off suggests that migration mitigates the negative effect of skill remoteness — indeed, losses from skill remoteness in a regression that includes a control for migration status are larger than in the baseline. It seems therefore natural to study geographic migration as a relevant channel to overcome mismatch frictions after layoff.

Consider the following regression:

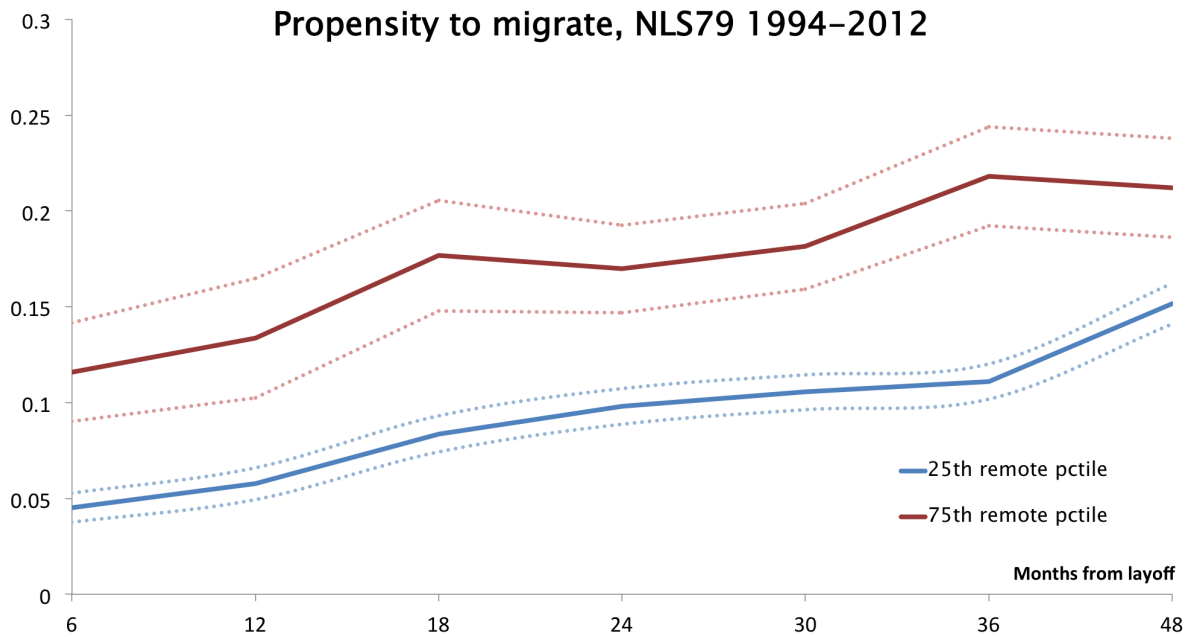
$$Pr\{\text{migrate}_{it+m} = 1\} = \alpha_m + \alpha_y + \alpha_c + \alpha_o + \alpha_{ind} + \beta_m \mathbf{X}_{it} + \gamma_m \text{remote}_{oct} + \epsilon_{it+m} \quad (3.4)$$

where the variable “migrate” is an indicator that takes value 1 if worker’s i city of residence at $t+m$ is different than at t . The coefficients are estimated using a logit specification in the NLSY79 data since 1994. As usual, standard errors are clustered at the MSA-year level.

The predicted probability of migration for workers at the 25th and at the 75th remoteness percentile is depicted in figure 3.6. Notice that the graph starts at $m = 6$ because less than 50 observations had migrate_{it+m} equal to 1 for $m < 6$. Skill-remote laid-off workers have a higher migration rate than skill-central ones by approximately 50%. The difference in migration rates is significant up to 4 years after layoff.

Geographical migration also appears directed in the sense of reducing workers’ local skill remoteness. This is depicted in figure 3.7: in the x axis is the skill remoteness at layoff (and before migration) and on the y axis the change in skill remoteness for the original occupation, as a result of geographic moves and irrespective of actual occupational change

Figure 3.6: The predicted probability of migration for laid-off workers at the 25th and at the 75th remoteness percentile.



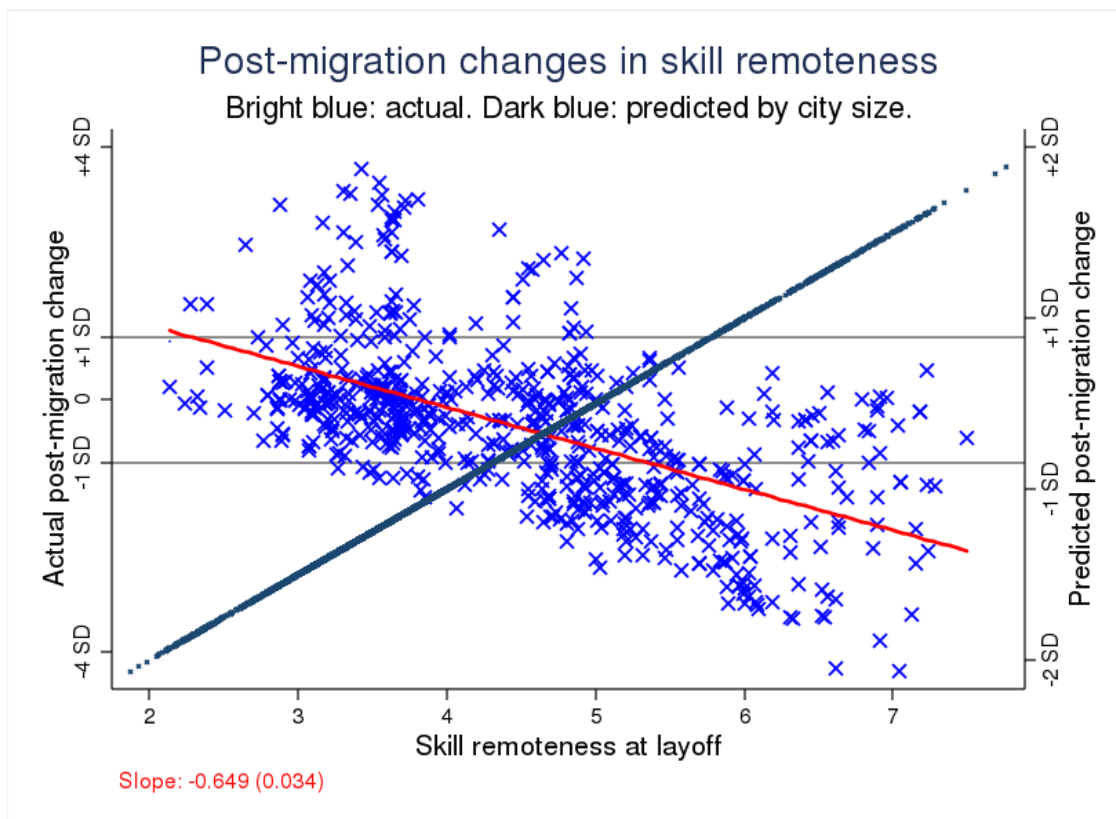
Note: intervals before 6 months after layoff are not reported because of the paucity of observations (less than 50 individuals migrate in the first 60 months after layoff, approximately 0.8% of the sample). Source: NLSY79 1994-2012.

or employment status. The estimated slope is -0.65. This is considerably more negative than what implied by random mobility (+0.47), where the probability that a worker moves to a city is proportional to the city's size.

3.6 Summary of empirical evidence

The previous section reported the results of several descriptive exercises that investigated how skill remoteness affects the wage level, re-employment probability, occupational mobility rate and propensity to migrate of laid-off workers. Skill-remote laid-off workers experience substantially lower earnings than their skill-central counterparts; these disparities amount to a total loss of more than \$14,000 and are significant for almost 30 months after layoff. They

Figure 3.7: Migration is directed towards cities where the movers' original occupation is less skill-remote. Source: NLSY79 1994-2012.



appear to be connected to skill mismatch in the new job rather than persistent joblessness: I show that workers who lose their job where their occupation is skill-remote have a 6% lower probability of being employed in each month during the first quarter after layoff and are 8% more likely to work in a different occupation. Furthermore, the average skill distance between the old and the new job tends to be larger by approximately half a standard deviation (0.05). Occupational change accounts for most of the losses during the first four months, but none of the further ones. These facts shed light on the effects of skill remoteness on individual employment histories and also provides some insights on aggregate employment adjustments. Indeed, economic downturns are precisely periods with unusually high layoff rates. To further investigate the role of skill remoteness in aggregate outcomes, I now provide a theoretical

framework that yields a natural role for skill remoteness in the unemployment rate and wage level.

CHAPTER 4

SKILL REMOTENESS IN A STYLIZED MODEL OF MISMATCH

I have provided robust evidence that labor market outcomes after layoff are affected by local skill remoteness at layoff. To formalize the notion of skill remoteness, I now develop a model that accommodates large-dimensional heterogeneity in both workers' and jobs' characteristics and individuates a natural measure of local skill remoteness in the value of search.

To see why, consider the intuition from section 2.2: different skill portfolios yield different sets of job opportunities. Presumably it is one thing to look for a job with an engineer's credentials (and skills), quite another to be searching with carpentry experience. However, it is not obvious a priori which set of skills is more advantageous in terms of employment possibilities: it depends on the occupational composition of the labor market. Indeed, in a city where laborers and construction workers are the predominant occupations, carpenters' skills may be just as in demand as engineers'. The model captures this intuition by incorporating two stylized features of the labor market: heterogeneous multi-dimensional skill profiles for workers and jobs, and local labor markets characterized by multiple occupations.

4.1 Set-up

The economy is composed by a number C of independent cities, each populated by several types of workers $i = 1, \dots, I$ and several types of jobs $j = 1, \dots, J$. Workers can be described by a skill profile ℓ_i , the vector $\{\ell_{is}\}_{s=1}^S$. Similarly, jobs are characterized by the vector $\{\ell_{js}\}_{s=1}^S$. Cities are assumed to display different costs for opening and maintaining vacancies, so they are characterized by different mixes of job openings available to unemployed workers. The vacancy costs are disciplined by the data. Migration costs across cities are infinite

and there is no movement of workers or jobs across cities — I maintain this assumption throughout the work for simplicity and, for ease of discussion, in what follows I concentrate on the steady state equilibrium of one city.¹

Matching technology Search is random and there is no search on-the-job. The number of meetings in the labor market depends only on the number of unemployed workers u and the number of job openings v through a Cobb-Douglas meeting function with elasticity γ :

$$\mu = Au^\gamma v^{1-\gamma}$$

where A is aggregate matching efficiency, an exogenous parameter that is equal across cities. The probability that a worker *meets* a job in her local labor market is therefore independent of her type:

$$\frac{\mu}{u} = A \left(\frac{v}{u} \right)^{1-\gamma} \equiv A\theta^{1-\gamma}$$

where θ is the aggregate labor market tightness.

Upon meeting, the worker and the job realize what type of match i, j they can form. Meetings become matches if the surplus from the specific match exceeds zero. A worker of type i , then, becomes employed in a job j with the following probability:

$$f_{ij} = \underbrace{A\theta^{1-\gamma} \frac{v_j}{v}}_{\text{Pr(meeting } j)}} \underbrace{\mathbb{I}\{S_{ij} > 0\}}_{\text{if } =1, \text{ match}}$$

1. I discuss aggregation explicitly in section 4.4 where I calibrate the model to the aggregate labor market in the U.S..

In general the average job finding rate for worker i depends on her type as follows:

$$f_i = \sum_{k=1}^J A \theta^{1-\gamma} \underbrace{\frac{v_k}{v}}_{\equiv \lambda_k} \mathbb{I}\{S_{ik} > 0\} \quad (4.1)$$

where λ_j is the probability of meeting a job of type j .

Value functions and match surplus equation The value functions of an unemployed and an employed worker are:

$$U_i = b + \beta \left[\sum_{k=1}^J \lambda_k \max\{W_{ik} - U_i, 0\} + (1 - \sum_{k=1}^J \lambda_k) U_i \right] \quad (4.2)$$

$$W_{ij} = w_{ij} + \beta [\delta U_i + (1 - \delta)(pW_{jj} + (1 - p)W_{ij})] \quad (4.3)$$

where b is the utility from home production, β the discount rate, λ_k the arrival probability of jobs of type k as specified in (4.1), w_{ij} the wage level in a match i, j , δ the exogenous separation rate and p the period probability of learning the job's skills.²

From the demand side, the value of a filled job in a match i, j is:

$$J_{ij} = y_{ij} - w_{ij} + \beta(1 - \delta)(pJ_{jj} + (1 - p)J_{ij}) \quad (4.4)$$

where y_{ij} is the productivity of an i, j match (assumed deterministic for now), w_{ij} the wage paid to the worker, and β , δ and p are parameters as above. Notice that there is no continuation value after a separation (probability δ) because the value of a vacancy V_j is zero in equilibrium. This assumption implies that there are no rents from simply posting a

2. Because the arrival probabilities λ_j depend on city-specific vacancy ratios, match productivities y_{ij} need not differ across labor markets for wages to be heterogeneous across space. Maintaining this assumption is not crucial for equilibrium results, but relaxing it complicates notation and adds little insight to the discussion of this simple theoretical framework.

job opening, a condition often referred to as “free entry” in the vacancy market.

The match productivity has two components: a job-specific one z_j that summarizes the overall skill-intensity of different occupations and a cost of mismatch that depends linearly on the difference between the worker’s and the job’s skill profiles.

$$y_{ij} = z_j - \alpha d_{ij} \tag{4.5}$$

We can think of α as the parameter that governs the cost of differences in skill profiles between workers and jobs in terms of lost production. Because the cost αd_{ij} is subtracted directly from production, it can be interpreted as the dollar amount of production lost each month because the worker is not yet producing output of adequate quality, or is not producing at all because of time spent in classes and training programs. Therefore we can interpret the parameter α as pinning down the monthly cost of training. Note that, when $\alpha = 0$, all matches i, j are profitable and the model equilibrium is equivalent to the homogeneous workers and jobs case.

It is convenient to express the model structure in terms of the match surplus S_{ij} . This is defined as the sum of net worker surplus $W_{ij} - U_i$ and net job surplus $J_{ij} - V_j$, and since V_j is assumed to be zero in equilibrium, we have

$$S_{ij} = \sigma S_{ij} + (1 - \sigma) S_{ij} = W_{ij} - U_i + J_{ij} \tag{4.6}$$

Using equation (4.6) simplifies the solution process significantly, as the expression for the surplus does not depend on the wage. The converse is not true, so once the surplus is solved for, the wage can be computed for any i, j pair.

Recall that σ is the worker’s bargaining power, so that the worker can extract a portion σ of the match surplus. Then, we can rewrite equations (4.2), (4.3) and (4.4) as a function

of S_{ij} . Then, using the definition of S_{ij} in (4.6), we obtain the following set of recursive non-linear equations for the match surplus:

$$S_{ij} = \frac{z_j}{1-\beta(1-\delta)} - \frac{\alpha d_{ij}}{1-\beta(1-\delta)(1-p)} - \frac{1-\beta\delta}{1-\beta(1-\delta)(1-p)} U_i + \frac{\beta(1-\delta)}{1-\beta(1-\delta)} \frac{\beta\delta p}{1-\beta(1-\delta)(1-p)} U_j \quad (4.7)$$

Equations (4.7) make good intuitive sense: the surplus of an i, j match increases in the job's productivity but decreases in the training cost αd_{ij} . This implies that, other things equal, matches with a high-productivity job are more likely to go through, unless the worker is so little qualified for the job that the overall surplus would be negative.

Notice that net surplus does not depend on wages, as these only implement a transfer between the job and the worker. Surplus, instead, increases in the intrinsic productivity of the job z_j and decreases in the mismatch cost αd_{ij} . Surplus of an i, j match is also decreasing in the value of unemployment as a type i , U_i . This is intuitive: if being a type i is “useful” for job search, in the sense that the potential matching set is larger for an i than for a j , then the worker has an incentive to pass on matches of the type i, j and wait for a better offer. Should the worker become separated again, the potential loss of skills i would be a significant drawback. The opposite is true of the value of unemployment as a j type, U_j . If U_j is large, the surplus of a match i, j raises as the worker is attracted to job j because the skills she acquires by being employed in j yield a high expected value of search.

4.2 Match surplus, skill proximity and skill remoteness

In general, the surplus of an i, j match S_{ij} can be written as follows:

$$S_{ij} = z_j - c_{ij} - g_1(M_i) + g(M_j)$$

where g_1 and g_2 are two linear, positive functions and

$$U_i = \frac{1}{1 - \beta(1 - \sum_{k=1}^J \lambda_k)} (b + \beta M_i)$$

where

$$M_i = \sum_{k=1}^J \lambda_k \max\{S_{ik}, 0\}$$

is the value of search as a type i worker.

M_i is proportional to the weighted average of i 's surpluses from meeting all other jobs j in her local labor market, where the weights are meeting probabilities λ_j . Some of the elements of this sum are zeros, since not all meetings yield a match. The larger the number of jobs for which $S_{ij} \leq 0$, the lower is the value of M_i . M_i also potentially varies with the occupational distribution of vacancies, thus across different local labor markets.

I refer to M_i as “skill proximity”, the opposite of skill remoteness. When the number of jobs a worker i could match with is large, and these jobs represent a large share of the vacancies in the local labor market, M_i is large and the worker’s portfolio is *skill-central*. Instead, if suitable jobs are few and not well-represented in the vacancy pool, the worker’s skill portfolio is *skill-remote*. At the extremes, when no jobs that a worker i could take are available, M_i is equal to 0. If $S_{ij} > 0, \forall j$, then M_i is maximized.

The proximity index M_i is a useful summary statistics for the employability of worker i . Through the sum of $\max\{S_{ij}, 0\}$, it also incorporates the expected mismatch cost upon re-employment — that is αd_{ij} for all j . Therefore, M_i is also predictive of the wages i will receive upon re-employment (see next section for details).

However, the value of M_i cannot be directly inferred from observables since we do not observe the values of S_{ij} . Through the assumption of linear cost of mismatch we can nonetheless make progress. Consider how the surplus in a i, j match depends linearly on productivity

z_j and cost αd_{ij} , both potentially measurable in the data. Parametrize the distance between i and j as the L1-norm between i 's and j 's skill profiles:

$$d_{ij} = \frac{1}{S} \sum_{s=1}^S |\ell_{is} - \ell_{js}|$$

where $\{\ell_{is}\}_{s=1}^S$ is the S-dimensional skill profile of worker i and $\{\ell_{js}\}_{s=1}^S$ the S-dimensional skill profile of job j .

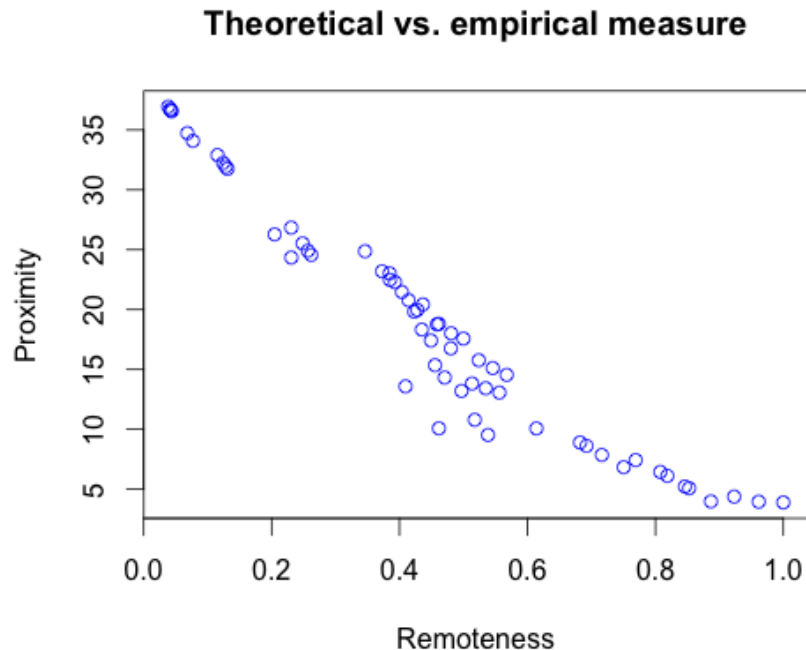
Consider then the following skill-remoteness index:

$$\widehat{M}_i = \sum_{k=1}^J \frac{v_k}{v} d_{ik} \quad (4.8)$$

For a given value of α and provided that jobs and workers can be empirically characterized as vectors of skills, all the variables in the third term are measurable in the data.

I argue that $M_i \approx -\widehat{M}_i$. Indeed, when \widehat{M}_i is large, the matching set for worker i is *small*, so M_i is small. \widehat{M}_i reaches its maximum value when all vacancies are concentrated in the occupation that is furthest from i . Provided that α is high enough, this implies that $M_i = 0$. Conversely, $\widehat{M}_i = 0$ when M_i is maximized, that is when all jobs are a suitable match for i . To confirm this intuition, figure 4.1 shows a comparison between the theoretical proximity index M_i and an implementation of the skill remoteness measure \widehat{M}_i that uses O*NET data on the skill content of occupations and occupational vacancies from HWOL. As α increases the cost of mismatch increases and vacancy creation becomes more and more skewed towards skill-central occupations. As a result, skill proximity M_i decreases and skill remoteness \widehat{M}_i increases. They do so almost linearly; for several values of α the two measures appear very close to being one a linear function of the other.

Figure 4.1: Evaluating the approximation of the theoretical proximity index with the empirical remoteness measure for several levels of training cost α . Source: HWOL and O*NET data in 2006.



4.3 Steady state equilibrium

I will consider the steady state equilibrium of the model set-up in the previous section. The steady state conditions include J equations to impose equilibrium in the vacancy markets, $I \times J$ wage equations for the equilibrium in the labor markets and I equations for stationarity of the unemployment rate in every occupational group.

Vacancy market Because of free entry in the vacancy market, in equilibrium vacancies are created until the marginal cost equals the marginal benefit:

$$\kappa_j = \beta \theta^{-\gamma} (1 - \sigma) \sum_{n=1}^I \frac{u_n}{u} \max\{S_{nj}, 0\} \quad (4.9)$$

where κ_j is a city-specific parameter that summarizes the flow cost of a vacancy and $(1 - \sigma)$ is the bargaining power of a job.

Wages Wages w_{ij} are negotiated at the beginning of every period and solve a Nash Bargaining problem with parameter σ so that:

$$w_{ij} = \arg \max (W_{ij} - U_i)^\sigma J_{ij}^{1-\sigma}$$

Substituting the value functions in the expression above and simplifying, we obtain:

$$w_{ij} = (1-\sigma) \frac{1 - \beta(1 - \delta)(1 - p)}{1 - \beta(1 - \delta)} z_j - (1-\sigma)\alpha d_{ij} + \sigma(1-\beta\delta) U_i - \beta\delta p \frac{1 + \beta(1 - \delta)p + \sigma(1 - \beta\delta)}{1 - \beta(1 - \delta)(1 - p)} U_j \quad (4.10)$$

The above expression indicates that the wage for a match i, j is increasing in the productivity of the job z_j and decreasing in the distance between the worker and the job skill profiles d_{ij} . Starting to work in a job j , the worker has probability p every period of learning the skills embedded in j . This implies that becoming employed in j may prevent the worker to search as a type i in the future: as a consequence, the wage w_{ij} is increasing in the value of unemployment as a type i to compensate for the lost expected value of search. However, if learning happens, the worker will be able to search as a type j : the more valuable is this option, embedded in U_j , the lower is the equilibrium wage a worker i accepts in a job j .

Employment and unemployment distributions In this economy workers of type i can be in three labor market states: unemployed, employed in a job with a different skill profile j or employed in a job with the same skill profile i . Equilibrium imposes that the inflows and outflows from each labor market state are equal.

Denote by u_{it} the mass of unemployed workers of type i at time t . Similarly, let e_{ijt} be the mass of workers of type i employed in jobs of type j at t . Workers are either employed

or unemployed: $\sum_{n=1}^I u_{nt} + \sum_k e_{nkt} = 1$.

Consider the inflows into and outflows from “mismatched unemployment” e_{ij} : inflows are the unemployed of type i that start a job in occupation j . The outflows come from workers who were previously employed in an i, j match but separated and workers who did not separate but learned and are therefore now in the e_{jj} group.

$$\delta e_{ijt} + p(1 - \delta)e_{ijt} = u_{it}\sigma\lambda_j\mathbb{I}\{S_{ij} > 0\} \quad (4.11)$$

Consider now the case when the worker and the job are “perfectly matched”: in this case learning does not matter and all matches that are not destroyed by the exogenous shock continue in the next period. Thus the only outflow comes from exogenous separations. There is also an inflows into the mass of i, i matches: the (lucky) newly employed in i, i matches and the workers who were previously employed in type i jobs, did not separate and learned the skills in job i :

$$\delta e_{iit} = u_{it}\sigma\lambda_i + (1 - \delta)p \sum_{n \neq i} e_{nit-1} \quad (4.12)$$

because $\mathbb{I}\{S_{ii} > 0\} = 1, \forall i$.

Finally, then, equilibrium unemployment rate is defined by:

$$\delta \sum_{k=1}^J e_{ikt} = u_{it} \left(1 - \sigma \sum_{k=1}^J \lambda_k \mathbb{I}\{S_{ik} > 0\} \right) \quad (4.13)$$

where the inflows originate in separation of employed workers of type i (regardless of what type of job they are employed in, since learning happens after separations) and the outflows reflect successful matching of type i workers with any kind of job. Substituting equation (4.11) and (4.12) in (4.13) and imposing that $u_{it} = u_{it-1}, \forall i$ yields a system of I equations for the equilibrium unemployment rate vector:

$$u_i^* \left[\sum_{k \neq i} \frac{v_k}{v} \mathbb{I}\{W_{ik} \geq U_i\} \right] = \frac{(1-\delta)(1-p)}{\delta} \sum_{n \neq i} \frac{v_i}{v} u_n^* \mathbb{I}\{W_{ni} \geq U_n\} + \frac{1}{1-(1-\delta)p} \sum_{k \neq i} \frac{v_k}{v} u_k^* \mathbb{I}\{W_{ik} \geq U_i\} \quad (4.14)$$

Equilibrium definition A steady state equilibrium (for city c) is a set of unemployment rates $\{u_i\}_{i=1}^I$, vacancy rates $\{v_j\}_{j=1}^J$ and wages $\{w_{ij}\} \forall i, j$ that satisfy:

- the S_{ij} equations (4.7) $\forall i, j$;
- the stationarity condition for the unemployment rate (4.14) $\forall i$;
- the wage determination condition (4.10) $\forall i, j$;
- the free-entry conditions (4.9) $\forall j$.

4.4 Calibrating the cost of mismatch

I calibrate a monthly version of the model with a number of worker types $I = 6$, job types $J = 6$, and cities, $C = 51$.³ The HWOL database features occupation-by-city vacancy rates only for 6 occupational groups and 51 urban areas. These 51 cities, however, account for more than half of the urban population, and 50% of the national labor force. I benchmark the equilibrium so that it reproduces the vacancy distribution observed in the data and then use the model's structure to study how changes in primitives affect aggregate outcomes.⁴

3. I avoid considerable computational burden by assuming that workers cannot search across locations. This hypothesis rests on the assumption that migration costs are sufficiently large to restrict the scope of job search, so that, at least in the medium term, migration cannot alleviate local labor market externalities (Kennan and Walker, 2011; Notowidigdo, 2013; Yagan, 2015). Although primarily used for simplicity, there is some direct evidence in favor of this assumption. For example, using a comprehensive dataset on online job searches, Marinescu and Rathelot (2016) find that more than 80% of applications that unemployed job seekers send are for jobs within the boundaries of their city of residence.

4. For a given value of aggregate market tightness θ , each city's equilibrium is solved through a three-layered loop procedure, whose details are provided in the Appendix. A final step ensures that the value of market tightness implied by equilibrium unemployment and vacancies across cities is consistent with the postulated aggregate θ .

In this section, I discuss exactly how the model parameters are chosen for the benchmark calibration, with a particular focus on α , the cost of training, and p , the probability of learning.

Most of the ingredients in the model can be recovered directly from the data or previous literature. Not so for α and p . These parameters govern the strength of mismatch in the economy. Specifically, notice that, if $\alpha = 0$ mismatch is costless and the model's equilibrium is equivalent to the textbook DMP model with homogeneous workers and homogeneous jobs, where the values of sectoral market tightness are equalized and the allocation of workers across occupations is efficient. If α is large, instead, mismatch has maximum bite as workers only become employed in one type of occupation regardless of the employment opportunities in other occupations. When $p = 1$ mismatch lasts only one period, so that in equilibrium most of employed workers are in i, i matches. When $p = 0$, instead, there is no learning and the model structure reproduces the sorting patterns in Shimer and Smith (2000), a model in which worker types do not evolve over time and are therefore interpreted as intrinsic characteristics rather than skills that can be learnt on the job. Different moments in the data are informative to estimate α and p . Specifically, I propose a calibration exercise that ties the magnitude of these parameters to the level of the aggregate unemployment rate and real wage growth.

In table 4.1, I present all the parameters to be calibrated and their counterparts in the data. First of all, I conduct the analysis for six occupational types: managerial, financial and business occupations, professional occupations, personal service and care occupations, sales and clerical occupations, production occupations, construction and transportation occupations. I use O*NET data to recover the distances between these occupational groups. Then I calibrate the discount rate β to reflect a 4% annual interest rate. The worker bargaining power is set at 0.5 as in Şahin, Song, Topa and Violante (2014). Following Hosios (1990), I abstract from within-market congestion externalities and set the elasticity of the matching

function equal to 0.5 as well. I calibrate the value of home production b to 0.4 as in Shimer (2005) or 0.95 as in Hagedorn and Manovskii (2010) — this choice is largely inconsequential for the equilibrium results. The average separation rate δ is 0.03 in May 2006 according to CPS longitudinal data.

Table 4.1: Calibrated parameters and respective data sources. Monthly frequency, data at May 2006.

Parameter	Interpretation	Value	Target data moment/ source
I, J	# of occupations	6	HWOL
β	Discounting	0.96	4% annual r
σ	Worker bargaining	0.5	Şahin, Song, Topa, Violante (2014)
γ	Matching elasticity	0.5	Hosios (1990)
δ	Separations	0.03	EU rate (CPS)
b	Home prod.	0.4-0.95	Shimer (2005); Hagedorn, Manovskii (2010)
$d_{ij}, \forall i, j$	Skill distance	0-0.35	Skill distances (O*NET)
A	Matching efficiency	1	Normalized
$\kappa_j, \forall j$	Vacancy costs	\$36-\$320	Vacancy shares (HWOL)
$z_j, \forall j$	Productivity	\$1,920-\$6,240	Avg. wage level (OES)
p	Learning	0.05	Real wage growth (BLS)
α	Training cost	\$133	Unemployment rate (CPS)

I calibrate the cost of maintaining a vacancy κ_j so that the distribution of job openings in the model reproduces the observed occupational vacancy shares in the HWOL data. Cost parameters κ_j are allowed to differ by occupational groups. Estimated costs display considerable variation: the cost to open, maintain and ultimately fill a vacancy for a clerical job is approximately \$40 per month. Filling a professional or managerial position, instead, demands resources equivalent to more than \$300 per month.⁵

Occupational distances d_{ij} are taken directly from the O*NET 2006 wave using the skill profiles described in section 2.2. Occupational productivities z_j , the learning speed p and the

5. There is some evidence, from Faberman, Menzio (2015), Hershbein, Kahn (2016) and Faberman, Kudlyak (2016), that vacancy duration is heterogeneous and so are vacancy requirements, both within and across occupations; the heterogeneous estimates of vacancy posting costs that I find in this work are consistent with this literature.

cost of training α are jointly chosen to minimize the distance between labor market moments in the model and in the data. Specifically, I target the level of aggregate unemployment, the average wage level for each occupation and the average yearly wage growth rate. Notice that I normalize the aggregate matching efficiency A to 1. The reason is that, for any level of aggregate unemployment and for fixed p and z_j , there exist many combinations of A and α that can match the moment in the data. Since the focus is the cost of mismatch rather than residual aggregate matching efficiency, I hold A constant at 1.⁶ The value of α that matches the moment in the data turns out to be \$133 per month for a full time worker with the average level of mismatch, that is \$0.85 per hour and approximately 2.7% of the average wage in the economy. The value of p is 0.05 per month, so that 95% of currently mismatched workers who do not separate will still be mismatched next period. The values of z_j range between a maximum of \$39 per hour for managerial jobs and a minimum of 10\$ per hour for service occupations.

Table 4.2: Model fit, aggregate moments, calibration at May 2006. Data: CPS and OES.

	Data	Model
Unemployment rate	4.6%	4.6%
Monthly job finding rate	0.56%	0.56%
Median hourly wage	\$15	\$15
Average hourly wage	\$24	\$24
Average yearly wage growth	2.7%	2.8%
Average wage by occup.		
<i>Managerial</i>	\$39	\$39
<i>Professional</i>	\$29	\$30
<i>Service</i>	\$12	\$16
<i>Clerical</i>	\$20	\$21
<i>Production</i>	\$17	\$16
<i>Trasportation</i>	\$14	\$14

6. In particular, α and A enter the job finding rate in the same way, so the effect on an increase in the former is undistinguishable from a decrease in the latter.

Table 4.2 details the model’s fit: the model performs well on all aggregate variable, including the unemployment rate, job finding rate and wage growth, but it slightly over-predicts median wages for middle-skill occupational groups (clerical and service).⁷ In ongoing work, I am also evaluating the model’s predictions for the dispersion in employment rates and occupational wages across cities.

4.5 Subsidized on-the-job training

The cost of training workers has seen a resurged interest after the 2008-09 Recession, as job losses were concentrated in declining sectors (Jiamovich and Siu, 2014) and many advocated re-training as a possible solution: for example, the U.S. government sponsored the Workforce Investment Act and greatly increased public spending in training programs for laid-off workers. On the other hand, increases in training costs are also likely to be more and more relevant in a labor market characterized by up-skilling, a phenomenon described in Shoag, Modestino and Ballance (2014) and Hershbein and Kahn (2016) for post-recession years. If jobs tasks become more and more complex, it is plausible to postulate that on-the-job training becomes more and more costly. Expanded licensing requirements also resembles increases in the cost of training, because they constitute an additional barrier to worker reallocation across occupations. This is cause for concern as these regulations become more prevalent in the U.S. economy (Mulholland and Young, 2016).⁸ In this work’s framework, a subsidized

7. A poor fit of middle-skill occupations’ wages is a direct consequence of the distance estimated from the O*NET skill data. The skill-based measure of training costs in the model is more stylized than what training costs presumably are in reality. For example, the model implies that in equilibrium a worker with service skills can take any type of job in the economy, including managerial or professional occupations. Though in the skill space service and professional occupations may be close, in the data they need not be so: worker reallocation between these groups of occupations is slowed down, for example, by licensing requirements or education requirements. The model does not have these dimensions and allows therefore for larger flows across occupational groups than the data. This results in an estimated large value of service skills and a predicted wage that is much higher than what we observe in the data.

8. A long-term positive trend in training costs has also been considered as a potential explanation for patterns in worker reallocation and turnover (see Cairó, 2013 and Hudomiet, 2015). Though my objective

training program can be understood as a reduction in the parameter α while increases in training costs due to up-skilling or licensing requirements correspond to an increase in α .

Using the general equilibrium of the model, I therefore assess the aggregate effects of two different scenarios: an increase and a decrease in the cost of training α by 5% over the benchmark level in May 2006. A change in α translates into a change in the skill-remoteness of the unemployed through two channels; it affects job creation and it modifies the composition of the unemployed pool. Specifically, an increase in the cost mismatch discourages vacancy posting in all occupations and disproportionately so in skill-remote ones. The intuition is that jobs in skill-remote occupations have a small probability to be matched with suitable workers to begin with, so it only takes a small change in α to “push them over the edge” and not hire at all. Similarly, skill-remote workers are less likely to be re-employed as α increases because fewer matches yield positive surplus for them. As a result, skill-remote workers are disproportionately represented among unemployed individuals and, as the cost of mismatch increases, so does the average skill remoteness of the unemployed.

I show that a 5% increase in the cost of mismatch raises the median skill remoteness among the unemployed by 4%, the average by 12% and the 75th percentile by 29%. A 5% increase in the cost of mismatch also leads to a 33% decrease in the average job finding rate, a 50% decrease in aggregate market tightness and a 40% increase in the aggregate unemployment rate. Average earnings change relatively little, but their dispersion increases by more than 15%, as the low-skilled are more often unemployed or mismatched and have lower earnings as a consequence. Furthermore, these negative consequences are borne out mostly by the low-skilled, whose wages and job finding rates go down more than high-skill workers. Subsidizing training yields opposite results but smaller magnitudes. A 5% decrease

in this section is somewhat less ambitious than explaining the declined dynamism of the U.S. economy, the comparative statics exercise is still informative for this literature as it shows that mismatch significantly reduces the scope for worker reallocation across occupations.

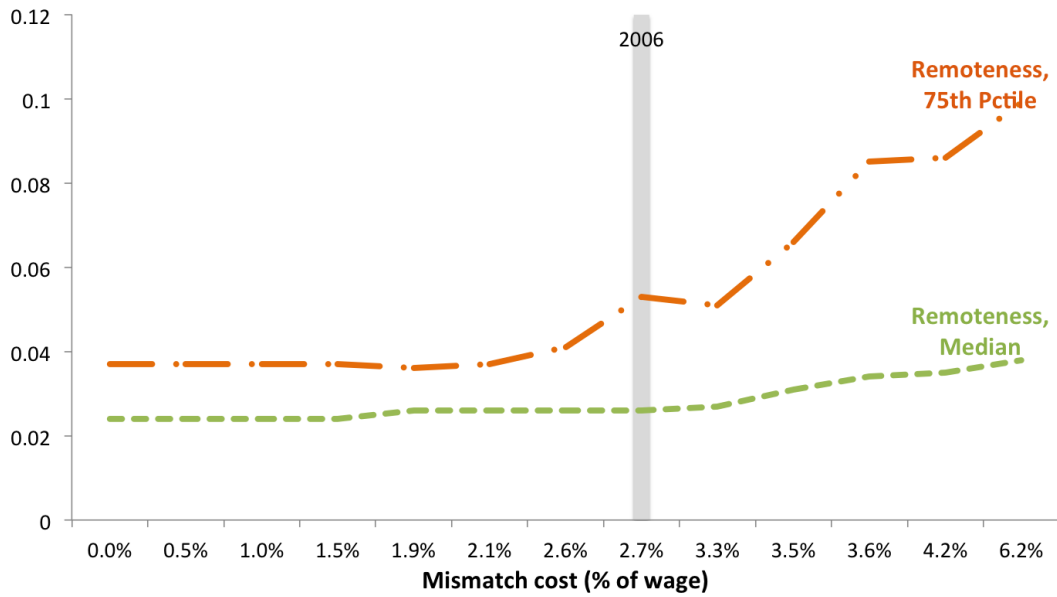
in the cost of mismatch does not change median remoteness, and reduces the average by 3% and the 75th remoteness percentile by at least 15%. It also reduces unemployment by 14%, increases the average job finding rate by 38% and the aggregate market tightness by 16%. These results are detailed in table 4.3 where I compare an economy calibrated to reproduce the 4.6% unemployment rate in the U.S. at May 2006 with an economy with the same fundamentals but an increased (or decreased) cost of mismatch by 5%.

Table 4.3: Aggregate effects of varying the cost of mismatch.

	May 2006	+ 5%	-5%
Cost of mismatch (% of wage)	2.9%	3.7%	2.7%
Aggregate u-rate	4.6%	8.6%	3.9%
Avg. monthly job finding rate	0.57	0.38	0.65
Aggregate market tightness	0.59	0.32	0.69
SD sectoral market tightness	0.06	0.18	0.01
Share of i, j matches	25%	21%	27%
Avg. hourly wages	\$24.70	\$19.16	\$26.60
Avg. yearly wage growth	2.7%	2.1%	3%
Avg. skill remoteness	0.025	0.028	0.024
Median skill remoteness	0.026	0.027	0.026
75th pctile skill remoteness	0.041	0.053	0.037

It is apparent that the sign of the changes in the cost of mismatch matters; an increment of 5% in training costs raises aggregate unemployment more than a 5% drop in costs brings it down. The effect of an increase in training costs on the distribution of skill remoteness among the unemployed is also non-linear: as α increases, the median skill remoteness of the unemployed increases, and so does the inter-quartile range to an even larger degree (see figure 4.2). This non-linearity is potentially important for aggregate outcomes, as becomes evident when one investigates the value of equilibrium unemployment as a function of a larger set of mismatch costs. This can be seen in figure 4.3, where several values of the hourly cost of training are depicted on the x -axis as a percentage of the average hourly wage, against the average job finding rate on the left-hand side y -axis (purple dashed line) and the aggregate

Figure 4.2: Median and 75th pctile of skill remoteness, as a function of the cost of the training. The latter increases more than the former.



unemployment rate on the right-hand side y -axis (blue solid line).

Figure 4.3: The aggregate unemployment rate increases when the cost of training increases, in a markedly non-linear fashion.

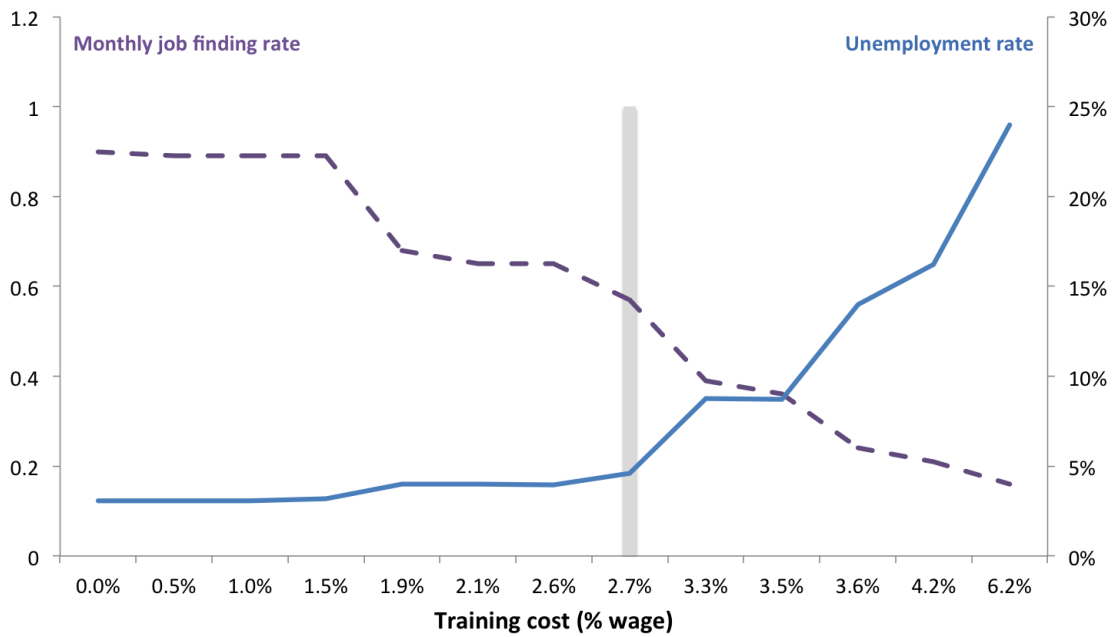
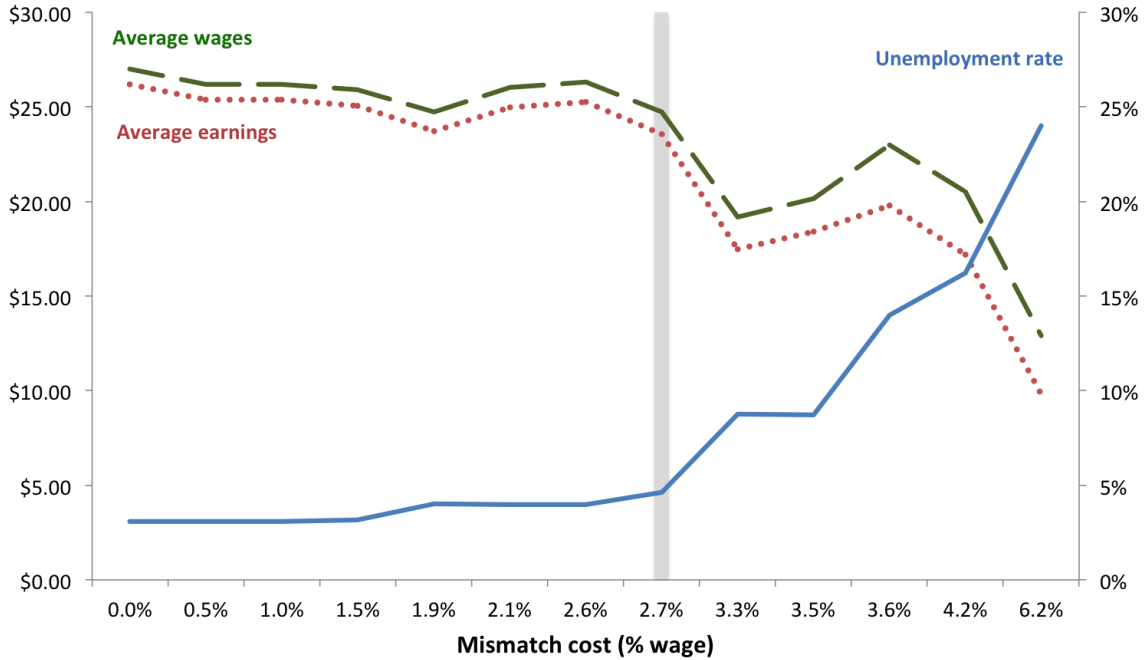


Figure 4.4: Average earnings and wages decrease when the cost of training increases.



The behavior of equilibrium unemployment as a function of training costs shares some similarities with distortions from tax rate increases. For small values of training costs, the aggregate unemployment rate is barely affected by its changes. However, the benchmark May 2006 calibration estimates training cost at 2.7% of the wage. It is precisely for values somewhat larger than 3% of the average wage that even small increases in the cost of mismatch are associated with large increases in the unemployment rate. The model in this work is mostly descriptive and further research is warranted to better understand the magnitude of mismatch costs: however, as occupational licensing and hiring regulation provisions become more and more widespread, the non-linearity in figure 4.3 suggests caution when extrapolating the effects of labor market regulations on aggregate employment from past data. Figure 4.4 makes a similar point for average earnings and wages. Therefore, much such as with tax rates, the magnitude of distortions induced by a marginal hike in training costs is likely to differ depending on the initial value.

What is the mechanism behind the positive relationship between the unemployment rate and the cost of mismatch? To gain some insight, recall that, as the cost of training α increases, the number of possible matches for which $S_{ij} > 0$ decreases. This is true for any type of worker i because the cost of training has gone up for all jobs, but the effect is going to be larger for workers who are skill-remote to begin with because it is amplified by the magnitude of distances d_{ij} .

This mechanism is illustrated in figure 4.5. The three panels depict the distribution of employees of type i (on the left y -axis) in jobs of type j (on the x -axis) for different levels of mismatch cost. Red indicates high and blue low frequency. The mismatch cost increases from top to bottom, left to right; the upper-left panel corresponds to the benchmark May 2006 calibration. There are two key messages from comparing the three figures: first of all, the model in its benchmark calibration reproduces the qualitative features of the occupational distribution of workers in the U.S., with most workers being in the same occupation for consecutive periods (i.e. the high-frequency diagonal). In addition, as the cost of training rises, the figures display more and more *white* squares at the corners. This means that those matches are no longer active because their surplus is negative and is equivalent to an increase in skill remoteness for workers whose set of feasible matches shrinks. Similarly to the sorting patterns in Shimer and Smith (2000), for example, workers of type i tend in general to be matched to jobs of type i and more so when training costs are high. The tighter is this relationship, the more employed workers are concentrated on the diagonal and the more likely is that workers who used to be profitably employed in i, j matches are now unemployed.

This pattern is only reinforced by general equilibrium forces. In general equilibrium there is an additional mechanism, related to the presence of trading externalities, that contributes to lowering re-employment rates and wages for skill-remote laid-off workers. In equilibrium, the lack (or abundance) of unemployed workers with specific skill sets discourages (or en-

Figure 4.5: As the cost of mismatch increases, the set of productive matches decreases.

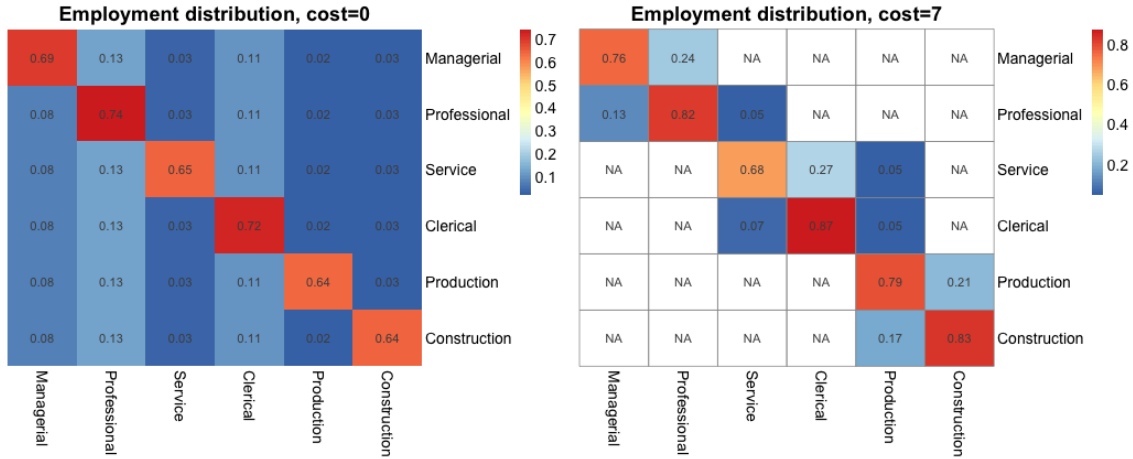
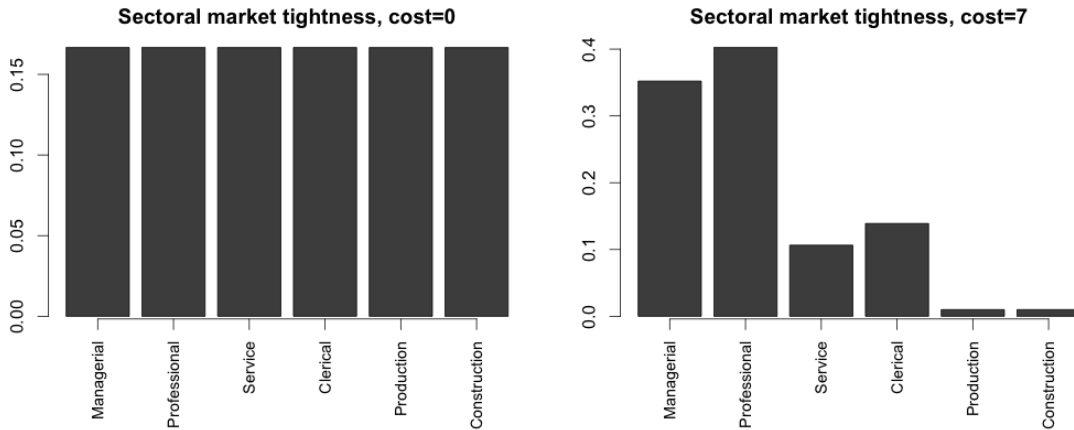


Figure 4.6: As the cost of mismatch increases, sectoral dispersion in mkt tightness increases.



courages) job creation in occupations that use those skills, proportionally to the intensity of use. In other words, it is precisely the fact that unemployed workers with specific skills are scarce that discourages firms to post vacancies demanding those skills: since the probability of filling jobs productively is low, job creation is low and unemployment, instead, is high. This can be seen in the three panels in figure 4.6: they depict the vacancy to unemployment ratio for each of the six occupational groups under different training costs assumption. When the cost of mismatch is 0, sectoral vacancies to unemployed ratios are equalized and employment is maximized. As the cost of mismatch increases, sectoral market tightnesses

are no longer equalized, reflecting differential incentives to post vacancies in different sectors. These two mechanisms, job acceptance and job creation, are both qualitatively important to determine aggregate employment as a function of mismatch.

4.6 Summary and concluding remarks

In this work, I propose local skill remoteness as a method to capture the extent to which a worker's skills differ from those jobs in specific labor markets demand. I derive a measure of skill remoteness in the context of a search-and-matching model with two-sided heterogeneity and implement it using data on the skill content of occupations and the occupational composition of city-level employment. I use O*NET data to describe occupations as vectors of skills. Then, I compute distances between occupations in the skill space to gauge how suitable skills that characterize one job are to the performance of another. Finally, I compute an employment-weighted average distance to consider the relative importance of different types of occupations across cities.

According to my measure, occupations in the same city display different skill remoteness values because of the disparate skills they entail and each occupation's skill remoteness varies across cities as well. Using a combination of micro-level data for U.S. workers, I attribute a value of skill remoteness to individuals according to the last occupation they held and the city in which they reside. I then assess how labor market outcomes for laid-off workers relate to the value of remoteness at layoff. I find that an unemployed person's local skill remoteness determines her chances of being re-employed, the job taken, the wage received upon re-employment, and their propensity to migrate.

During the first 30 months after layoff, skill-remote workers earn more than \$14,000 less than skill-central workers and losses are due primarily to lower wages at re-employment — though skill-remote workers also have longer unemployment duration by about 1.5 weeks.

Occupational and geographic mobility rates also vary according to skill remoteness at layoff; skill-remote workers are 8% more likely to be in a different occupation upon re-employment, and the skill distance between the previous and current occupations is, on average, half a standard deviation higher. Skill-remote workers also have a 50% higher probability of migrating to a different city than the one in which layoff occurred, and, in doing so, they typically reduce their skill remoteness by 25%.

I interpret these results through the lens of a frictional labor market model with two-sided heterogeneity. The model highlights the role of the local labor market's skill structure in determining the scope of worker reallocation, the level of wages and the unemployment rate. In my quantitative analysis, I find that the relationship between the cost of mismatch and aggregate unemployment rate is positive and highly non-linear. Although chiefly qualitative, the model's results suggest that the differential effects of policies that promote worker reallocation such as occupational training, or that hamper worker reallocation such as licensing, differ according to the initial degree of mismatch.

The skill remoteness approach emphasizes that skill disparities between workers and jobs affect labor market outcomes for laid-off laid-off workers. However, differences in skill profiles are not the only factors that affect worker reallocation across occupations. Recent literature suggests that occupational licensing is common in the U.S., raising concerns about its effect on employment, especially for low-skilled workers (Mulholland and Young, 2016). Since licensing requirements vary across states, a combined study of licensing regulations and local skill structure differences would enhance the geographic accuracy of the local skill remoteness measure that I propose, and improve its predictive power regarding worker transitions across occupations.

A complementary approach to studying skill remoteness would be to use the magnitude of cross-occupational flows to gauge distance between jobs. Unlike the skill-based measure used in this work, a flow-based measure would capture impediments to worker reallocation

other than those based solely on skill discrepancies, potentially combined with idiosyncratic factors and temporary shocks. During exploratory analysis, I found that the distance between occupations accurately predicts worker flows, except for (heavily licensed) healthcare occupations and job changes for younger workers, which are usually larger than for older workers and involve some degree of learning (Neal 1995, 1999). Since the flow-based approach is agnostic of mismatch sources, in ongoing work I am pursuing a comparison of the two frameworks.

This work addresses the question of how the *level* of mismatch affects the *level* of unemployment in equilibrium. A natural extension of this analysis is to study how *changes* in mismatch affect *changes* in the unemployment rate. Specifically, it may be that the composition of the unemployed pool skews towards more skill-remote workers during recessions. Although I do not develop this theme in this work, I consider the role of skill remoteness over the business cycle part of a broader research agenda. This work provides evidence for the role of skill remoteness in individual and aggregate labor market outcomes. Promising future research lies in assessing whether the composition of the unemployed pool interacts with the business cycle, and how it relates to the cyclical nature of wage losses after layoff, the acceleration of long-term trends such as polarization and up-skilling during downturns, and the prevalence of “jobless recoveries” after recent recessions.

REFERENCES

- [1] Fredrik Andersson, John C. Haltiwanger, Mark J. Kutzbach, Henry O. Pollakowski, and Daniel H. Weinberg. Job displacement and the duration of joblessness: The role of spatial mismatch. Working paper, National Bureau of Economic Research, 2014.
- [2] David Autor, David Dorn, and Gordon H. Hanson. The china syndrome: Local labor market effects of import competition in the united states. *The American Economic Review*, 2013.
- [3] David Autor, David Dorn, Gordon H. Hanson, and Jae Song. Trade adjustment: Worker-level evidence. *The Quarterly Journal of Economics*, 2014.
- [4] David Autor, Frank Levy, and Richard J. Murnane. The skill content of recent technological change: an empirical explorations. *The Quarterly Journal of Economics*, 2003.
- [5] David H. Autor, Lawrence F. Katz, and Melissa S. Kearney. Trends in u.s. wage inequality: Revising the revisionists. *Review of Economics and Statistics*, 2(90), 2008.
- [6] Regis Barnichon and Andrew Figura. Labor market heterogeneity and the aggregate matching function. *American Economic Journal: Macroeconomics*, 4(7), 2015.
- [7] Hoyt Bleakley and Jeffrey Lin. Thick-market effects and churning in the labor market: Evidence from u.s. cities. *Journal of Urban Economics*, 2-3(72), 2012.
- [8] Isabel Cairó. The slowdown in business employment dynamics: The role of changing skill demands. *Working paper*, 2013.
- [9] Lorenzo Caliendo, Maximiliano Dvorkin, and Fernando Parro. Trade and labor market dynamics. *Working Paper*, 2015.
- [10] Antonio Ciccone and Robert E. Hall. Productivity and the density of economic activity. *The American Economic Review*, 1(86), 1996.
- [11] Antonio Ciccone and Giovanni Peri. Identifying human capital externalities: Theory with applications. *Review of Economic Studies*, 2(73), 2006.
- [12] Don Davis and Jonathan Dingel. The comparative advantage of cities. *Working Paper*, 2015.
- [13] Steven J. Davis and John Haltiwanger. Gross job creation, gross job destruction and employment reallocation. *Quarterly Journal of Economics*, 1992.
- [14] Steven J. Davis and John Haltiwanger. Labor market fluidity and economic performance. *Working Paper*, 2014.

- [15] Steven J. Davis, John Haltiwanger, and Scott Schuh. Job creation and destruction. 1996.
- [16] Steven J. Davis and Till von Wachter. Recession and the cost of job loss. *Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution*, 42(2), 2011.
- [17] Ryan Decker, John Haltiwanger, Ron Jarmin, and Xavier Miranda. The secular decline in business dynamism in the u.s. *Working paper*, 2014.
- [18] Maximiliano Dvorkin. Sectoral shocks, reallocation and unemployment in competitive labor markets. *Working paper*, 2014.
- [19] R. Jason Faberman and Marianna Kudlyak. What does online job search tell us about the labor market? *Economic perspectives*, 1, 2016.
- [20] R. Jason Faberman and Guido Menzio. Evidence on the relationship between recruiting and the starting wage. *Working paper*, 2015.
- [21] Henry Farber. The incidence and costs of job loss: 1982-91. *Brookings Papers: Microeconomics*, 1993.
- [22] Enrique Fernandez-Macias, John Hurley, and Donald Storrie. Transformation of the employment structure in the eu and usa, 1995-2007. *Palgrave Macmillan*, 2012.
- [23] Shigeru Fujita. Declining labor turnover and turbulence. *Working Paper*, 2015.
- [24] Christina Gathmann and Uta Schoenberg. How general is human capital? a task-based approach. *Journal of Labor Economics*, 28(1), 2010.
- [25] Maarten Goos and Alan Manning. Lousy and lovely jobs: The rising polarization of work in britain. *Review of Economics and Statistics*, 89(1), 2007.
- [26] Fatih Guvenen, Burhan Kuruscu, Satoshi Tanaka, and David Wiczer. Multidimensional skill mismatch. *Working Paper*, 2014.
- [27] Robert E. Hall and Sam Schulhofer-Wohl. Measuring job-finding rates and matching efficiency with heterogeneous jobseekers. *Working Paper*, 2016.
- [28] John Haltiwanger. Top ten signs of declining business dynamism and entrepreneurship in the u.s. *Working paper*, 2015.
- [29] James J. Heckman and Guilherme L. Sedlacek. Heterogeneity, aggregation and market wage functions: An empirical model of self-selection in the labor market. *Journal of Political Economy*, 93, 1985.
- [30] James J. Heckman and Guilherme L. Sedlacek. Self-selection and the distribution of hourly wages. *Journal of Labor Economics*, 8(1), 1990.

- [31] James J. Heckman and Guilherme L. Sedlacek. Self-selection and the distribution of hourly wages. *Journal of Labor Economics*, 8(1), 1990.
- [32] Brad Hershbein and Lisa Kahn. Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *Working paper*, 2016.
- [33] Benedikt Herz and Thijs van Rens. Accounting for mismatch unemployment. *Working Paper*, 2015.
- [34] Bart Hobijn. The industry-occupation mix of u.s. job openings and hires. *Working Paper Series, Federal Reserve Bank of San Francisco*, 2012.
- [35] Chang-Tai Hsieh and Enrico Moretti. Why do cities matter? local growth and aggregate growth. *Working Paper*, 2004.
- [36] Christopher Huckfeldt. Understanding the scarring effect of recessions. *Working paper*, 2016.
- [37] Péter Hudomiet. The role of occupation specific adaptation costs in explaining the educational gap in unemployment. *Working paper*, 2015.
- [38] Louis S. Jacobson, Robert J. LaLonde, and Daniel G. Sullivan. Earnings losses of displaced workers. *The American Economic Review*, 83(4), 1993.
- [39] Nir Jaimovich and Henry Siu. The trend is the cycle: Job polarization and jobless recoveries. *Working paper*, 2014.
- [40] Gregor Jarosch. Searching for job security and the consequences of job loss. *Working paper*, 2015.
- [41] Gueorgui Kambourov and Iourii Manovskii. Occupational mobility and wage inequality. *Review of Economic Studies*, 76(2), 2009.
- [42] Gueorgui Kambourov and Iourii Manovskii. Occupational specificity of human capital. *International Economic Review*, 50(1), 2009.
- [43] Lawrence F. Katz and David H. Autor. Changes in the wage structure and earnings inequality. *Handbook of Labor Economics*, 3, 1999.
- [44] John Kennan and James R. Walker. The effect of expected income on individual migration decisions. *Econometrica*, 79(1), 2011.
- [45] Pawel Krolikowski. Job heterogeneity and aggregate labor market fluctuations. *Working Paper*, 2014.
- [46] Edward P. Lazear. Firm-specific human capital: a skill-weights approach. *Journal of Political Economy*, 117(3), 2009.

- [47] Ilse Lindenlaub. Sorting multidimensional types: theory and application. *Working Paper*, 2015.
- [48] Ilse Lindenlaub and Fabien Postel-Vinay. Multidimensional sorting under random search. *Working Paper*, 2016.
- [49] Jeremy Lise and Fabien Postel-Vinay. Multidimensional skills, sorting and human capital accumulation. *Working paper*, 2015.
- [50] Ioana Marinescu and Roland Rathelot. Mismatch unemployment and the geography of job search. *Working Paper*, 2016.
- [51] Alicia Sasser Modestino, Daniel Shoag, and Joshia Ballance. Upskilling: do employers demand greater skill when workers are plentiful? *Working paper*, 2014.
- [52] Enrico Moretti. Human capital externalities in cities. *Handbook of Regional and Urban Economics*,, 2004.
- [53] Enrico Moretti. Local labor markets. *Handbook of Labor Economics*, 4b, 2011.
- [54] Dale T. Mortensen and Christopher A. Pissarides. Job creation and job destruction in the theory of unemployment. *The Review of Economic Studies*, 61(3), 1994.
- [55] Sean E. Mulholland and Andrew T. Young. Occupational licensing and interstate migration. *Cato Journal*, 1, 2016.
- [56] Derek Neal. Industry-specific human capital: Evidence from displaced workers. *Journal of Labor Economics*, 13(4):653–677, 1995.
- [57] Derek Neal. The complexity of job mobility among young men. *Journal of Labor Economics*, 17(2), 1999.
- [58] Chris Nekarda. A longitudinal analysis of the current population survey: Assessing the role of geographic mobility. *Working paper*, 2009.
- [59] Matthew J. Notowidigdo. The incidence of local labor market shocks. *Working Paper*, 2013.
- [60] Henry G. Overman and Diego Puga. Labor pooling as a source of agglomeration: An empirical investigation. *NBER chapters, in: Agglomeration Economics*, 2010.
- [61] Christina Patterson, Ayşegül Şahin, Giorgio Topa, and Giovanni L. Violante. Working hard in the wrong place: A mismatch-based explanation to the uk productivity puzzle. *European Economic Review*, (Forthcoming), 2016.
- [62] Ronni Pavan. Career choice and wage growth. *Journal of Labor Economics*, 29(3), 2011.

- [63] Barbara Petrongolo and Christopher A. Pissarides. Looking into the black box: A survey of the matching function. *Journal of Economic Literature*, 2(39), 2001.
- [64] Maxim Poletaev and Chris Robinson. Human capital specificity: Evidence from the dictionary of occupational titles and displaced worker surveys, 1984-2000. *Journal of Labor Economics*, 26(3), 2008.
- [65] Ayşegül Sahin, Joseph Song, Giorgio Topa, and Giovanni L. Violante. Mismatch unemployment. *American Economic Review*, 104(11), 2014.
- [66] Robert Shimer. The cyclical behavior of unemployment and vacancies. *American Economic Review*, 95(1), 2005.
- [67] Robert Shimer. Mismatch. *American Economic Review*, 97(4), 2007.
- [68] Robert Shimer. The impact of young workers on the aggregate labor market. *Quarterly Journal of Economics*, 116(3), 2014.
- [69] Robert Shimer and Richard Rogerson. Search in macroeconomic models of the labor market. *Handbook of Labor Economics*, 4A, 2010.
- [70] Robert Shimer and Lones Smith. Assortative matching and search. *Econometrica*, 68(2), 2000.
- [71] Robert Shimer and Lones Smith. Matching, search, and heterogeneity. *Advances in Macroeconomics (BE Journals in Macroeconomics)*, 1(1), 2001.
- [72] Till von Wachter and Stefan Bender. In the right place at the wrong time: The role of firms and luck in young workers' careers. *American Economic Review*, 96(5), 2006.
- [73] Danny Yagan. Is the great recession really over? longitudinal evidence of enduring employment impacts. *Working Paper*, 2016.
- [74] Shintaro Yamaguchi. Tasks and heterogeneous human capital. *Journal of Labor Economics*, 30(1), 2012.

APPENDIX A

DATA APPENDIX

A.1 Major occupational groups

- 11 Management Occupations
- 13 Business and Financial Operations Occupations
- 15 Computer and Mathematical Occupations
- 17 Architecture and Engineering Occupations
- 19 Life, Physical, and Social Science Occupations
- 21 Community and Social Services Occupations
- 23 Legal Occupations
- 25 Education, Training, and Library Occupations
- 27 Arts, Design, Entertainment, Sports, and Media Occupations
- 29 Healthcare Practitioners and Technical Occupations
- 31 Healthcare Support Occupations
- 33 Protective Service Occupations
- 35 Food Preparation and Serving Related Occupations
- 37 Building and Grounds Cleaning and Maintenance Occupations
- 39 Personal Care and Service Occupations
- 41 Sales and Related Occupations
- 43 Office and Administrative Support Occupations
- 45 Farming, Fishing, and Forestry Occupations
- 47 Construction and Extraction Occupations
- 49 Installation, Maintenance, and Repair Occupations

- 51 Production Occupations
- 53 Transportation and Material Moving Occupations

A.2 Skills

- Active Learning
- Active Listening
- Complex Problem Solving
- Coordination
- Critical Thinking
- Equip. Maintenance
- Equip. Selection
- Installation
- Instructing
- Judgment/Decision Making
- Learning Strategies
- Financial Management
- Materials Management
- Personnel Management
- Mathematics
- Monitoring
- Negotiation
- Operation Monitoring
- Operation and Control
- Operations Analysis
- Persuasion
- Programming
- Quality Control Analysis
- Reading Comprehension
- Repairing
- Science
- Service Orientation
- Social Perceptiveness
- Speaking
- Systems Analysis
- Systems Evaluation
- Technology Design
- Time Management

- Troubleshooting

- Writing

Figure A.1: Example of the O*NET Skills questionnaire. Highlighted in orange, the level score which is the basis of the skill distances used in constructing the local skill remoteness measure.

17. Complex Problem Solving

Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.

A. How important is COMPLEX PROBLEM SOLVING to the performance of *your current job*?

Not Important*	Somewhat Important	Important	Very Important	Extremely Important
①	②	③	④	⑤

* If you marked Not Important, skip LEVEL below and go on to the next skill.

B. What level of COMPLEX PROBLEM SOLVING is needed to perform *your current job*?

	Lay out tools to complete a job		Redesign a floor layout to take advantage of new manufacturing techniques		Develop and implement a plan to provide emergency relief for a major metropolitan area	
①	②	③	④	⑤	⑥	⑦ Highest Level

A.3 O*NET: brief description of the data

The Occupational Network (O*NET) dataset is a detailed data source that describes occupations in the United States from a varied set of different dimensions, including their skill content.

The information in O*NET is collected through individual-level questionnaires that are addressed to both job incumbents and occupational experts. Information for O*NET is collected using a two-stage design: first a statistically random sample of businesses expected to employ workers in the targeted occupations is identified and, second, a random sample of workers in those occupations within those businesses will be selected. For occupations where

it would be difficult to sample workers, such as those that have a small number of workers or ones in which employees work in remote locations, occupation experts are identified from professional and/or trade association membership lists. In addition to the questionnaires completed by workers and occupation experts, additional ratings are provided by occupation analysts. Responses from all three sources — workers, occupation experts, and occupation analysts — are used to provide information for each occupation.

O*NET classifies occupations according to its own taxonomy: the O*NET-SOC occupational classification system. This is based on the Standard Occupational Classification (SOC) and periodically revised to keep up with an ever-changing labor market. The last revision of the O*NET-SOC taxonomy was in 2010. Regardless of whether the taxonomy is being updated, a new version of the O*NET occupational descriptors is released yearly, so to reflect changes in job requirements and characteristics. As the updating procedure does not follow a systematic schedule, the literature has been divided on whether it is appropriate to take advantage of the time variation in O*NET or not. In my main results, I remain agnostic and use the data as face value, judging that the U.S. DOL is trustworthy in both measuring and updating the content of occupations. Using the 2000 O*NET value only leaves my results unchanged if not strengthened.

A.4 Skills versus tasks

My empirical analysis concentrates on differences in the *skill* content of occupations. Other occupational characteristics, such as tasks, have been utilized in the literature for the analysis of skill-biased technical change and labor market adjustments following trade shocks (see, among many others, Autor, Levy, Murnane, 2003 and Autor, Dorn, Hanson and Song, 2014). However, I choose to anchor my main analysis to measures of skills because my goal is to explicitly take into account how suitable are the skills supplied by a worker to many different

jobs.

The definition of skills in the O*NET data suits the bill perfectly: a skill in O*NET is “the ability to perform a task well, usually developed over time through training or experience, that can be used to do work in many jobs or in learning”. Tasks, instead, tend to amplify differences between occupations by the use of specific textual descriptions rather than level scores. Take the tasks that judges and engineers perform: how to identify what “ruling on admissibility of evidence and methods of conducting testimony” and “conducting automotive design reviews” have in common? How to judge the similarity between these two tasks? The literature had used principal component analysis to reduce all tasks to three main components, interpreted as cognitive, manual and interpersonal. This work provides a complementary but distinct answer by looking at the underlying skills that sustain the performance of apparently different tasks. In the example of “ruling on admissibility of evidence and methods of conducting testimony” and “conducting automotive design reviews”, the related skill is presumably *complex problem solving* — used at a high level both by judges and engineers. Furthermore, the fact that skill data are available in a reliable and standardized format is an additional benefit of choosing skills over tasks in this context.

A.5 Vacancy and employment shares data sources

Although there are between 720 and 955 occupations each year in the O*NET, I collapse them to 22 2-digits SOC groups to reduce measurement error when I match the O*NET with household surveys. This prevents the occurrence of occupation-city cells that are very sparsely populated.

Choosing 22 occupational groups helps preserving an informative signal-to-noise ratio in the data and keeping the dimensions of heterogeneity tractable (for a similar strategy, see occupational groups in Davis and Dingel 2015). It also poses some challenges when it comes

to measuring vacancy data.¹

The most detailed dataset containing vacancy data for U.S. metropolitan areas by occupation is the Help Wanted On Line (HWOL) by The Conference Board (TCB). Popularized by Şahin et al. (2014), the HWOL is designed to cover the universe of online job ads for the U.S. from internet job boards or in newswork online editions.² However, HWOL features a rather unsatisfactory degree of detail at the city-by-occupation level: 51 metropolitan areas and 6 occupational groups since May 2005. Given that there are approximately 390 metropolitan statistical areas in the U.S. — the number slightly fluctuates over time as Census’ classifications are redesigned — it seems that using the HWOL data for only 51 of them could significantly curtail, and possibly bias, my empirical analysis. This consideration is only reinforced if we recognize that conforming the analysis to the HWOL data would also imply starting in mid-2005 and aggregate the occupations at a level that is even coarser than 1-digit SOC level.

Guided by the logic of the matching function sketched out in the theory, I therefore resolve to look for a proxy. I find a suitable one in employment shares. Consider a standard Cobb-Douglas matching function for the number of matches in jobs of type j , $\bar{\mu}_j$, as a

1. In my analysis, I exclude military occupations and teachers (SOC=25), because their salary appears considerably less dispersed across space and less volatile over time than other occupational groups. I suspect this is because wages in those sectors tend to be closely tied to unionization bargaining instead of than market forces. All the results are robust to these exclusions.

2. HWOL measures the number of new, first-time online jobs and jobs reposted from the previous month in about a thousand of internet job sites, such as Monster, Craigslist and CareerBuilder, and smaller job sites that serve niche markets and smaller geographic areas. As mentioned in Şahin et al. (2014), though the same ad can appear on multiple job boards, TCB uses “a sophisticated unduplication algorithm that identifies unique advertised vacancies on the basis of the combination of company name, job title/description, city or state.” The convention is that one ad is equal to one vacancy. More importantly, the HWOL data displays an upward time trend, probably due to the growing use of online job boards over time. Şahin et al. (2014) show, however, that the HWOL mirrors official vacancy data from JOLTS quite well and conclude that the positive trend does not appear to be a concern.

function of type j vacancies v_j :

$$\bar{\mu}_j = \sum_{i=1}^I \mu_{ij} = \left(\frac{u}{v}\right)^{1-\gamma} \frac{v_j}{v} \sum_{i=1}^I \mathbb{I}\{\sigma S_{ij} > 0\}$$

The number of matches with a job j is the sum over all types of workers $i = 1, 2, \dots, I$ with a job of type j . This is a function of the aggregate meeting probability $\left(\frac{u}{v}\right)^{1-\gamma}$, the frequency of a j job $\frac{v_j}{v}$ and whether matching is profitable or not.³ Now divide both sides by μ the total number of matches:

$$\frac{\bar{\mu}_j}{\mu} = \frac{\bar{\mu}_j}{\sum_{j=1}^J \mu_j} = \frac{v_j}{v} \frac{\sum_i \mathbb{I}\{\sigma S_{ij} > 0\}}{\sum_{j=1}^J \frac{v_j}{v} \sum_i \mathbb{I}\{\sigma S_{ij} > 0\}}$$

When plotting the share of employment versus the share of job openings in occupation j across cities (see figure A.2), we notice a strongly positive relationship, as predicted by the matching function manipulations detailed above.

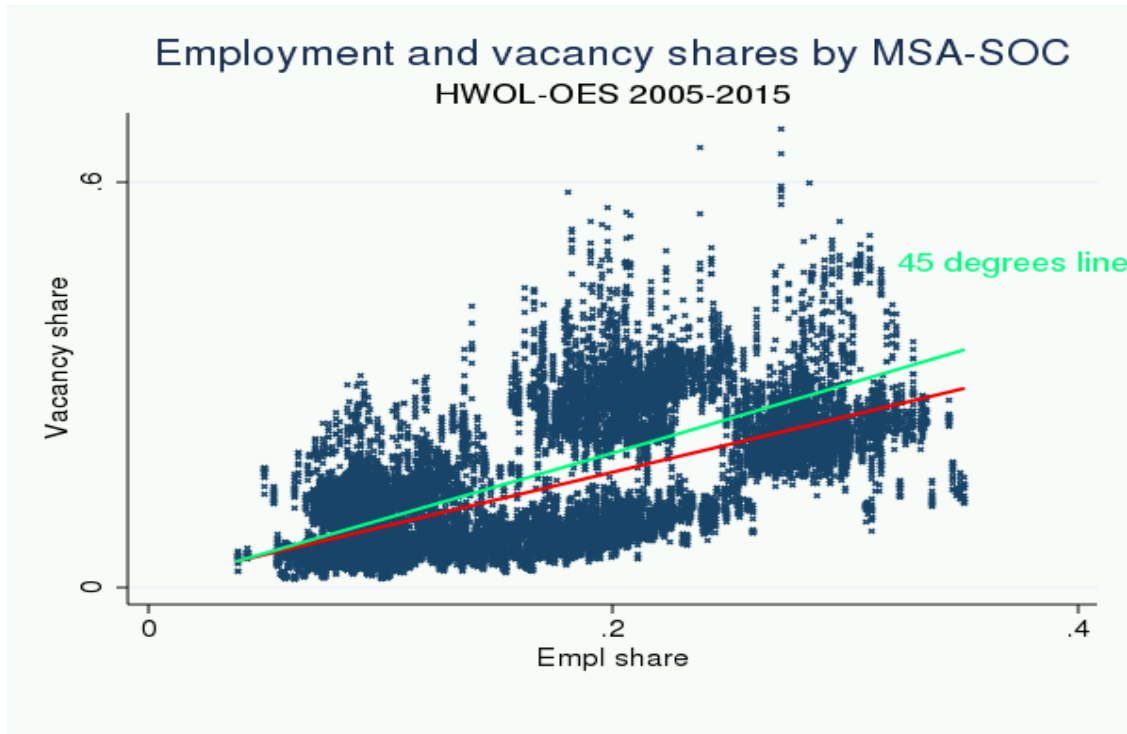
To avoid measurement error in occupational flows, I use employment stocks from the Occupational Employment Statistics not from the Current Population Survey. The OES is a dataset that tracks occupational employment over U.S. metropolitan areas with a considerable level of detail and breadth. A Bureau of Labor Statistics (BLS) program, the OES produces employment and wage estimates for over 800 occupations in metropolitan and nonmetropolitan areas through a semi-annual mail survey of non-farm establishments.

To compare vacancy and employment shares for the occupations and cities common to both the HWOL and OES, figure A.2 portrays the following series: on the y -axis the number of job openings in a specific occupation and city over the total number of vacancies posted in that city, and on the x -axis, the number of people employed in a specific occupation and city divided by the total number of employed workers in that city. The two series are strongly

3. Here, I normalize the aggregate efficiency of the matching function to one.

positively related and the linear regression line is quite close to the 45 degrees one. Because using employment shares instead of vacancy shares does not seem to introduce considerable bias and the availability of employment shares data is larger than for vacancy shares, I use the former and not the latter in my main empirical analysis.

Figure A.2: Employment and vacancy shares for 51 metropolitan statistical areas and 6 occupational groups, HWOL and OES monthly data 2005-2015.



A.6 Wage trimming procedure

I dropped all observations that pertain to teachers (SOC 25) because they tend to be public employees whose wage is usually set in non-market mechanisms. In particular, union negotiations often do not resemble the atomized wage bargaining process I will use in the model.

I also drop agricultural occupations (SOC 45) because of their peculiarly seasonal wage

volatility. The omission of agricultural occupations is inconsequential, given the small shares of employment these jobs represent.

I also performed some imputations: where the hourly wage is missing but the annual wage is provided, I impute the hourly wage by dividing the annual wage by the number of paid weeks reported and then by the number of weekly hours worked. If either weeks or hours are missing but the worker responds negatively to the question about part-time status, I presume that the worker works 40 hours per week and 52 weeks a year. If the worker works part-time and no hourly wage is reported, the observation is dropped. This affects less than 0.1% of the sample and the results are robust to my imputation procedure.

Finally, in the above regression, both the first and last percentile of the wage distribution are omitted from the analysis for robustness. Including them only reinforces my results but may give excessive importance to outliers. I also replicated the results while omitting the top and bottom 5% of the wage distribution and using log wages. Results are unchanged.

APPENDIX B

DESCRIPTIVE APPENDIX

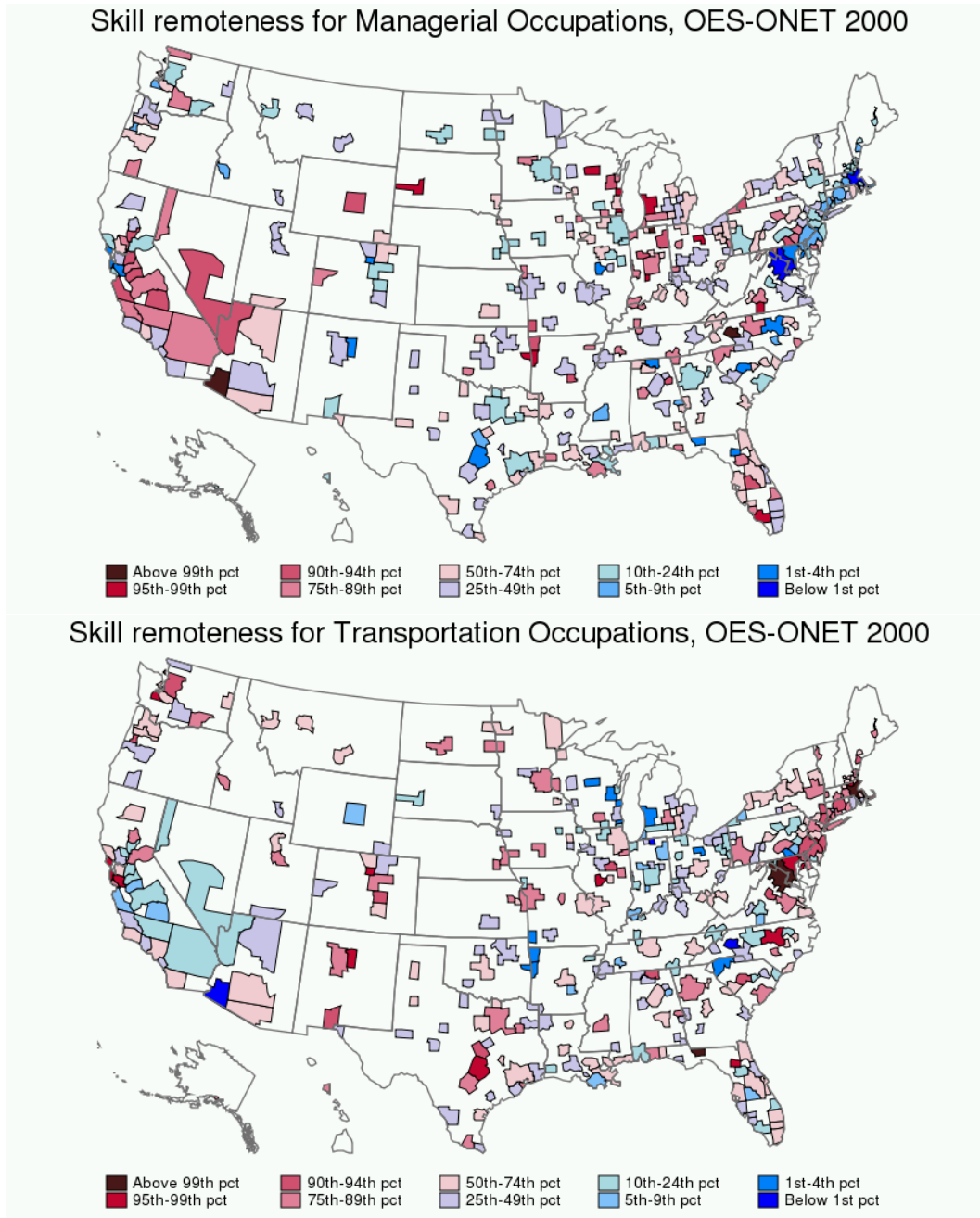
B.1 Summary statistics

The local skill remoteness index used in the main body of the work has been normalized to have a unit standard deviation. Here, I report summary statistics for the raw measure, as per the first line in table 2.2, for different groups.

Table B.1: Average skill remoteness by demographics and city size groups. CPS 2000-2015.

Group	Average skill remoteness
All	0.11
Males	0.12
Females	0.11
Young (<25)	0.11
Prime age (26-55)	0.12
Mature (56+)	0.11
< High School	0.11
High School	0.11
Some college	0.12
College+	0.13
Small city (50,000-100,000)	0.10
Medium city (100,001-750,000)	0.11
Large city (750,000-1.5 million)	0.12
Very large city (1.5 million +)	0.13

Figure B.1: Skill remoteness values across U.S. MSAs for distinct occupational groups.



Note: in the top panel, **managerial occupations**. In the bottom panel, **transportation occupations**. Blue indicates low skill remoteness values (1st-25th percentile) and red high skill remoteness values (75th-99th percentiles). Source: CPS-O*NET 2005.

B.2 Matching

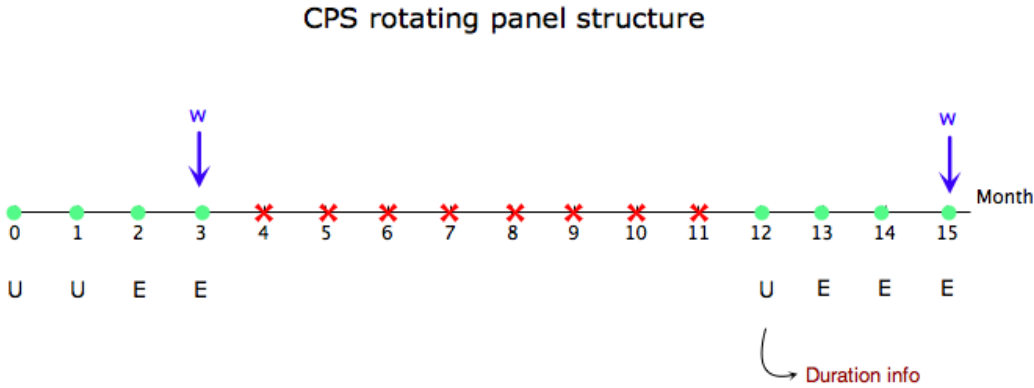
Since the O*NET data are released typically twelve to sixteen months after the information is collected, so that the 2015 survey release pertains to 2014, the 2014 one to 2013 and so on, I match the t OES shares with the $t + 1$ O*NET release. I also match O*NET data from the 2002 release (pertaining to 2001) to the 2000 OES survey, under the assumption that skill profiles for 2-digits occupations did not change substantially in that year. I do not use the 2001 release of O*NET because it is not constructed with criteria consistent with following years — in particular, O*NET surveys before 2002 were not employee-level but only addressed to “occupational experts”. This matching procedure turns out to be inconsequential for the final results.

The approach I choose in this work concentrates on *skill* differences. This choice is motivated by the objective of this work: constructing a measure of mismatch that explicitly takes into account how *suitable* are the skills supplied by a worker to many different jobs. In this sense, the goal of this section is implementing a convincing measure of the transferability of human capital across jobs. The definition of skills in the O*NET data suits the bill perfectly: a skill in O*NET is “the ability to perform a task well, usually developed over time through training or experience, that can be used to do work in many jobs or in learning”. Obviously, this does not exclude that variables such as knowledge, abilities or tasks may be used fruitfully in estimating discrepancies between occupations. Considering skills, knowledge and abilities poses scaling and measurement issues that increase the number of *ad hoc* choices the researcher has to make in constructing the mismatch index, while they do not alter the overall conclusions of the work nor add considerable predictive power for the outcomes of interest.

The task approach, instead, cannot be dismissed as easily. In addition, it has been used successfully and insightfully in much of the literature on specific human capital and the

labor market response to trade shocks. However, devising a classification for tasks that incorporates the richness of the underlying data while preserving ease of use is particularly challenging. Tasks, as exemplified in the previous descriptions of judges and engineers, tend to amplify differences between occupations by the use of specific textual descriptions rather than level scores. In other words, how to identify what “ruling on admissibility of evidence and methods of conducting testimony” and “conducting automotive design reviews” have in common? How to judge the similarity between these two tasks? The literature had used principal component analysis to reduce all tasks to three main components, interpreted as cognitive, manual and interpersonal. For reasons outlined above, this work provides a complementary but distinct answer by looking at the underlying skills that sustain the performance of apparently different tasks. In the example of “ruling on admissibility of evidence and methods of conducting testimony” and “conducting automotive design reviews”, the related skill is presumably complex problem solving — used at a high level both by judges and engineers. Finally, the fact that skill data are available in a reliable and standardized format is an additional benefit of choosing skills over tasks.

Figure B.2: **The CPS 4-8-4 panel scheme:** example with an initial unemployment spell. Green dots denote interview months; blue “w” letters denote interview months in which wage information is collected.



B.3 Augmented CPS

It is possible to augment the time dimension of the CPS panels by using the unemployment information duration at month 12. As depicted in figure B.2, each household in the CPS is interviewed for 4 consecutive months, then is out of the sample for 8 months, and interviewed again for a final 4-months period, with a total of 8 observations per household. There is no information on months 4-11, though employment status may be recovered if the respondent is unemployed at month 12 and provides information on how many weeks have passed since she was last employed. For example, if at month 12 the respondent has unemployed for 9 weeks, the employment status for month 11 and 10 may be filled in with “unemployed”. Though I recognize that the resulting sample is no longer representative of the overall population of U.S. laid-off workers, I still find this exercise useful because it significantly extends the panel dimension of the data. Using these imputations, I run the same logit specification for regression 3.2 and find similar coefficients for the first quarter after layoff, a mildly significant effect 4 months after layoff and only coefficients that are not statistically different from zero from 4 months onwards. Concerned that attrition in the CPS, including from geographical migration, may be responsible for such noisy results I performed the same analysis in the NLSY79 panels and found slightly larger and noisier coefficients but with the same persistence: employment effects of local skill mismatch are indistinguishable from 0 after a quarter.

B.4 Selection on unobservables concerns

There is a concern that skill-remote and skill-central workers differ in other unobservable dimensions that are correlated with wage and mobility outcomes. Then, the results of the regressions may reflect the effect of such unobservables, not of local skill remoteness. It is helpful to think of this unobservable characteristic as “quality”: if skill-remote workers

happen to be of lower “quality”, then the negative effect of skill remoteness on wages might be just a reflection of this characteristic.

I investigate this issue in three steps: first of all, I include in every regression specification extensive controls for observable characteristics that may lead to selection: for example, individual’s educational attainment and occupational affiliation, and several characteristics of their cities and occupations that have been shown in the literature to lead to sorting. Namely, city size — allowed to vary by occupational groups —, the share of college educated people, the share of workers in the same occupational groups and a set of fixed effects for city, industry and time. Any unobservable dimension of relevance must be orthogonal to these individual and aggregate factors and still able to drive selection.

Furthermore, while a simple quality selection story naturally fits the wage results in figure 3.1, the intuition for why lower quality workers might migrate and change occupation more often is less clear-cut: after all, for intrinsically less productive, the benefit of migration or occupational change is likely to be limited. Therefore, not only the unobservable variable would have to be orthogonal to all the observable factors included in the regression, it also has to be able to explain convincingly both the wage, employment and mobility patterns over time. Such a factor is harder to identify.

Nonetheless, I look for evidence in favor of omitted variable bias in the NLSY and find no evidence for it. Figure B.3 and B.4 plot the residuals from a Mincerian regression of wage levels and year-over-year wage growth that includes all the controls in (3.1) but for local skill remoteness. They are contrasted with the value of remoteness for the last period of employment ($t - 1$, given that layoff happens at t). The graphs support the hypothesis that there is no correlation between the two, thus I conclude that the data does not support the presence of a significant omitted variable problem.

Figure B.3: Residual wage level and skill remoteness. NLSY79 1994-2012.

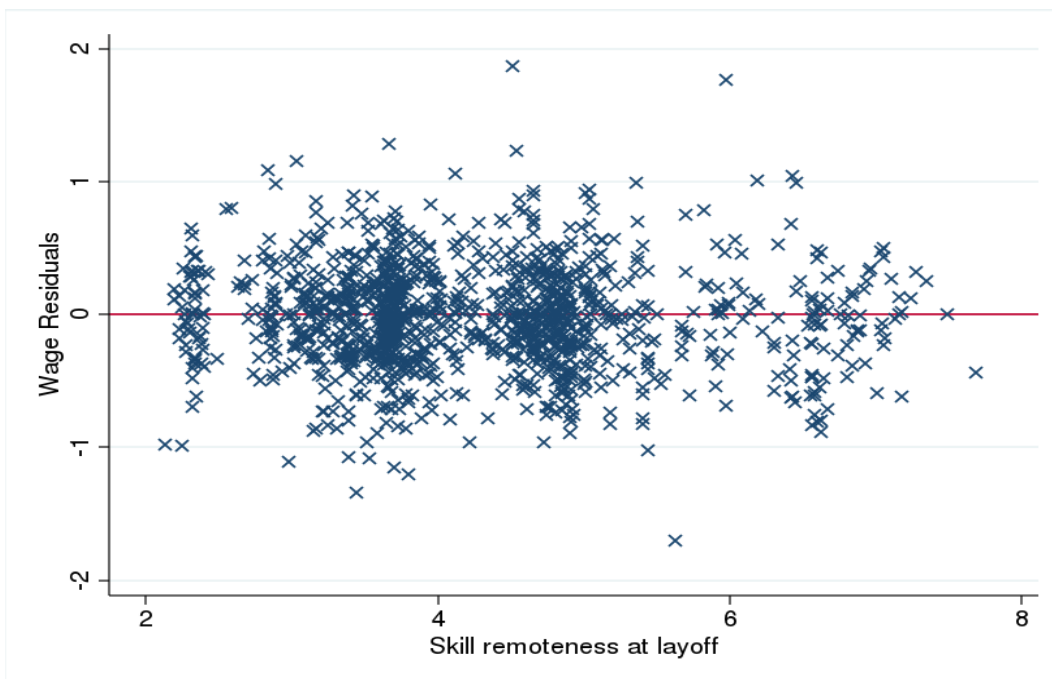
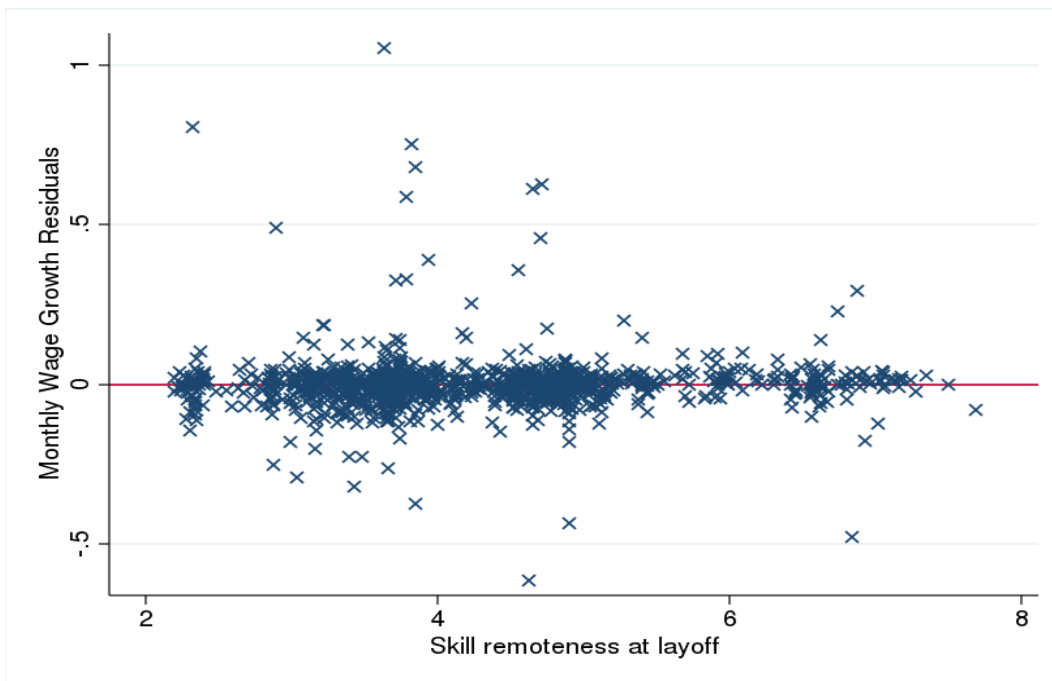


Figure B.4: Residual wage growth and skill remoteness. NLSY79 1994-2012.



B.5 NLSY79: brief description of the data

The National Longitudinal Survey of Youth 1979 is a comprehensive survey of American residents born in 1979. The data is maintained by NORC at The University of Chicago and is one of the most reliable high-quality panels available to researchers in the US. NLSY79 data are available from 1979 to 2012. The survey has been re-designed in 1994 to implement, among other improvements, dependent-coding techniques that make employment and occupational affiliation data more reliable.

In particular, NLSY79 respondents answer questions about current and previously held jobs and, from this information, a longitudinal record spanning from the date of the first interview through the most current interview date is constructed for each respondent. As a result, the NLSY79 Work History Data provide researchers with a week-by-week longitudinal work record of each NLSY79 respondent from January 1, 1978 through the current survey date. Together with the Employer History roster, the Work History data provide information on virtually all unemployment and jobs spells reported by NLSY79 respondents.

APPENDIX C

THEORY APPENDIX

C.1 Algorithm

The model is solved in a three-layered loop procedure: in the inner loop, I solve for the surplus matrix by iterating equation (4.7) for given values of θ , $u_i, \forall i$ and $v_j, \forall j$, the latter obtained from the data. The surplus equation is non-linear, therefore it cannot be solved analytically; however, the non-linearities are tractable enough because they only involve max operators and the set-up preserves the contraction mapping property of the canonical search-and-matching models. This implies that convergence is fast and robust for several starting points. In the middle loop, given a guess for θ and the computed $S_{ij} \forall i, j$, I simultaneously solve equations (4.11),(4.12) and (4.13) to obtain a vector of sectoral unemployment rate $u_i, \forall i$ compatible with the surplus matrix and the related distribution of employed workers over jobs, $e_{ij} \forall i, j$. At this stage, I also compute the wage level in all matches i, j consistent with $u_i, \forall i$ and θ . These two loops conclude the partial equilibrium analysis and provide a set of unemployment rates $\{u_i\}_{i=1}^I$ and wages $\{w_{ij}\} \forall i, j$ that are consistent with a fixed value of θ and a vector of local vacancy shares $v_j/v, \forall j$.

To move on to general equilibrium, we must endogenize the choice of θ , the labor market tightness. This is done in the outer loop, the third step of the solution procedure. Recall that, at the end of middle loop, a vector of sectoral unemployment rates u_i is computed. I use it to update the guess for market tightness θ given the empirical distribution of vacancies across jobs $v_j, \forall j$. I then iterate the whole procedure until convergence, that is until the initial guess of θ is “close” to the value computed through the equilibrium loops. The last step is a rather standard one and calibrates the flow cost of vacancies κ_j to reproduce the distribution of $v_j, \forall j$ observed in the data. This finally produces the general equilibrium of

the model, given parameters.