Finding the Right Fit: How Skill Mismatch Impacts Wage Growth*

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Abstract

I leverage a 2% sample of the German Social Security Data to study how wages change around different kinds of labor market transitions. The results are consistent with idiosyncratic matching at the occupation, but not the employer, level. For men, wages increase by .055 log points following a voluntary employer transition that does not involve an occupation transition and .101 log points following voluntary employer transition that does involve an occupation transition. I build a model where workers differ in their cognitive, manual, and interactive skills, which creates comparative advantage in certain occupations. I estimate this model and show that most of the wage gains for young workers following an occupational transition are due to improved matching of worker skill with occupation tasks, and not movements along an occupational ladder. Women also see 12% larger comparative advantage gains than men, suggesting the aggregate productivity gains from equalizing employment opportunities are underestimated by a pure absolute advantage model.

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1 Introduction

Life cycle wage growth is a key source of cross sectional wage inequality, and we know that employer to employer transitions account for a a third of the wage growth early in men's work-lives[1]. However, employer transitions may or may not involve a change in occupation. Furthermore occupation transitions may occur without an employer transition. Despite this it is not known how occupation transitions affect wage growth early in the work life cycle; nor is it known what role is played by employer transitions that do not involve occupation transitions.

In this paper I leverage a 2% sample of the German Social Security data to separately study how wages grow around employer and occupation transitions. Using an event study design I find that wages follow a consistent qualitative pattern around employer changes, falling prior to a switch, increasing at the moment of change and accelerating thereafter. However, the quantitative features of this pattern are quite different if the employer transition involves an occupation transition. For men, wage growth at an employer transition is .101 log points if the transition involves a change in occupation and .055 if it does not. Moreover wages decline by .077 log points prior to an employer transition that involves and occupation change and only .005 log points prior to a switch that does not. The quality of my occupational data also means I am able to study wage gains following occupation transitions that do not involve a change in employer. In this case wages exhibit qualitatively different time paths. Workers who make pure occupation transitions see a small *increase* in their wages prior to a switch, and wage gains at a switch are also much smaller than at employer transitions regardless of if they involve a change in occupation.

Past work finds that wage gains at employer transitions are largest at the beginning of the work life cycle. This suggests that the difference in wage gains at occupation-employer and pure employer transitions may vary with experience.[2] To investigate this I use a novel non-parametric regression that estimates how the impact of employer and occupation transitions

[1] Topel and Ward [1992]

[2] Throughout the paper I use the term "pure employer transition" to refer to employer to employer transitions that do not involve a change in occupation. "Pure occupation transitions" refer to changes in occupation absent a change in employer.

on wages changes over the life cycle. Wage growth at all transitions is highest in the first 10 years of a worker's career and declines monotonically during this time before flattening off. This decline is steepest for occupation-employer transitions, and by 10 years of potential experience wage gains at occupation-employer changes are not statistically different from wage gains at pure employer changes.

I then investigate if the wage growth premium at early career occupation-employer transitions can be explained by an occupational ladder. That is, if wage growth at early career occupation transitions be explained by workers moving to better paying occupations. To assist in this investigation I develop a model in which workers must allocate time to various occupation-specific tasks at which they are differentially skilled. If there is only one task, wage gains at mobility episodes must be a result of moving to better paying occupations. In this case the model is easily mapped into a simple fixed effect estimating equation with additively separable fixed worker, firm, and occupation productivities. Wage gains at occupation transitions in my regressions are then equal to gains in the average productivity of the occupations. I find that occupation fixed effect gains do not account for wage growth at occupation-employer transitions, but do account for gains at pure occupation transitions.

When the number of skills and tasks is greater than 1 the model naturally gives rise to notion of mismatch that purely reflects a worker's comparative advantage in an occupation. I estimate my model to understand if changes in this mismatch term can account for wage growth at occupation-employer transitions. To estimate the model, I first remove average productivity by removing occupation, employer and experience specific mean wages. The model then implies that worker relative skills can be estimated by running individual-specific linear regressions on task measures. I use manual, cognitive and interpersonal task data to directly measure worker's relative skills in those tasks. I use these skill measures to estimate the change in match quality at occupation transitions and find that it can well account for wage growth at occupation-employer changes.

I also estimate my key results separately by gender to highlight important differences in life cycle wage dynamics of men and women. Women make occupation-employer transitions much less frequently than men, but see 40% larger log wage gains at occupation-employer mobility episodes and have 12% larger comparative advantage gains at these episodes than men. This result begs the question why women do not switch occupation more often. One plausible explanation is that job offer structures are systematically more favorable to men than women. If this is the case, then productivity gains from equalizing employment opportunities are underestimated by a pure absolute advantage model because they do not account for improvements in horizontal matching.

This study has significant bearing for a large set of theoretical and empirical work. Most prominently the literature on employer an occupation transitions. A seminal paper in this literature is Topel and Ward [1992] who use LEED data to show employer transitions are a key source of early career wage growth. Neal [1999] studies NLSY data with a focus on explaining why employer-occupation moves tend to precede pure employer moves. Loprest [1992] uses NLSY data and finds that women see *smaller* wage gains at *unseparated* employer mobility episodes than men. Groes et al. [2014] use Danish administrative data study occupational mobility along vertically ranked occupations. In a recent working paper Busch [2020] uses a quantile regression approach to study wage dispersion at the moment of an employer and occupation transitions. My paper contributes to this literature in three ways: I separately study the impact occupation and employer mobility at different levels of experience; I uncover the time path of wages around transitions; and I quantitatively study the role of comparative and absolute advantage in wage growth at occupation transitions.

By estimating the role of comparative and absolute advantage this paper also relates to studies that try to understand worker-job match quality. Lise and Postel-Vinay [2020] and Guvenen et al. [2020] use the National Longitudinal Survey of Youth and Armed Services Vocational Aptitude Battery test data to construct measures of skill task mismatch. Lise and Postel-Vinay [2020] use their mismatch measure to estimate a structural model of multiple skills and search, and show a model with a single skill dimension substantially overestimates the importance of unobserved heterogeneity. Fredriksson et al. [2018] use Swedish administrative data to estimate mismatch using direct data on skills and use their mismatch measure to find support for predictions of a model of learning a la Jovanovic [1984]. Yamaguchi [2012] estimates skill *distributions* from task using a Kahlman filter. This paper contributes to this literature in 2 ways. Firstly I construct a novel measure of mismatch that separates absolute and comparative advantage and show both are need to rationalize wage gains at occupational mobility episodes. The importance of these components depends on whether an occupation transition has coincided with an employer transition. Secondly, I develop a procedure to directly estimate relative *individual* skill directions in my data. Skill is unobserved in many data sets, so this procedure allows future researches to approximate the relative skill distributions in an economy with longitudinal earnings and task data.

The model I use to distinguish comparative and absolute advantage builds on other models of skill task matching such as Lazear [2009], Gathmann and Schönberg [2010], Autor and Handel [2013], and Cavounidis and Lang [2020]. Autor and Handel [2013], construct a Roy model of occupation selection in a task framework. Gathmann and Schönberg [2010] derive an estimating equation for task tenure with a set of 15 task-specific skills. Cavounidis and Lang [2020] use a model of employer specific task weights to show how credit constraints can affect worker skill investment. My primary contribution to this literature is that I derive a simple log-linear estimating equation which makes intuitively clear the trade-offs of comparative and absolute advantage in this framework.

This paper also has bearing for the literature which decomposes wage variance by employer and worker absolute advantage (Abowd et al. [1999], Card et al. [2013], Song et al. [2018]). The literature often assumes wages are the sum of firm and worker fixed effects plus educational controls. My results suggest that individual and occupation fixed effects may not be separable. Thus it may not generally be possible to distinguish changes in variance due to individual effects from changes due to occupation fixed effects.

For similar reasons, this study speaks to the literature that examines the role of firm and occupation pay premiums on the gender pay gap (e.g. Card et al. [2015], Bruns [2019]). Goldin et al. [2017] finds that the expansion of the gender pay gap over the life cycle can be explained in large part by occupation fixed effects. My results suggest that occupation fixed effects alone may underestimate the role occupation level discrimination plays in the expansion of the gender pay gap, as fixed effects may not wholly account for worker-occupation match quality.

The remainder of this paper is organized as follows. Section 2 describes the SIAB and BERUFENET data. Section 3 develops motivating empirical results for the paper. Section 4 constructs a simple model with matching of multidimensional skills and tasks for rationalizing wage growth at occupation transitions. Section 5 describes the procedure for estimating skill directions in data and shows how matching can account for wage growth at occupation-employer transitions. Section 6 concludes.

2 Data

2.1 SIAB

My main data source for this project is the Sample of Integrated Labor Market Biographies, or SIAB, which consists of a 2% sample of German Social Security records[3]. The SIAB has been widely used in labor economics, though an exhaustive list of articles that make use of this data would be too large to put here.

The SIAB is ideal for the study of occupational mobility in a number of respects. Firstly, the decision to change occupation is significant, and unlike comparable data sets such as the SIPP and the monthly CPS the panels in the SIAB are long enough to capture the long-run consequences of that decision. Secondly occupation changes are somewhat infrequent, and so a large sample size is needed to adequately capture how the effects of changing occupation vary by different subgroups. My final sample of men consists of 150,000 fairly homogeneous individuals each of whom I observe for 10-35 years.[4] Finally, the because the SIAB is an administrative data set, there is plausibly less spurious occupational mobility. In Porter [2020] I discuss how measurement error in occupational classification can cause wide shifts in mobility variables and substantial degrees of bias. In the SIAB, occupations are directly reported by the employer making the mobility data much more reliable than in survey based measures.[5] I use the finest detail set of occupations available to me (341 categories). However, because there is still the possibility that different employers will misidentify similar occupations, I have replicated my main results using the 30 broad occupation segments as

[3] For details on the version of the SIAB I use please see: Antoni et al. [2019b].

[4] By comparison, the PSID contains around 18 thousand individuals in total.

[5] A quick comparison of the implied annual raw occupational mobility rate for the SIAB and the CPS reveals this. The raw probability of changing occupation in the CPS is roughly 45% annually, which is implausibly large. By contrast, it is roughly 10% annually in the SIAB.

in Busch [2020]. While not presented here for brevity, I find almost identical estimates of wage gains at different mobility episodes using this scheme.

The SIAB is a complex data set and requires a great deal of preparation to be used, I therefore follow a standard procedure recommended by Dauth and Eppelsheimer [2020] in the preparation of my data. My sample period ranges from 1975 to 2010. In principle, data is available through 2017, however there was a significant shift in the occupational coding system that occurred in 2011 which makes it difficult to compare results before and after this year. To further ensure a consistent sample, and keep my results comparable with Topel and Ward [1992][6], I select workers who are employed full-time, whose first employer is located in West Germany and who I can observe for at least 7 of the first 10 years after labor market entry, defined as the first observation for which the individual works full-time not including apprenticeships. These restrictions ensure that there is significant labour market attachment among the individuals in my sample. I put my data into a yearly panel, selecting the highest wage job available on June 30th of that year. I select June 30th as establishment level variables (such as employer fixed effect estimates) available in a companion data-set, the BHP, are aggregated up through June 30th of each year. I run my analysis separately for male and female workers. My sample of men consists of around 150 thousand individuals, 2.5 million person-year observations. My sample of women consists of 98 thousand individuals, 1.0 million person-year observations. Occupation and employer mobility are defined as the individual having a different occupation code or employer ID from the last non-missing observation. In my regressions on wage growth this will amount to the individual simply having a different occupation or employer than in the last year, since both occupation and employer codes are needed for non-missing wages.

My estimates on wages all use the real log daily wage, but one limitation of the SIAB is that wages are top coded. Dauth and Eppelsheimer [2020] suggest a correction methodology for imputing top coded wages, which I follow almost exactly and so I omit the description

[6] One difference between my paper and Topel and Ward [1992] is that I am only able to estimate *establishment* changes using SIAB data. Thus, my estimates of employer change will also include workers who stay at the same parent company, but change the branch they work at. This may lead to a slight underestimation of wage gains at employer changes relative to Topel and Ward [1992].

of the imputation process here. The only difference between my imputation procedure and theirs is that I include occupation fixed effects and a quadratic of occupation tenure in my regression specification for imputing top coded wages. I include these controls to mitigate bias in my estimates on wage changes at occupation transitions. This being said no imputation procedure is perfect, so care should be taken in interpreting these results in the context of the upper tail of the wage distribution.

2.2 BERUFENET

My primary source on task data is BERUFENET data, a German analog to the O*net database in the United States, cleaned according to Dengler et al. [2014].[7] The database is used for career guidance and placement. It consists of expert selected occupational "requirements", which are a group of around 8000 specific tasks assigned to approximately 3900 specific occupations at different points in time. Dengler et al. [2014] then identify these requirements as being part of the "core" activities, "additional" activities or not part of occupation's activities. As an example, "knitting" is a core requirement for the occupation knitter, but only an additional requirement for "machine and system operator - textile engineering". These requirements are then manually compiled into five task categories[8]. Examples of requirements in each task category are highlighted in table 1. Overall, the categories seem to divide tasks along fairly intuitive lines. For example non-routine analytical tasks contain activities like management and design, while manual routine tasks contain tasks such as farming or machine operation.

Dengler et al. [2014] compute task indices for each category by taking the proportion of activities that fall into the respective category at the most detailed level of occupation available (7-digit) as:

$$\tau_{ojt} = \frac{\text{number of requirements in task type j in occupation o in year t}}{\text{number of requirements in occupation o in year t}}$$

[7] I elect to use the BERUFENET data as opposed to BiBB data used by Gathmann and Schönberg [2010] because it is more comparable to the task polarization literature in the United States which use "expert-based" measures of task. These expert-based measures of tasks do not fall prey to occupational coding errors unlike survey-based measures of tasks.

[8] They are compiled separately by 3 different people and then cross validated.

Tasks are then aggregated to the 3-digit occupation level by taking a weighted average of these indices, where the weights correspond to the proportion of people in the 3-digit category who work at the specific 7-digit category as:

$$\bar{\tau}_{kjt} = \sum_{o \in k} \tau_{ojt} \frac{N_{ot}}{N_{kt}}$$

I then take the arithmetic mean of these aggregated task codes across the three years of the observation period (2011, 2012, 2013) and merge the task indices onto the corresponding 3-digit occupation codes (kldb1988) as:

$$\bar{\tau}_{kj} = \frac{\bar{\tau}_{kj2011} + \bar{\tau}_{kj2012} + \bar{\tau}_{kj2013}}{3}$$

For more details on the task data, and how it is constructed see Dengler et al. [2014].

3 The Impact of Labor Market Transitions on Wages

Figure 1 plots log wages by labor market entry cohort and year from 1975 to 2010. Each line corresponds to the average yearly log wage of individuals with the same labor market entry year. Redder lines correspond to earlier labor market entry cohorts, bluer lines correspond to later cohorts. The figure shows that log wages increase by around .45 log points over men's work lives and .4 log points over women's work lives. There is some dispersion in this increase, with earlier entry cohorts seeing larger increases in their wages at the beginning of their life cycle. Wage profiles of different cohorts consistently follow a inverse-U shaped pattern. Wages increase most quickly at the beginning of a worker's career, then flatten out and finally dip slightly later in the life cycle.

What role do occupation-to-occupation and employer-to-employer transitions play in this pattern? Past empirical work studying voluntary labor market transitions has focused on the role played by transitions *at the moment* of change. Yet voluntary labor market transitions may also serve as escapes from poor matches or set workers on higher wage growth paths. To give a sense of this figure 2 plots cumulative wage growth (cumulative changes in the log wage) for four mutually exclusive transition groups. The first group is comprised of workers who make only an occupation change at 5 years of potential experience and make no other such transitions in their first 10 years of labor market experience.[9] The second and third groups are the same for workers who make only an employer change, and workers who make simultaneous occupation-employer transitions.[10] The final group consists of workers who make no transitions in their first 10 years of labor market experience. The advantage of separating workers in this manner is that I ensure no transitions are made prior to 5 years of potential experience. Thus any trends before 5th year of potential experience are not due to repeat transitions or unemployment.

The figure reveals the basic benefit that occupation-employer transitions provide is twofold. Prior to transition, the group that changes occupation and employer sees substantially slower wage growth than their peers of all other categories. However following the transition there is an immediate jump in wage and a sharp reversal in trend. This allows the group of occupation-employer movers to "catch up" to their peers in other groups. Two years after the change is made, occupation employer switchers have experienced more cumulative wage growth than their peers who make no transitions. To get a sense of the importance of this change I compute the trend in wage growth for the occupation-employer movers and non-movers in the 3 years prior to the switch. I then extrapolate cumulative changes in wages from 5 years onward to ten years of potential experience based on this trend. The results are given in panel (c) for men and panel (d) for women. Taking the results at face value, occupation-employer movers would have approximately .12 log points lower wages at 10 years of experience in the absence of a change, corresponding to around 30% of lifetime wage growth.

Why do workers who make occupation-employer transitions see slower wage growth than their peers prior to the transition? Worker-occupation matching provides one plausible explanation. In models of learning and match quality following Jovanovic [1979] workers have unknown job specific productivities which the market can learn about by observing worker output. Workers who tend to leave their occupations will be precisely those who learn they are relatively poor fits for those occupations. Those workers will thus have slower

[9] Throughout the paper years of potential experience is defined as the year minus the workers year of labor market entry.

[10] Occupation and employer transitions are defined as a worker having a different occupation or employer code from their previously observed code.

wage growth than their peers prior to making transitions.

3.1 Wage Paths Around Mobility Episodes

The key problem with the exercise presented in figure 2 is that it focuses on highly selected groups. In this section I extend the the exercise by performing an event study on different transition categories. The event study specification takes inspiration from the unemployment scarring literature following Jacobson et al. [1993]. The form of the regression is given by:

$$\omega_{it} = \alpha_i + \iota_t + \sum_{c \in \mathcal{C}} \sum_{k_c=-6}^{30} \delta_{c,k_c} D_{it}^{c,k_c} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \varepsilon_{it} \tag{1}$$

Where ω_{it} is the log wage, α_i is an individual fixed effect, ι_t is a time fixed effect and $\boldsymbol{X}_{it}$ is a vector of varying controls. The variables $D_{it}^{c,k}$ are typical event study indicators for transition category c. They take on a value of 1 if the individual made their first transition of type c k_c periods ago and are 0 otherwise[11]. Mathematically, if t_c^* is the year the individual first makes c then $k_c = t - t_c^*$. The set of transition categories is denoted by $\mathcal{C}$. Its elements are mutually exclusive within a period, that is no individual makes two transitions of different kinds in the same year. I drop observations for switchers for whom $k_c < 7$ for all $c \in \mathcal{C}$. The value δ_{c,k_c} thus gives a comparison of log wages for individuals who have made transition c k periods ago to individuals who will not make *any* transitions.

I consider the following set of indicators for transitions:

$$\mathcal{C} = \{O_{it}, E_{it}^{\mathrm{n}}, E_{it}^{\mathrm{u}}, B_{it}^{\mathrm{n}}, B_{it}^{\mathrm{u}}\}$$

E_{it}^{n} is an indicator for an individual making an employer to employer transition and no occupation transition between $t-1$ and t and E_{it}^{u} is an indicator for an individual making an employer to unemployment to employer transition between $t-1$ and t and no occupation transition between $t-1$ and t.[12] The indicators B_{it}^{n} and B_{it}^{u} represent the same for employer transitions that involve an occupation transition, and O_{it} is an indicator for the worker

[11] In the subsequent section I relax this restriction and consider any transition of a given category.

[12] Employer and occupation transitions are defined as the worker having a different employer or occupation code.

making an occupation transition and no employer transition[13]

As the impact of occupation switching following an unemployment spell has been studied in Huckfeldt [2021] my focus is to understand the role of occupational transitions that do not involve spells of unemployment. I thus focus on results for employer to employer switches instead of employer to unemployment to employer switches. I run equation 1 for $\mathcal{C}$ separately by gender with controls for education, quadratic and cubic potential experience terms, occupation tenure and employer tenure. I plot the values δ_{c,k_c} for the switches in $\mathcal{C}$ that do not involve unemployment spells along with a 95% confidence interval with standard errors clustered at the individual level. Transitions take place from -1 to 0 as indicated by the vertical line. The first column presents the results for men, the second column presents the results for women.

It should be emphasized that the results from this exercise are *not* intended to be "causal". Job-to-job switches are forward looking decisions, and so the necessary assumptions for a difference in difference specification are not satisfied. Never the less this exercises still reveals interesting and under-studied empirical facts about the forces at play in labor market decisions.

Figure 2 shows the results from this exercise and it reveals several novel findings. Beginning with my results on employer to employer transitions, the Ashenfelter dip (the drop in wages prior to an employer transition) is by far the strongest for occupation-employer transitions. Indeed, negative pre-trends are barely present for pure employer transitions. In the seven years prior to their first *pure employer* transition men's wages grow .005 log points less than non-movers, and women's wages grow .024 log points more than non-movers. By contrast in the seven years before their first *occupation-employer* transition both men and women's wages grow .077 log points less than non-movers.[14] However workers who make occupation-employer transitions recover these wage losses with substantial wage gains at the moment of transition, and trends in wages are also substantially more positive following any employer transition. At the year of change men who make occupation-employer tran-

[13] I do not separate unemployment transitions for this group as the set of workers who become unemployed, change occupation and keep the same employer is likely to be quite small.

[14] As discussed in the previous section this indicates learning about match quality would occur primarily at the occupation level.

sitions see their wages rise .101 log points more than non-movers, and women who make such changes see their wages rise by .156 log points more than non-movers. By contrast, men who make pure employer changes only see their wages rise .055 log points more than non-movers, and women who make such changes see their wages rise by .097 log points more than non-movers. Wage gains at the moment of change are thus 80% larger when employer transitions involve a change in occupation.

That women see larger wage gains at employer transitions than men is somewhat puzzling in light of past literature on gender discrimination. Goldin et al. [2017] finds that controlling for occupation fixed effects substantially reduces the expansion of the gender wage gap over the life cycle, and Loprest [1992] finds that women see *smaller* log wage gains at employer transitions (which may or may not involve a change in occupation) than men. Appendix section F resolves this discrepancy by showing that occupation-employer switching probabilities are substantially lower for women throughout the work life cycle. Thus even though they see larger gains from doing so, women are less likely to move into better paying and better matched occupations. Employer switching will thus appear less beneficial when not conditioned on a change in occupation. This may be do to gender discrimination in hiring, or it may be do to women facing a higher fixed cost of changing occupations.

I now turn to my results on pure occupation transitions. They suggest that occupation transitions differ qualitatively depending on if they involve a change in employer. Wage jumps at pure occupation transitions are much smaller and not necessarily different from prior trends. This is possibly consistent with a model of promotions and career tracks. Workers who perform well may be promoted to occupations that have different titles, but similar tasks. Indeed, these incremental pay increases may be associated with incremental changes in occupation titles that are masked by the coarseness of my occupation variable. For example, promotions from "software engineer" to "senior software engineer". This would lead to the observed pattern of incremental improvements in wages before and through pure occupation transitions.

3.2 Differences in the Impact of Mobility by Experience

In this section I investigate how wage growth at transitions differs by experience. Allowing for heterogeneity by experience poses a concern for the usual event study equation given in equation 1. As pointed out by Sun and Abraham [2020], event studies of this form do not have a clearly defined control group in the presence of heterogeneous treatment effects. In the context of job mobility this is compounded by the presence of pre-trends and forward looking behavior. As the findings from these job mobility regressions are not causal, it is desirable to have a clearly defined comparison group. For this reason I opt to estimate my results by experience according to a slightly different specification given by 2. In the absence of controls this specification simply compares mean wages of movers at a potential experience level relative to the mean wage of non-movers at that experience level. When I turn to my model, equation 2 has the additional benefit of being easily mapped into theoretical objects. By contrast the coefficients of interest in equation 1 are a linear combination of differences in log wages for different treatment groups at different time periods[15]. While the results from these two comparisons could in principle be quite different it is comforting that my results remain qualitatively consistent across specifications.

Formally the equation I use to estimate the impact of transitions on wage growth at different experience levels is:

$$\begin{aligned}\Delta\omega_{i,t+s} =& \alpha_x + \sum_{x=1}^{20} \varsigma_{x,s} O_{it}^{x} + \sum_{x=1}^{20} \rho_{x,s}^{u} E_{it}^{u,x} + \sum_{x=1}^{20} \rho_{x,s}^{n} E_{it}^{n,x} + \\ & \sum_{x=1}^{20} \lambda_{x,s}^{n} B_{it}^{n,x} + \sum_{x=1}^{20} \lambda_{x,s}^{u} B_{it}^{u,x} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \varepsilon_{it}^{s}\end{aligned} \tag{2}$$

Where $O_{it}^{x} = O_{it} \cdot \mathbf{1}\{x_{it} = x\}$, α_x is a set of experience fixed effects and X_{it} is a vector of controls. This constitutes a set of stacked regressions which, in practice, I will run for $s \in \{-1, 0, 1, 2\}$. Without controls, the coefficients represent pure mean differences. For example the coefficient $\varsigma_{x,s}$ is the difference in mean wage growth s periods from t of workers who make a pure occupation move at potential experience x, and workers who make no

[15]The term linear combination is deliberate and stems from Sun and Abraham [2020] theorem 1. Weights on log wage changes need not be in in the interval [0,1] or indeed be positive.

moves at experience x. Mathematically:

$$\varsigma_x = \mathbb{E}[\Delta\omega_{it}|x_{it} = x, O^x_{it} = 1] - \mathbb{E}[\Delta\omega_{it}|x_{it} = x, E^x_{it} + B^x_{it} + O^x_{it} = 0]$$

The coefficients $\rho^n_{x,s}$ and $\lambda^n_{x,s}$ represent the same for employer to employer transitions that do and do not involve a change in occupation respectively. The coefficients $\rho^u_{x,s}$ and $\lambda^u_{x,s}$ represent the same for employer to unemployment to employer transitions that do and do not involve a change in occupation respectively. I refer to this difference as the "excess" wage growth s periods after a move at potential experience x.

Figures 4 and 5 presents my results from running equation 2 on transitions that do not involve an unemployment spell for men and women respectively. The controls include quadratics in lagged employer and occupation tenure interacted with experience, firm fixed effect differences, and interacted indicators for current and past education levels. The inclusion of different controls does little to change the results in this or subsequent sections. Thus, to economize on exposition, I omit results with alternative control specifications. The format in which I choose to present the event study is as follows: For each figure panel (a) represents the year before the switch; panel (b) represents the year of the switch; panel (c) represents the year after the switch; and panel (d) represents two years after the switch.

I begin by considering what happens in the period prior to the switch, $t-2$ to $t-1$. In the pre-period, wage growth is slowest for the coincidence of occupation-employer switches. As previously discussed suggests that this group is likely less well matched to their job when compared to their peers. Again, in a model of matching and information acquisition workers who change occupations would have received negative signals about their current match quality. Thus they should be expected to have slower mean wage growth *prior* to the incidence of a switch. Consistent with my results in earlier sections, occupation-employer switchers see the slowest pre-period growth. Pre-trends appear to exhibit moderate heterogeneity by experience, with growth prior to a switch becoming slightly less negative the later the switch occurs in the workers life cycle.

Turning to wage growth at the moment of the change the most striking result is that excess growth is largest at the start of the life cycle and declines monotonically with experience. For men, simultaneous occupation-employer movers see excess wage gains starting at .108

log points at 1 year of experience, decline to .025 log points at 10 years of experience and then flatten off to 0 log points at 20 years of experience. For pure employer transitions excess wage gains start at .063 log points at 1 year of experience, decline to .017 log points at 10 years of experience and slowly decline to 0 at 20 years of experience. For pure occupation transitions gains start at .046 log points at 1 year of experience, decline to .017 log points at 10 years of experience, and decline to 0 log points at 20 years of experience.[16] Why do wage gains at transitions exhibit this declining pattern? One possible explanation is that as workers accumulate assets over the life cycle non-pecuniary features of occupations and employers become more important. This would mean wage gains at transitions are smaller later in life because workers switch for reasons unrelated to their wages.

Another complementary explanation that explains the decline for occupation transitions is that workers seek occupations with tasks that better align with their skill sets. In my model I examine the role of skill task matching in wage determination, and show it can be at most a null consideration for log wages. Because there is a finite upper bound to the gains from switching, workers who are well matched to their occupation may not see large gains from the change. This is corroborated by the fact that the estimated matching gains at occupation transitions decline substantially the later the transition occurs in the life cycle.

4 Model

Why are early-career wage jumps for workers who make occupation-employer transitions larger than wage jumps for workers who make pure employer transitions? Are workers

[16] As I show in appendix section B the wage gains estimated via 2 is lower than the level estimated from Topel and Ward [1992]'s methodology. One plausible explanation for this is the difference in how I compute counterfactual wage growth in absence of a switch. Topel and Ward [1992] compute counterfactual wage growth via a mincer regression with cubic controls for employer tenure and experience. If these variables do not fully capture within job wage growth gains at transitions using their specification will be overestimated. This seems likely as Gathmann and Schönberg [2010] find substantial returns to task tenure even once firm tenure and experience are accounted for. On the other hand, my methodology may underestimate wage gains at transitions if stayers have systematically higher wage growth potential than switchers. Reassuringly though, my results remain *qualitatively* consistent with Topel and Ward's methodology: wage gains due to early career employer switches are large and decline with potential experience.

simply moving to higher paying occupations or are they moving to occupations that better fit their skill sets? In this section I develop a simple, tractable, micro-founded model of skill task matching which I use to understand these mechanisms.

The economy is inhabited by a set of individuals $i \in I$ and a set of occupation-employer pairs $(j,k) \in J \times K$ which I refer to as "jobs.". The output of an i j match is given by the production technology:[17]

$$y_j(l) = e^{\phi_j} L^{\alpha} \tag{3}$$

Where $\alpha > 0$ is the returns to scale on labor and ϕ_j is a firm specific productivity shifter. The variable L is a labor aggregator supplied by a single individual who applies their skills to occupation specific tasks. The worker is expected to perform each task h a occupation specific fraction $b_{k,h} \in [0,1]$ of the time where $\sum_{h=1}^{n} b_{k,h} = 1$. Performing each task is associated with a occupation specific productivity $a_{k,h} > 0$, and the worker is endowed with their own $n \times 1$ vector of task specific productivities $\boldsymbol{s}_i = [s_i^1, ..., s_i^n]' \geq \mathbf{0}$[18]. The variable l takes the form:

$$L(i,j,k) = \sum_{h=1}^{n} a_{k,h} b_{k,h} s_{i,h} = \sum_{h=1}^{n} \tau_{k,h} s_{i,h} = \boldsymbol{\tau}_k \boldsymbol{s}_i \tag{4}$$

Where $\tau_{k,h} \equiv a_{k,h} b_{k,h}$ and $\boldsymbol{\tau}_k = [\tau_k^1, ..., \tau_k^n]'$. Plugging equation 4 into equation 5 gives:

$$y(i,j,k) = e^{\phi_j} (\boldsymbol{\tau}_k' \boldsymbol{s}_i)^{\alpha} \tag{5}$$

The total pecuniary gains from the employer hiring the worker are thus determined by the weight the employer places on the worker's skills. If the worker is skilled in tasks that are valued by the job, that is $s_{i,h}$ is high when $\tau_{k,h}$ is high, total output generated by the match will be larger. This also means the firm may not want to hire highly skilled workers if their skills are not well matched to the tasks needed by the job. Consider two workers with skill vectors $s_1 = (3,3,1)$ and $s_2 = (1,1,3)$. In the extreme case where $b_k^3 = 1$ the job only requires the third task be performed. In this case output from the second worker will be greater even though the first worker is, in a sense, more skilled. I formalize this intuition in the context of wages with the following proposition:

[17] I assume that hiring the worker does not alter the firm's other input costs.

[18] In what follows all bolded variables will represent vectors and the $'$ symbol denotes a matrix transpose.

Proposition 1. *Suppose that output is split according to a employer specific fraction $e^{-\zeta_j} \in [0, 1]$, then we can write the log wage ω_{ijk}*

$$\omega_{ijk} = \phi_j - \zeta_j + \alpha(\ln||\boldsymbol{\tau}_k|| + \ln||\boldsymbol{s}_i|| + \ln\cos\theta_{ik}) \tag{6}$$

Where θ_{ik} is the angle between $\boldsymbol{\tau}_k$ and $\boldsymbol{s}_i$.

Proof. See section A.1. □

This proposition states that wages can be written as the sum of five terms. The first two terms ϕ_j and $-\zeta_j$ reflect a firm specific wage premium. The third term $\alpha\ln||\boldsymbol{\tau}_k||$ reflects the magnitude of the task vector. It is the potential benefit of being employed in the occupation if the individual's skills are perfectly matched with the occupation's tasks. It can thus be thought of as the absolute advantage of being employed in the occupation. The fourth term $\alpha\ln||\boldsymbol{s}_i||$ reflects the magnitude of the individual's skill vector. It is the potential benefit of employing the individual if their skills align perfectly with the job's task requirements. In this sense it can be seen as the individual's absolute advantage. The last term is $\alpha\ln\cos\theta_{ik}$. This term is the log of the cosine of the angle between the individual's skill vector and the occupation's task vector. It lies strictly in the interval $(-\infty, 0]$ and represents the degree of match quality between the individual's skills and the occupation's tasks. When the individual's skill vector is perfectly aligned with the occupation's task vector $\theta_{ik} = 0$, $\cos\theta_{ik} = 1$ and so $\ln\cos\theta_{ik} = 0$. If the individual's skills were completely misaligned with the occupation's task requirements we would have $\theta_{ik} = \frac{\pi}{2}$. In this case the task vector is orthogonal to the individual's skill vector and $\ln\cos\theta_{ik} \to -\infty$ as θ_{ik} approaches $\frac{\pi}{2}$ from the left. I thus interpret

$$m_{ik} = -\ln\cos\theta_{ik}$$

as the mismatch of the individual skills to the occupation's task. Note that this mismatch term purely reflects the individual's comparative advantage in the occupation as it is unaffected by the scale of the skill vector or the task vector.

It is worth noting how my measure of mismatch differs from the existing literature. Most existing studies which estimate mismatch define it as absolute or squared deviations of skill relative to some reference quantity. For example, Fredriksson et al. [2018] define mismatch as $m \equiv \sum_h |s_i^h - \bar{s}_{jk}^h|$ where $\bar{s}_{jk}^h$ is the average level of skill h in that employer and occupation. Guvenen et al. [2020] have a number of mismatch notions in their paper, but empirically select $m = \sum_h \varrho_h |q(s_i^h) - q(\tau_k^h)|$ where $q(s_i^h)$ is the skill percentile rank of i in h, $q(\tau_k^h)$ is the percentile rank of the occupation's skill requirement and ϱ_h is a weighting component. A key difference between my measure of mismatch and these is that mine is invariant to changes in the scale of the skill and task vectors. Consider two workers, Buggs and Daffy, who perform the same job but have different skills. Both worker's quantile rank of skill exceeds the job's quantile task requirement in all dimensions, but Buggs is 50% more productive at everything than Daffy. In notation $\boldsymbol{s}_B = 1.5\boldsymbol{s}_D$ and $q(s_D^h) > q(\tau_k^h)$. In both alternative mismatch measures Buggs is *more* mismatched to his occupation than Daffy, while in my measure of mismatch he is equally mismatched as Daffy. This somewhat amounts to a difference in how one treats over or under qualification. My measure only captures the misalignment of worker skills to their job's tasks. Over-qualification in my mismatch measure occurs at a skill specific level and is invariant to changes in the vetor's magnitude. Over or under qualification in the absolute sense is caputred by the terms $||\boldsymbol{s}_i||$, $||\boldsymbol{\tau}_i||$ and ϕ_j. A social planner has an incentive to pair workers and firms with high absolute advantage terms. If Buggs was substantially more skilled than Daffy along a *single* dimension then my measure of mismatch may be higher if the occupation does not well utilize that skill.

Let us now consider what happens to wages under a pure occupation transition from k to k_1. We can write excess wage growth as:

$$\Delta\omega_{ijk} = \alpha(\ln||\boldsymbol{\tau}_{k_1}|| - \ln||\boldsymbol{\tau}_k|| + \ln\cos\theta_{ik_1} - \ln\cos\theta_{ik}) \tag{7}$$

Equation 7 rationalizes excess wage growth at occupation transitions as the sum of two terms. The first term reflects movements along a career ladder in the form of changes in absolute advantage, and it reflects movements to occupations which have a greater productivity magnitude $||\boldsymbol{\tau}||$. The second term reflects improvements in the matching of skills with occupation specific tasks. Gains in $\ln\cos\theta(\boldsymbol{s}, \boldsymbol{\tau})$ can be seen as an improvements in comparative advantage. Geometrically, this component reflects the alignment of a person's skills with the requirements of the occupation. Hence an increase in $\ln\cos\theta_{ik}$ represents improved alignment of individual specific skills to occupation specific tasks.

One advantage of skill task matching is that it intuitively explains why workers in low paying occupations do not switch to higher paying occupations without the need for transition costs or assumptions about the non-pecuniary features of occupations. Heart surgeons may make more than economists, but it is unlikely an economist could find someone who would pay them to perform a coronary bypass. Economists are thus resigned to run regressions instead of performing heart surgery because, given their skills, they can make more doing that task. Economists may well love the idea of performing heart surgery, but their lack of applicable skill is what prevents them from finding a good paying career doing so. If an economist does choose to become a heart surgeon, the "transition cost" they would pay in a dynamic model would be a time opportunity cost of accumulating the requisite skills.

One special case of particular interest is when $n = 1$, i.e. there is only a single task for workers to perform and so their skills are one-dimensional. This also corresponds to the only case where skill occupy a totally ordered set. Note that because skills and tasks occupy the same orthant, the angle between $\boldsymbol{s}$ and $\boldsymbol{\tau}$ (henceforth $\theta(\boldsymbol{s}, \boldsymbol{\tau})$) will always fall in the interval $[0, \frac{\pi}{2}]$. [19] In the case where $n = 1$ this will imply $\theta(\boldsymbol{s}, \boldsymbol{\tau}) = 0$ always, and so $\ln \cos \theta(\boldsymbol{s}, \boldsymbol{\tau}) = 0$ always. Letting $\psi_j = \alpha\phi_j - \zeta_j$, $\gamma_k = \alpha||\boldsymbol{\tau}_k||$ and $\eta_i = \alpha||\boldsymbol{s}_i||$ we can write:

$$\omega_{ijk} = \psi_j + \gamma_k + \eta_i \tag{8}$$

The assumption of one dimensional skill implies that individual and occupation characteristics are *additively separable* in logs. In other words, there are no "matching" effects when $n = 1$. In this special case wages can be estimated using the following implied estimating equation:

$$\omega_{it} = \psi_{j(i,t)} + \gamma_{k(i,t)} + \eta_i + \varepsilon_{it} \tag{9}$$

Where ε_{it} is a mean zero and iid noise.

In the next section I explore this testable implication and show that it is inconsistent with a number of empirical facts. In particular, occupation fixed effects are unable to rationalize the excess wage growth at occupational transitions found in the previous section. I show that skill task matching rationalizes the remaining of excess wage growth. In the model this

[19] More analytically note $\boldsymbol{\tau} \geq 0$, $\boldsymbol{s} \geq 0 \Rightarrow \boldsymbol{s}'\boldsymbol{\tau} \geq 0$

implies that the dimensionality of the skill vector must therefore be greater than 1 and skills do not occupy a totally ordered set[20].

4.1 Testing for Vertically Ranked Occupations

One possible explanation for wage growth at occupational mobility episodes is that workers move up a occupation "ladder". That is, they simply move to occupations that are more highly paid on average. As discussed in the previous section this would be the case in a model with totally ordered, i.e. one dimensional, skill. In this case log wages are purely explained by additively separable occupation, employer and individual fixed effects as indicated by equation 9. In this section I test these implications in the data by studying the role of absolute advantage in occupation transitions.

One concern with using the model presented in the previous section to analyze wage growth is that it does not allow for wages to change independently of employer and occupation transitions. To account for wage growth within jobs I assume that a worker's absolute advantage evolves in a Mincerian form according to:

$$||\boldsymbol{s}_{it}|| = ||s_{i0}|| f(x_{it}) e^{\xi_{it}}, \xi_{it} \sim \text{ i.i.d. } N(0, \sigma_{\zeta}^2) \tag{10}$$

Where recall x_{it} is potential experience. With a process for within job wage growth in hand I can now prove the following proposition:

Proposition 2. *If wages are determined as in section 4, skill is uni-dimensional and evolves according to 10 and* $\mathbb{E}[\Delta\psi_{k(i,t)}|x_{it} = x, B_{it}^n = 1] = \mathbb{E}[\Delta\psi_{k(i,t)}|x_{it} = x, E_{it}^n = 1]$ *then:*

$$\mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, O_{it} = 1] = \varsigma_{x,0} \tag{11}$$

$$\mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, B_{it}^n = 1] = \lambda_{x,0}^n - \rho_{x,0}^n \tag{12}$$

Where $\varsigma_{x,0}$, $\lambda_{x,0}^n$ *and* $\rho_{x,0}^n$ *are the population regression coefficients from equation 2.*

Proof. See section A.2 □

[20] This relates to the theory of multiple intelligences proposed by Howard Gardner. Gardner theorized that, rather than having a single form of intellect, humans have multiple forms of intellect. My results suggest this theory has economic bearing. For a review of this theory see Gardner and Hatch [1989].

Proposition 2 says that, in the case of pure absolute advantage, there is a precise link between the coefficients in 2 at mobility episodes and occupation fixed effect gains. This suggests two simple graphical tests of absolute advantage. Firstly, the coefficients $\varsigma_{x,0}$ in 2 should be the fixed effect gain at pure occupation transitions above the horizontal axis. Secondly, if *employer* fixed effect gains are equal at pure employer and occupation-employer transitions, the coefficients $\lambda^n_{x,0}$ should be the *occupation* fixed effect gain at occupation-employer transitions plus the coefficients $\rho^n_{x,0}$.

Proposition 2 requires that

$$\mathbb{E}[\Delta\psi_{k(i,t)}|x_{it} = x, B^n_{it} = 1] = \mathbb{E}[\Delta\psi_{k(i,t)}|x_{it} = x, E^n_{it} = 1]$$

i.e. that firm fixed effect changes at pure employer transitions are a relevant counterfactual for firm fixed effect changes at occupation-employer transitions. If occupation-employer transitions see excessively large movements in firm fixed effects this could generate a gap between occupation fixed effect changes and regression coefficient differences. To address this concern in practice, I control for firm fixed effects changes in 2. This should remove differences in $\lambda^n_{x,0}$ and $\rho^n_{x,0}$ which arise due to differences in firm fixed effect gains between the two groups. However, the qualitative results of this section are unchanged if I do not include firm fixed effect controls.

To test the implications of pure absolute advantage model I first estimate occupation fixed effects by running the following regression separately for men and women:

$$\omega_{it} = \psi_j + \gamma_k + \eta_i + \boldsymbol{X}_{it}\boldsymbol{\beta} + \varepsilon_{it} \tag{13}$$

Where η_i are individual fixed effects, γ_k are the occupation fixed effects, and ψ_j is represented by indicators for employer fixed effect percentiles[21]. X_{it} contains experience cubic education indicator interactions; year fixed effects; occupation and employer tenure quadratics.

If fixed effect growth drives excess wage growth early at occupational transitions, then it should be strongest in the first 10 years of labor market experience. I thus compute sample analogues of:

$$\mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, O_{it} = 1] \text{ and } \mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, B_{it} = 1] + \rho^n_{x,0}$$

[21] Employer fixed effect percentiles are computed as in Antoni et al. [2019a].

for $1 \leq x \leq 10$ as the mean estimated fixed effects plus the estimated coefficient $\hat{\rho}^n_{x,0}$. I then plot these along with the estimated coefficients $\hat{\varsigma}_{x,0}$ and $\hat{\lambda}^n_{x,0}$ and compare differences in the levels of the curves[22].

Figure 6 shows the results of running this experiment separately for men and women. It shows that adding occupation fixed effect changes does little to close the gap between pure employer and occupation-employer transitions. In the first 5 years of experience, excess wage growth at simultaneous occupation-employer transitions is greatly underestimated by occupation fixed effect gains for both men and women. For pure occupation transitions fixed effect gains still underestimate wage gains at the first two years of experience, but provide a fairly accurate picture thereafter.[23]

Though the results on early career occupation fixed gains are qualitatively similar for men and women there are large quantitative differences. Women see approximately 2 times larger fixed effect growth[24] at occupation-employer transitions than men. One possible explanation is that gender discrimination in hiring may cause women to be employed in lower-paying occupations on average. When I condition on occupation-employer changes I may select the few women who are able to escape this employment trap. If those "successful" women tend to start in lower paying occupations than their male counterparts but have similar destination occupations, their observed fixed effect increase will be larger. Thus my results on fixed effect changes are consistent with a world in which there is gender discrimination at the level of occupational entry.

Taken in sum, the results from this section show that for both men and women a model of uni-dimensional skill is unable to rationalize wage gains at early career occupation-employer

[22]The results presented here use coefficients from 2 are estimated using controls for occupation-employer lagged tenure, education, unemployment and firm fixed effect changes. Results without controls would strengthen the qualitative result that occupation fixed effect changes do not explain wage growth at occupation-employer changes as the gap $\hat{\lambda}^n_{x,0} - \hat{\rho}^n_{x,0}$ is larger in that case.

[23]One concern about the exercises presented in this section is that workers select into to occupations which they anticipate will have higher absolute advantage in the future. I test for this in appendix section E by allowing occupation absolute advantage to trend over time. Allowing for trending absolute advantage only serves to strengthen the qualitative result that an absolute advantage model cannot explain wage growth at transitions.

[24]Computed as the sample analog of $\frac{\sum_x \mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it}=x, B_{it}=1, male=0]}{\sum_x \mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it}=x, B_{it}=1, male=1]}$.

mobility episodes. This is particularly problematic for that model since these are precisely the potential experience levels when occupation-employer changes occur most frequently. For pure occupation transitions the uni-dimensional model performs better, but is still unable to account for wage gains in the first two years of experience.

4.1.1 Further Tests of Additive Separability

I now conduct further tests of the pure vertical differentiation model implied by one dimensional skill. As in Card et al. [2013], additive separability of individual and occupation fixed effects implies symmetric wage gains at occupation transitions. Equation 9 implies that if γ_A, γ_B are the Ath and Bth quartile of occupation fixed effects, then average wage gains due to an occupational transition between A and B ($\Delta\mathbb{E}[\omega_{A\to B}]$) should approximately satisfy:

$$\Delta\mathbb{E}[\omega_{A\to B}] \approx \gamma_A - \gamma_B = -(\gamma_B - \gamma_A) \approx -\Delta\mathbb{E}[\omega_{B\to A}]$$

Figure 7 tests this hypothesis in the style of Card et al. [2013] for men. Occupation fixed effects are estimated as in section 4.1, I then plot log wages in a event study around transition between occupation fixed effect quartiles and check to see if the transitions are symmetric. Compared to the analogous figure in Card et al. [2013] (pp. 984) wage gains exhibit substantially less symmetry. This is further evidence that pure separability of individual and occupation fixed effects is unlikely to hold in the data.

Another test inspired by Card et al. [2013] is that, under the null hypothesis of additive separability, we would likely expect errors conditional on occupation fixed effect decile and individual fixed effect decile to be zero. Figure 8 conducts a version of this exercise with occupation fixed effect deciles and individual mean wage deciles for men. The scale of the errors is an order of magnitude larger than the equivalent figure in Card et al. [2013] (pp. 996), providing further evidence that additive separability of individual and occupation fixed effects is unlikely to provide a reasonable approximation in the data.

These two exercises show that additive separability of individual and occupation fixed effects is very unlikely to hold. In particular, it appears to be a substantially worse assumption than additive separability of individual and employer fixed effects. This suggests an important role for skill task matching at the occupation level. This occurs when the dimensionality of skill is *greater* than one, i.e. workers sort according to their comparative advantage in occupations. Taken with my finding that fixed effect gains do not explain wage growth at occupation-employer transitions, this is strong evidence that a model with a pure occupational ladder is unable to capture a number of stylized facts about wage growth. In the following section I provide evidence that a model of multidimensional skill can reconcile this discrepancy. I conclude that individual skill is likely to be multidimensional in nature and therefore matching is an important consideration for occupation specific wage growth.

5 Testing Model Implications: Comparative Advantage Gains

Thus far I have only shown a negative result: one dimensional skill provides a poor fit for stylized facts about wages. In this section I show direct evidence that matching improves at episodes of early-career occupation-employer mobility, and together with fixed effect increase can account for excess wage growth. Thus multidimensional skill can reconcile the discrepancies I found in the previous section.

The goal of this section is to estimate gains in the matching term θ_{ik}. Imposing constant returns to scale in 6 gives:

$$\omega_{ijk} = \phi_j - \zeta_j + \ln||\boldsymbol{\tau}_k|| + \ln||\boldsymbol{s}_i|| + \ln\cos\theta_{ik} \tag{14}$$

Currently, matching terms are not separately identified from absolute advantage terms. This problem can be ameliorated by making distributional assumptions on $\boldsymbol{\tau}_k$ and $\boldsymbol{s}_i$. Letting x denote i's potential experience level, and denoting their skill at experience x as $\boldsymbol{s}_{ix}$ I assume:

Assumption 1. *Lognormal skill magnitudes with experience specific means:*

$$||\boldsymbol{s}_{xi}|| = f(x)e^{\xi_{it}}, \xi_{it} \sim \text{ i.i.d. } N(0, \sigma_\zeta^2)$$

Assumption 2. *Equal average mismatch across, employer, occupation cells:*

$$\mathbb{E}[\ln\cos\theta_{ik}|j,k] = -\bar{m}_x$$

Assumptions 1 and 2 are quite strong. Assumption 1 states that a worker's absolute advantage depends only on their experience and an individual specific idiosyncratic noise. This would be violated in the case of sorting of high absolute advantage individuals by occupation or firm. In this case the term ξ_{it} would not be idiosyncratic, and so $\mathbb{E}[\xi_{it}|j,k] \neq 0$ in general. Assumption 2 says that average mismatch across employers and occupations is constant. This would be violated, for example, if certain occupations or employers have better matching technologies than others. It would also be violated in the case of "learning by doing" or skill investment. In these cases the direction of individual skill vectors will systematically approach the direction the task vector with the accumulation of experience. Individuals with high experience levels would then have lower levels of mismatch constituting a violation of the assumption.

The benefit to making assumptions 1 and 2 is that relative skill directions can be directly estimated from the data via a series of simple linear regressions. Under assumptions 1 & 2, the experience, employer and occupation specific mean log wage is:

$$\begin{aligned}\mu_{jkx} \equiv \mathbb{E}[\omega_{ijk}|x,j,k] = \mathbb{E}[\phi_j - \zeta_j + \ln||\boldsymbol{\tau}_k|| + \ln f(x) + \ln\cos\theta_{ik} + \xi_{it}|x,j,k] \\ = \phi_j - \zeta_j + \ln||\boldsymbol{\tau}_k|| + \ln f(x) - \bar{m}_x\end{aligned}$$

Hence we can write:

$$\omega_{ijk} - \mu_{jkx} = \ln\cos\theta_{ik} + \bar{m}_x + \xi_{it}$$

With $\xi_{it} \sim N(0, \sigma_\xi^2)$. Taking exponents of both sides gives:

$$e^{\omega_{ijk}-\mu_{jkx}} = \frac{\cos\theta_{ik}}{e^{-\bar{m}_x}} \cdot e^{\xi_{it}}$$

A first order Taylor expansion around ξ_{it} gives:

$$e^{\omega_{ijk}-\mu_{jkx}} \approx \frac{\cos\theta_{ik}}{e^{-\bar{m}_x}} + \epsilon_{itk} \tag{15}$$

Where $\epsilon_{itk} \sim N(0, \frac{\cos\theta_{ik}}{e^{-\bar{m}_x}} \cdot \sigma_\xi^2)$ is a heteroskedastic error term. Note that

$$\cos\theta_{ik} = \tilde{\boldsymbol{s}}_i' \tilde{\boldsymbol{\tau}}_k \tag{16}$$

Where $\tilde{\boldsymbol{s}}_i = \frac{\boldsymbol{s}_i}{||\boldsymbol{s}_i||}$, $\tilde{\boldsymbol{\tau}}_k = \frac{\boldsymbol{\tau}_k}{||\boldsymbol{\tau}_k||}$ are the normalized skill vectors. We can then write equation 15 as:

$$e^{\omega_{ijk} - \mu_{jkx}} \approx \frac{\tilde{\boldsymbol{s}}_i}{e^{-\bar{m}_x}}' \tilde{\boldsymbol{\tau}}_k + \epsilon_{ikt} \tag{17}$$

This suggests the following estimation procedure:

1. Estimate μ_{jkx} as the mean log wage by experience, employer fixed effect percentile and occupation.

2. Normalize occupation specific task vector data from BERUFENET to have a constant magnitude of 1.

3. Run regressions of $e^{\omega_{ijk} - \mu_{jkx}}$ on the normalized task vectors separately by person to estimate $\frac{\tilde{\boldsymbol{s}}_i}{e^{-\bar{m}_x}}$.

4. Re-scale person's skill magnitude to be 1 and take the inner product with the normalized task vector to estimate $\frac{\cos \hat{\theta}_{ik}}{e^{-\bar{m}_x}}$.

5. Once estimates of $\frac{\cos \hat{\theta}_{ik}}{e^{-\bar{m}_x}}$ are obtained, take mean log changes at pure occupation changes and occupation-employer changes to estimate the change in mismatch at those events.

The estimated mismatch gains for an individual moving from k to k' log changes from step 5 can be written as:

$$\Delta \ln \frac{\cos \hat{\theta}_{ik}}{e^{-\bar{m}_x}} = \ln \cos \hat{\theta}_{ik'} - \ln \cos \hat{\theta}_{ik} + (\bar{m}_{x+1} - \bar{m}_x)$$

Where the second term follows from the fact that the worker has one more year of potential experience. Assuming mismatch declines on average with potential experience then gains in mismatch will be somewhat underestimated by this procedure. However, it should be noted that in my model mismatch can only decline at episodes of occupational mobility. Hence, relative to changes for actual movers the term $(\bar{m}_{x+1} - \bar{m}_x)$ will be quite small. Thus any biased estimated at moments of change should be minimal.

If there is substantial learning by doing or skill investment that changes the angle of the skill vector then mismatch will change *within* occupation. In this case the bias at mobility episodes will be larger. Of course, for this to be the case mismatch would still need to be an essential part of wage growth. The qualitative conclusion of this paper that horizontal matching impacts wage growth would therefore remain the same.

5.1 Matching Estimation Results

Results from the estimation procedure in the previous section are show in figure 9. These figures show the mean gain in the estimated matching term $\ln \cos \theta_{ik}$ above the wage gains of non movers (the dashed line) and pure employer movers (the dot-dashed line). Examining the figures, it appears that improved matching primarily takes place through simultaneous occupation-employer transitions. Indeed, for high levels of potential experience, match quality appears to *decline* slightly for pure-occupation transitions, though it remains close to zero for most levels of experience. The results for men suggest that matching explains most of the excess wage gains from occupation-employer transitions above pure employer transitions at the moment of transition. However, matching estimates provide a substantially worse estimate of the immediate wage gains from pure occupation transitions. The matching results for women are qualitatively similar, though it appears that occupational absolute advantage growth plays a comparatively larger role for women than men at occupation-employer transitions.

The level of matching gains at occupation-employer transitions for women is 12%[25] larger than the matching gains for men. This suggests that women who actually make occupation-employer transitions are better suited for their destination occupations than their male counterparts. This shows that there may be substantial productivity improvements to be had from eliminating gender discrimination in hiring. Marginal female candidates will, on average, be better matches for potential destination occupations than marginal male candidates. Thus more equal hiring standards for female candidates will lead to better matching of skills to tasks. Note that this is distinct from matching of absolute advantage, that is high $||\boldsymbol{\tau}_k||$ to high $||\boldsymbol{s}_i||$. Reducing gender discrimination may also lead to more absolute advantage matching, but my results show something distinct from this. That is, matching along comparative advantage lines improves with less gender discrimination.

[25]Computed as the sample analog of $\frac{\sum_x \mathbb{E}[\Delta \ln \cos \hat{\theta}_{ik} | x_{it}=x, B_{it}=1, male=0]}{\sum_x \mathbb{E}[\Delta \ln \cos \hat{\theta}_{ik} | x_{it}=x, B_{it}=1, male=1]}$.

To fully test the model of multidimensional skill presented in 4 I need to compute the *sum* of the comparative advantage component $\alpha \ln \cos \theta_{ik}$ and the absolute advantage component $\alpha \ln ||\boldsymbol{\tau}_k||$ as in equation 7 and add that to the appropriate counterfactual. The second row of figure 9 presents this exercise. Combined comparative and absolute advantage do a remarkably good job of accounting for wage growth at occupation transitions. I conclude that a model of multidimensional skill is able to account for the stylized facts about wage growth at occupation transitions while a model of one dimensional skill is not.

5.1.1 Matching Over Time and Labor Market Entry Cohorts

The emergence of information technology over the past half century might be expected to result in improving match quality over time. In this section I use the match quality estimates from the previous section to estimate trends in horizontal match quality. To test this I run the following regression separately by gender:

$$\hat{m}_{it} = \alpha + \zeta Y_t + \boldsymbol{X}_{it}\boldsymbol{\beta} + \varepsilon_{it} \tag{18}$$

Where $\hat{m}_{it}$ is the individuals level of mismatch as estimated by the previous section, Y_t represents the number of years since 1975 and $\boldsymbol{X}_{it}$ represents a vector of controls.

Tables 2 and 3 present the results of running equation 18 separately for men and women with and without controls. The first column runs 18 without controls, the second column includes controls for experience, and the last column includes controls for experience, occupation fixed effect, firm fixed effect, occupation and firm tenure and education.

The results are quite striking, rather than improving during my sample period horizontal mismatch appears to have worsened substantially. One possible explanation is that occupations for which it is more difficult to find good matches are becoming more common. This has some credence, controlling for occupation fixed effects reduces the increase in mismatch for both men and women but it would also violate assumption 2. A more concerning explanation is that equality of opportunity has been falling in Germany during my sample period. Chetty et al. [2016] find that equality of opportunity declined substantially from the 1940s to the 1980s. Worsening opportunities could mean that workers born to poor households who are potentially good matches for high paying occupations are less able to enter those occupations. However Stockhausen [2018] finds little evidence of worsening equality of opportunity during this sample period for Germany. Cyclical forces may also play a role, figure 10 plots the unemployment rate during my sample period. Though not pictured for brevity, mismatch does rise following unemployment shocks. As unemployment is trending upwards for my sample it may also cause a rise in my mismatch measure.

One interesting feature of my time trend estimates is that trends are substantially less positive for women. This means that, relative to men, matching is improving for women over my sample period. If one believes gender discrimination has declined over this time frame, then women are likely being afforded greater opportunities for better matches. One would then expect that trends in mismatch are more negative for women than men which is precisely what I observe.

6 Conclusion

This paper investigates the role of occupational mobility in lifetime wage growth and the sources of wage growth at mobility episodes. I find that episodes of occupation-employer mobility are associated with large persistent wage gains which vary substantially by experience. Wage gains constitute a sharp reversal in trend consistent with a learning model where workers leave occupations for which they are poorly matched. Changes in occupation fixed effects do not explain wage gains at occupation employer transitions and occupation fixed effects, unlike firm fixed effects, do not appear to be approximately additively separable. These facts imply that a model of one dimensional skill cannot rationalize wage growth at occupation transitions. By contrast a simple model of skill task matching with three skill dimensions appears to do relatively well in accounting for the facts about wage growth. I use such a model to develop a novel micro-founded notion of skill task mismatch which is unaffected by individual and occupational absolute advantage. I use task data to directly estimate this matching component and show that skill task mismatch can account for wage growth at occupation employer transitions. Mismatch has been increasing over time in Germany, but this trend is substantially less positive for women suggesting that greater equality of opportunity has had a net positive effect on productivity.

My result that matching is a key part of wage growth at occupation transitions has important policy implications. Firstly, government sponsored job training programs should go beyond simply raising worker human capital levels. Instead these training programs should highly targeted, and seek to equip workers with socially desirable skills that allow them to match with existing occupations. Secondly, because human capital is not perfectly transferable across occupations, structural change may increase aggregate mismatch in the economy. Therefore policies that seek to induce structural change, such as moving to green energy sources, should possibly include targeted job training to mitigate a potential rise in mismatch.

My results leave substantial room for future research. The production structure and notion of mismatch employed by my model could be embedded into a search and matching framework to better understand the role of wage bargaining. Additionally, precise interpretation of my results on gender differences requires more formal modelling than I have presented here. On the empirical front, future research could relax the assumptions I have made to estimate skill by allowing for learning by doing. This will likely improve the fit of the model by offloading within occupation wage growth to years after after a switch.

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Tables

Table 1: Examples of activities in task categories from Dengler et al. [2014].

Category Name	Examples
1. Analytical non-routine tasks.	Management, software development, design.
2. Interactive non-routine tasks.	Support, counselling, service.
3. Cognitive routine tasks.	Network Technology, measurement, monitoring
4. Manual non-routine tasks.	Dancing, bespoke/custom production, manual focused therapy.
5. Manual routine tasks.	Farming, construction, operating machines.

Table 2: Trends in Mismatch Over Time Under Various Control Specifications, Men

	(1)	(2)	(3)
	$-\ln\cos\theta_{ik}$	$-\ln\cos\theta_{ik}$	$-\ln\cos\theta_{ik}$
Years Since 1975	0.005	0.013	0.005
	(0.000)	(0.001)	(0.001)
Experience Controls		✓	✓
Education Controls			✓
Occupation Fixed Effects			✓
Firm FE Percentiles			✓
Tenure Controls			✓
N	1066329	1066329	965040

This table presents various regressions of experience and year on match quality. The sample consists of West German men born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, and who hold at least 3 occupations during their life. Sample years range from 1975-2010. Standard errors in parenthesis.

Table 3: Trends in Mismatch Over Time Under Various Control Specifications, Women

	(1)	(2)	(3)
	$-\ln\cos\theta_{ik}$	$-\ln\cos\theta_{ik}$	$-\ln\cos\theta_{ik}$
Years Since 1975	0.003	0.004	-0.002
	(0.001)	(0.002)	(0.002)
Experience Controls		✓	✓
Education Controls			✓
Occupation Fixed Effects			✓
Firm FE Percentiles			✓
Tenure Controls			✓
N	278867	278867	239420

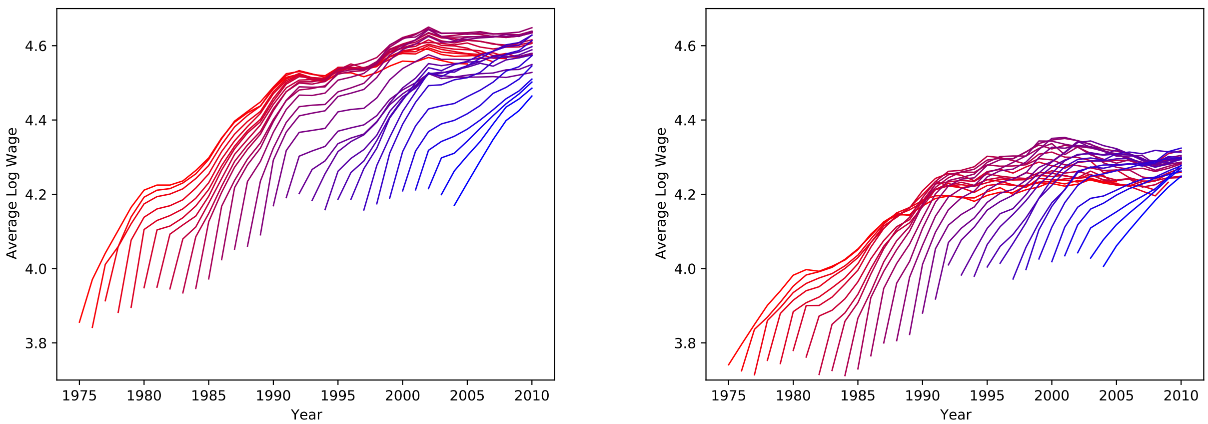
This table presents various regressions of experience and year on match quality. The sample consists of West German women born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, and who hold at least 3 occupations during their life. Sample years range from 1975-2010. Standard errors in parenthesis.

Figures

Figure 1: Mean Log Wages by Labor Market Entry Cohort Over Time

(a) Men

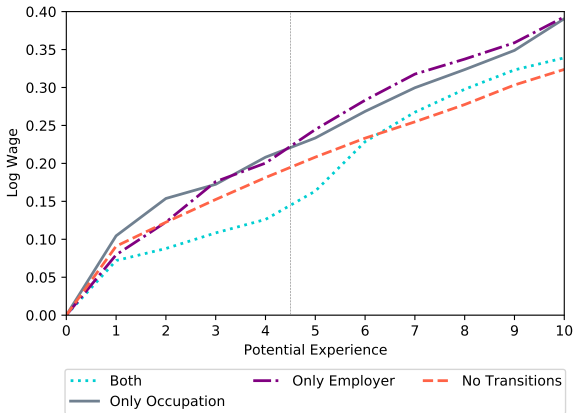
(b) Women



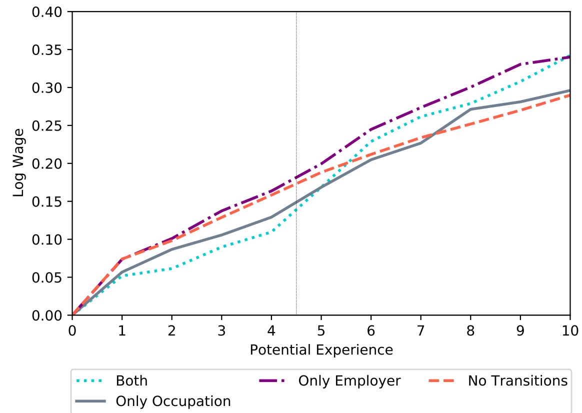
This figure shows the average log wage over time by year of labor market entry and year for men and women. Each colored line denotes a different entry cohort. The sample consists of West Germans born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010.

Figure 2: Cumulative Log Wage Growth Around Employer and Occupation Transitions at 5 years of Experience

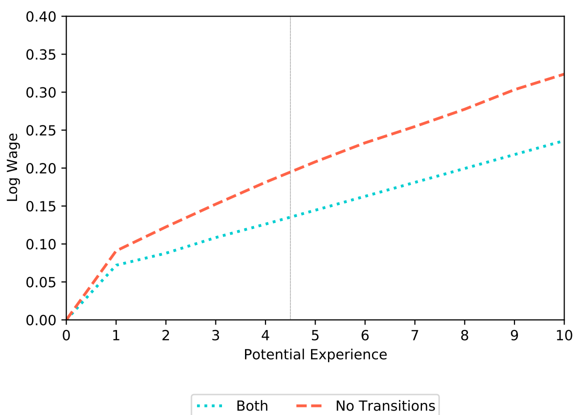
(a) Men, Actual



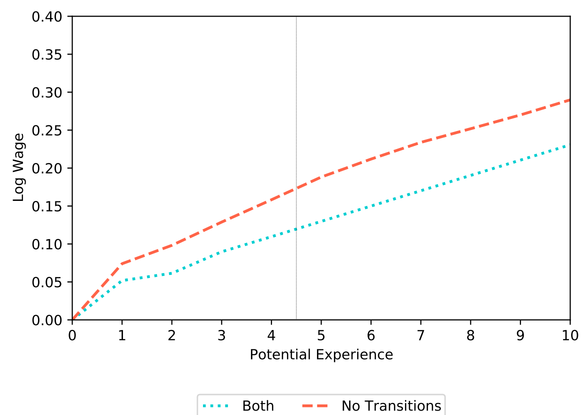
(b) Women, Actual



(c) Men, Extrapolated



(d) Women, Extrapolated

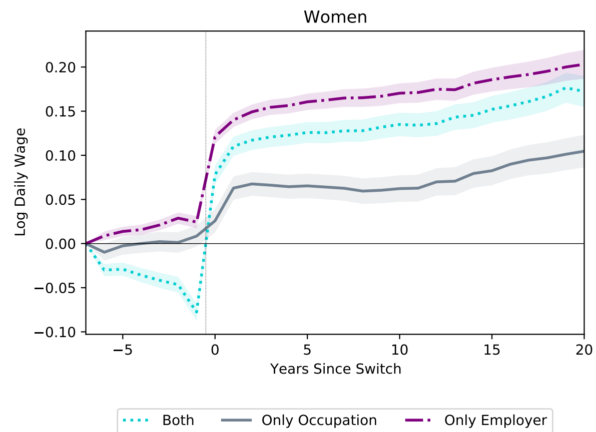


This first two rows of this figure shows the cumulative change in mean log wage for individuals who only make one specific transition at 5 years of potential experience and individuals who make no transitions in the first 10 years of potential experience. The second two rows extrapolate trends prior to transitions out to ten years of potential experience for occupation-employer movers and non-movers. The sample consists of West Germans born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010.

Figure 3: Event Study of Log Wage Response Around Occupation and Employer Mobility Episodes

(a) Men

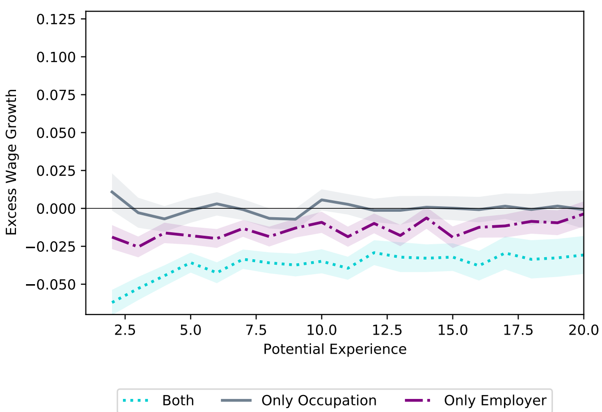
(b) Women



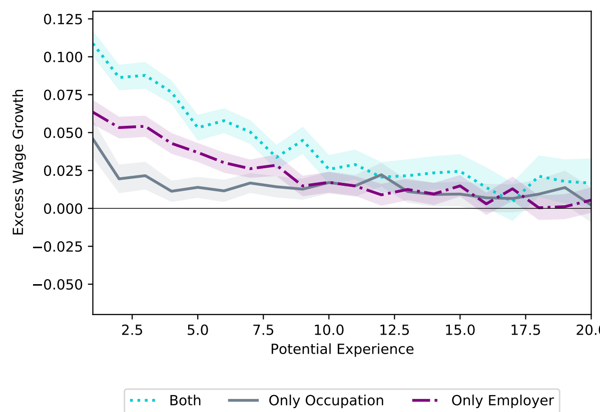
This figure gives the results from running the event study given by equation 1 separately by gender on my primary sample controlling for education indicators and a quadratic of potential experience, establishment tenure and occupation tenure. The figure plots δ_{c,k_c} where c is the mobility category and k represents the years since the switch. The mobility categories are pure employer, pure occupation and simultaneous occupation-employer transitions that do not involve an intermittent unemployment spell. The samples consists of West Germans born after 1955 with at least 7 years of experience in their first 10 years after labor market entry. The sample period ranges from 1975-2010. Shaded areas represent a 95% confidence interval computed. Standard errors are clustered at the individual level.

Figure 4: Excess Wage Growth By Experience, Men

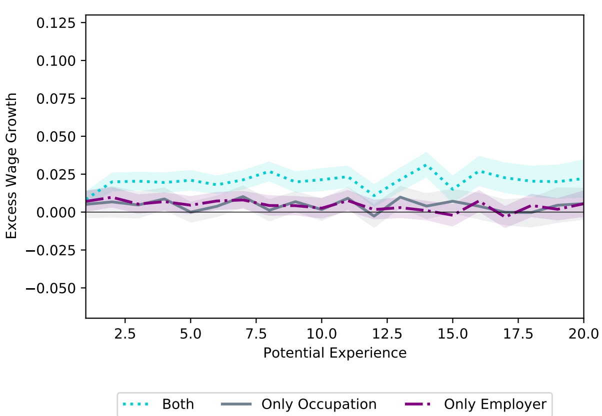
(a) One Year Before Switch



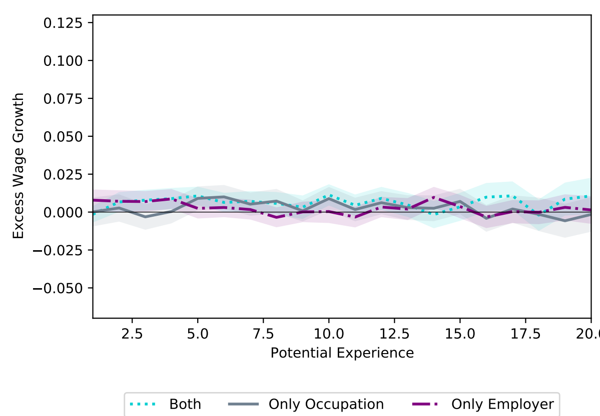
(b) Year of Switch



(c) One Year After Switch



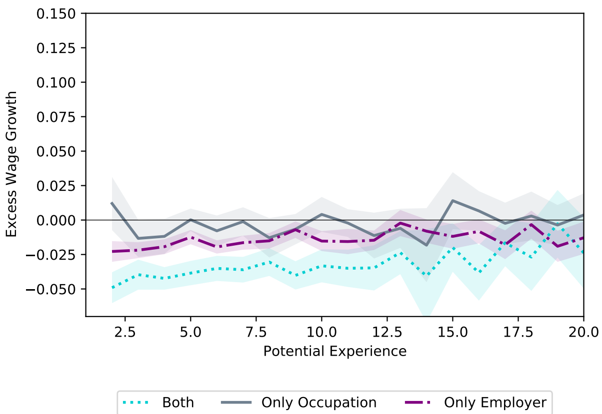
(d) Two Years After Switch



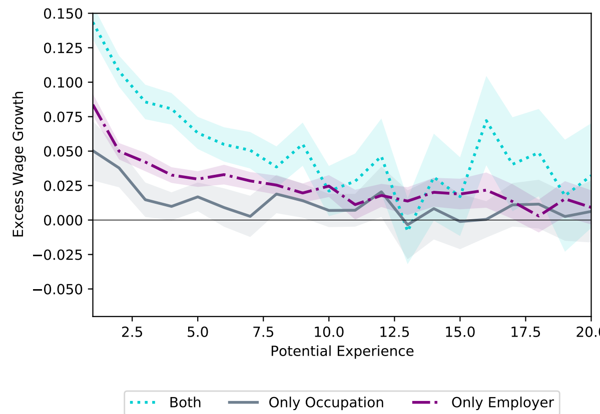
This figure gives the results from running the event study given by equation 2 with controls for lagged tenure experience interactions, parsimonious indicators for current and lagged education and employer fixed effect changes. The sample consists of West German women born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. Shaded areas represent a 95% confidence interval computed with standard errors clustered at the individual level.

Figure 5: Excess Wage Growth By Experience, Women

(a) One Year Before Switch

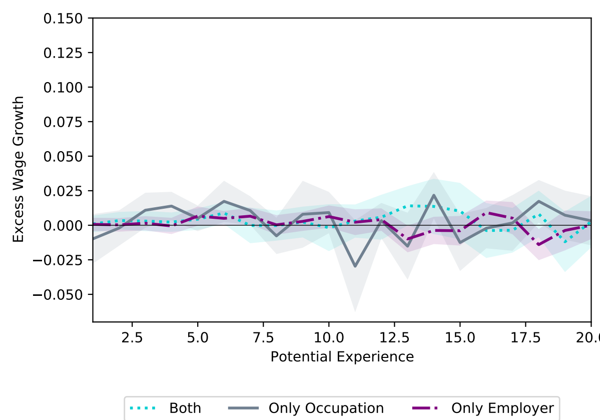


(b) Year of Switch



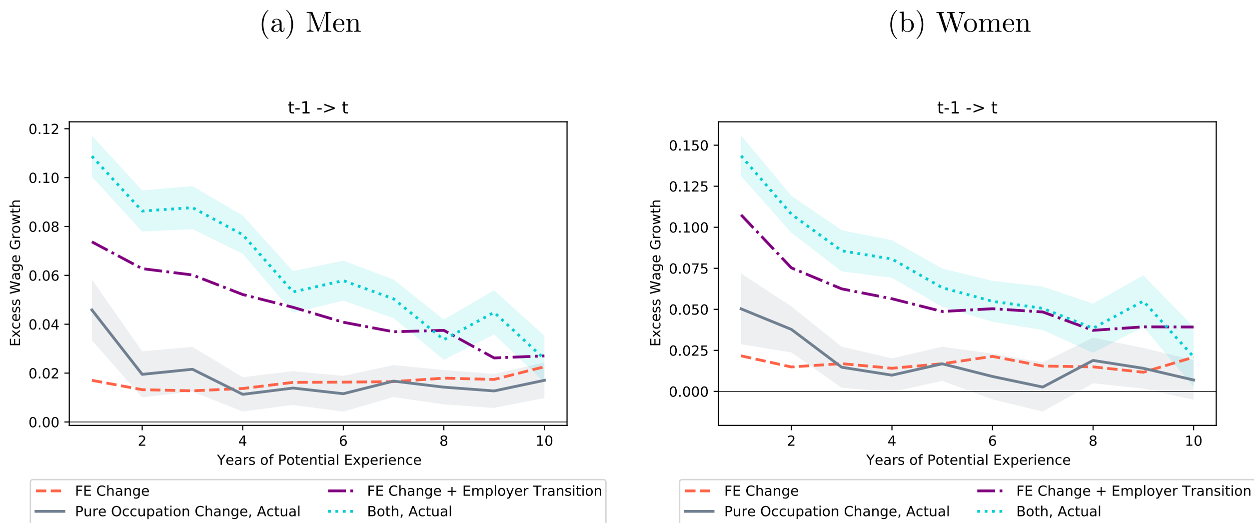
(c) One Year After Switch

(d) Two Years After Switch



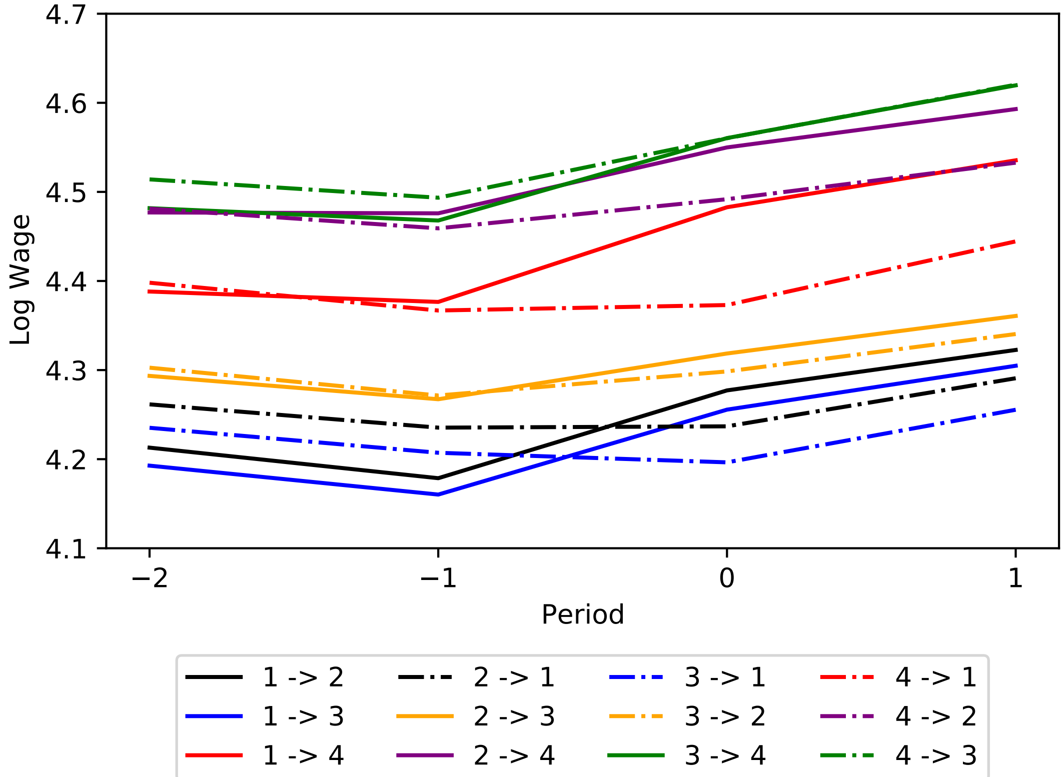
This figure gives the results from running the event study given by equation 2 with controls for lagged tenure experience interactions, unemployment, parsimonious indicators for current and lagged education and employer fixed effect changes. The sample consists of West German women born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. Shaded areas represent a 95% confidence interval computed with standard errors clustered at the individual level.

Figure 6: Average Occupation Fixed Effect Gain Above Counterfactual



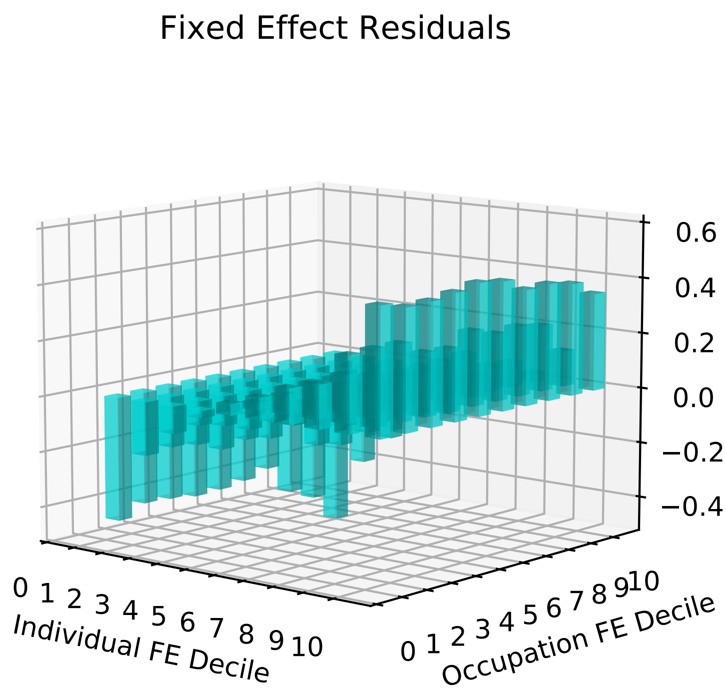
This figure shows the average change in the occupation fixed effect at occupational mobility episodes compared to actual wage gains at those episodes. The sample consists of West Germans born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010.

Figure 7: Mean Wages of Occupation Switchers Classified by Origin and Destination Occupation Fixed Effect Quartiles



This figure shows log wages before and after a transition between occupation fixed effect quartiles. The sample consists of West German men born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. Transitions take place between -1 and 0. A dotted lines represent a transition to a lower quartile and a solid line of the same color represents the symmetric transition to a higher quartile.

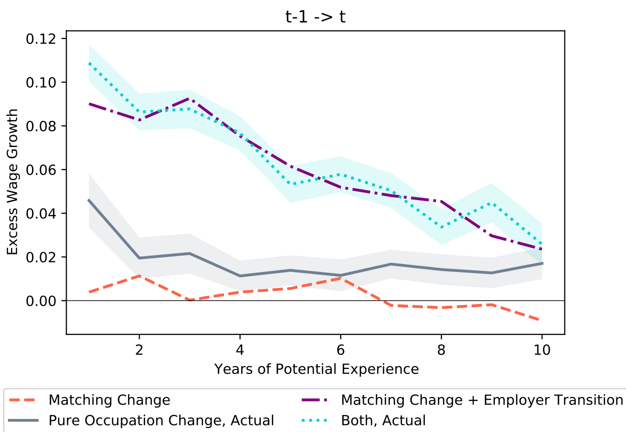
Figure 8: Residuals Conditional on Individual Mean Wage Decile and Occupation Fixed Effect Decile



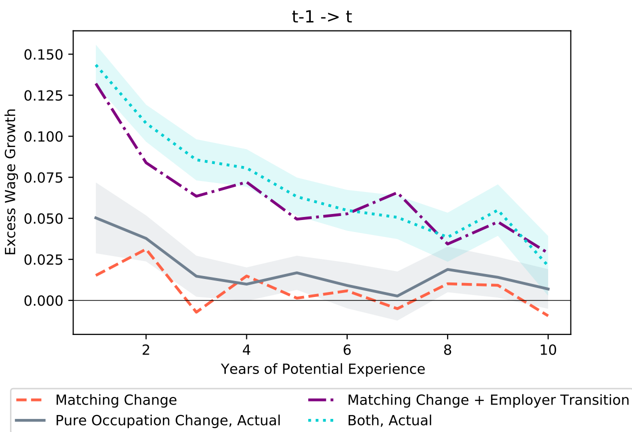
This figure shows regression residuals by mean wage and occupation fixed effect. The sample consists of West German men born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010.

Figure 9: Model Estimates: Wage Gains Above Counterfactual Wage Growth

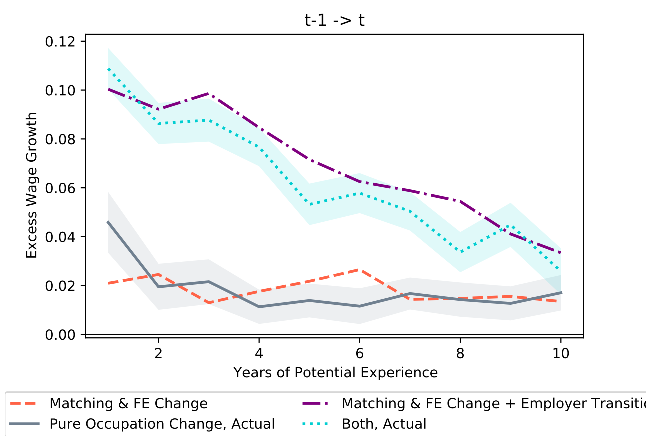
(a) Men, Just Matching



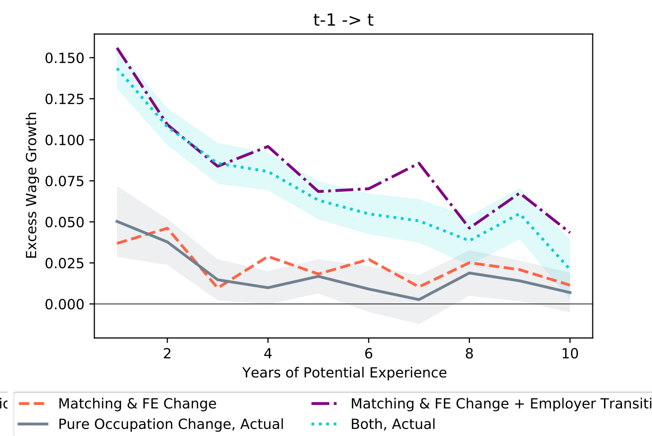
(b) Women, Just Matching



(c) Men, Matching and Fixed Effect

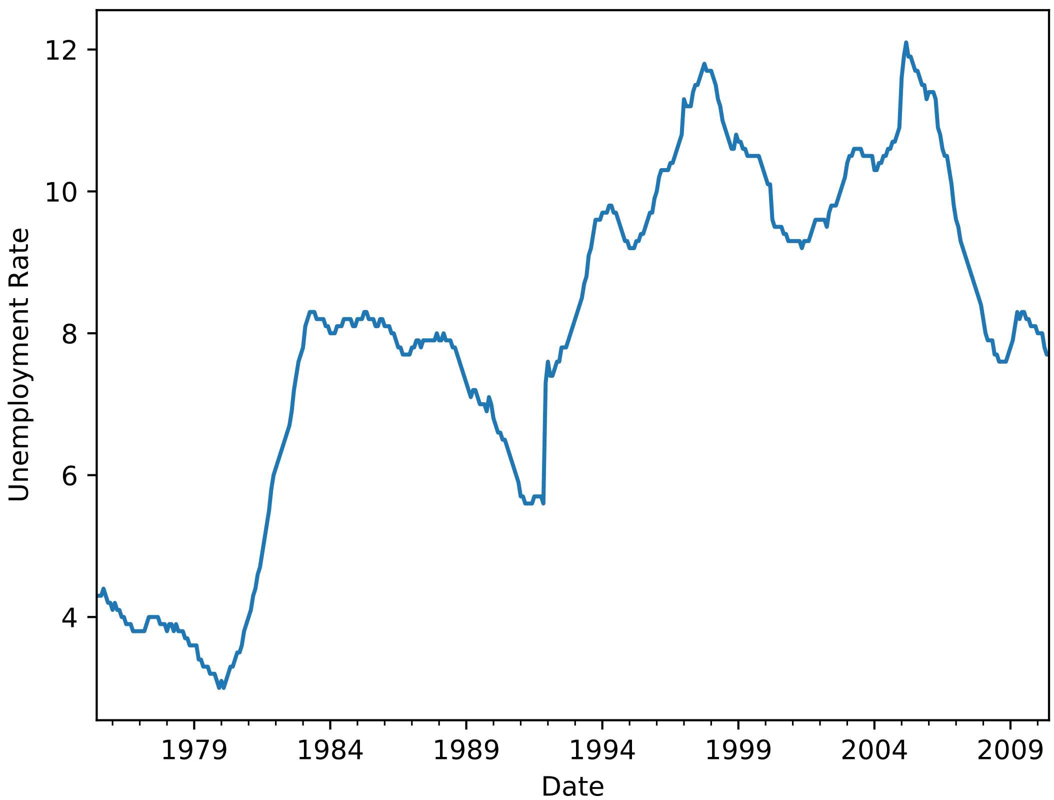


(d) Women, Matching and Fixed Effect



This figure shows the average change in the occupational matching quality and fixed effects at occupational mobility episodes compared to actual wage gains at those episodes. The sample consists of West Germans born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. Shaded areas represent a 95% confidence interval computed with standard errors clustered at the individual level.

Figure 10: Monthly Seasonally Adjusted Unemployment Rate in From 1975-2010



This figure shows the monthly seasonally adjusted German unemployment rate for my sample period. Data is from the OECD via the St. Louis Fed OECD.

A Proofs

A.1 Proof of Proposition 1

Proof. The output of an i, j, k match is given by:

$$y_{ijk} = e^{\phi_j}(\boldsymbol{\tau}_k'\boldsymbol{s}_i)^\alpha \tag{19}$$

Output is split according to the constant fraction $e^{\zeta_j} \in [0,1]$, so that the wage can be written as:

$$w_{ijk} = e^{\zeta_j} y_{ijk} = e^{\phi_j - \zeta_j}(\boldsymbol{\tau}_k'\boldsymbol{s}_i)^\alpha \tag{20}$$

Note that $\boldsymbol{\tau}_k$ and $\boldsymbol{s}_i$ lie in the same inner product space. By the definition of the cosine function in an inner product space, the cosine of the angle between the two vectors (θ_{ik}) is:

$$cos(\theta_{ik}) \equiv \frac{\boldsymbol{\tau}_k'\boldsymbol{s}_i}{||\boldsymbol{s}_i||\cdot||\boldsymbol{\tau}_k||} = \frac{e^{(\phi_j-\zeta_j)/\alpha}\boldsymbol{\tau}_k'\boldsymbol{s}_i}{e^{(\phi_j-\zeta_j)/\alpha}||\boldsymbol{s}_i||\cdot||\boldsymbol{\tau}_k||} = \frac{w_{ijk}^{\frac{1}{\alpha}}}{e^{(\phi_j-\zeta_j)/\alpha}||\boldsymbol{s}_i||\cdot||\boldsymbol{\tau}_k||} \tag{21}$$

Note that we can rewrite equation 21 as:

$$w_{ijk} = e^{\phi_j - \zeta_j}(||\boldsymbol{\tau}_k||\cdot||\boldsymbol{s}_i||\cdot cos(\theta_{ik}))^\alpha \tag{22}$$

Equation 22 is intuitive, since $\boldsymbol{s}_i \geq 0$ and $\boldsymbol{\tau}_k \geq 0$, $\alpha > 0$ we have $cos(\theta_{ik})^\alpha \in [0,1]$. Thus equation 22 says that the true output is a fraction of what the hypothetical output would be if the individual's and the occupation's skills were perfectly aligned. Taking logs:

$$\omega_{ijk} = \phi_j - \zeta_j + \alpha(\ln||\boldsymbol{\tau}_k|| + \ln||\boldsymbol{s}_i|| + \ln\cos\theta_{ik}).$$

Which is the desired result. $\square$

A.2 Proof of Proposition 2

Proof. Note that each individual's absolute advantage evolves according to:

$$\eta_{it} = \alpha\ln||\boldsymbol{s}_{xi}|| = ||s_{i0}|| + \ln f(x_{it}) + \xi_{it}, \xi_{it} \sim \text{ i.i.d. } N(0, \sigma_\zeta^2)$$

Wage differences within person in that case are given by:

$$\Delta\omega_{it} = \Delta\psi_{j(i,t)} + \Delta\gamma_{k(i,t)} + \Delta\ln f(x_{it}) + \Delta\varepsilon_{it} + \Delta\xi_{it}$$

Noting that $\Delta \ln f(x_{it}) = \ln f(x) - \ln f(x-1) \equiv \nu_x$, that is, f is a function of i and t only insofar as x is function of i and t, the mean gain in fixed effects at an a given experience and mobility combination are:

$$\mathbb{E}[\Delta\omega_{it}|x_{it} = x, O_{it} = 1] = \mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, O_{it} = 1] + \nu_x$$

$$\mathbb{E}[\Delta\omega_{it}|x_{it} = x, E^n_{it} = 1] = \mathbb{E}[\Delta\psi_{j(i,t)}|x_{it} = x, E^n_{it} = 1] + \nu_x$$

$$\mathbb{E}[\Delta\omega_{it}|x_{it} = x, B^n_{it} = 1] = \mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, B^n_{it} = 1] + \mathbb{E}[\Delta\psi_{j(i,t)}|x_{it} = x, B^n_{it} = 1] + \nu_x$$

Under the assumption that $\mathbb{E}[\Delta\psi_{k(i,t)}|x_{it} = x, B^n_{it} = 1] = \mathbb{E}[\Delta\psi_{k(i,t)}|x_{it} = x, E^n_{it} = 1]$ the wage gains at occupational mobility episodes are given by:

$$\mathbb{E}[\Delta\omega_{it}|x_{it} = x, O_{it} = 1] = \mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, O_{it} = 1] + \nu_x$$

$$\mathbb{E}[\Delta\omega_{it}|x_{it} = x, B^n_{it} = 1] = \mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, B^n_{it} = 1] + \mathbb{E}[\Delta\omega_{it}|x_{it} = x, E^n_{it} = 1] - \nu_x + \nu_x$$

Noting $\nu_x = \mathbb{E}[\Delta\omega_{it+s}|x_{it} = x, N_{it} = 1]$ where N_{it} is an indicator for no changes occurring and rearranging terms we arrive at:

$$\begin{aligned}\mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, O_{it} = 1] =& \mathbb{E}[\Delta\omega_{it}|x_{it} = x, O_{it} = 1] - \mathbb{E}[\Delta\omega_{it+s}|x_{it} = x, N_{it} = 1] \\ =& \varsigma_{x,0}\end{aligned} \tag{23}$$

$$\begin{aligned}\mathbb{E}[\Delta\gamma_{k(i,t)}|x_{it} = x, B^n_{it} = 1] =& (\mathbb{E}[\Delta\omega_{it}|x_{it} = x, B^n_{it} = 1] - \mathbb{E}[\Delta\omega_{it+s}|x_{it} = x, N_{it} = 1]) \\ & -(\mathbb{E}[\Delta\omega_{it}|x_{it} = x, E^n_{it} = 1] - \mathbb{E}[\Delta\omega_{it+s}|x_{it} = x, N_{it} = 1]) \\ =& \lambda^n_{x,0} - \rho^n_{x,0}\end{aligned} \tag{24}$$

Which is the desired result. □

B Topel Ward Replication

In this section I replicate the methodology from Topel and Ward [1992] as both a point of comparison and to understand how occupational changes affect wage growth for narrow in the population. Since Topel and Ward [1992] run their results exclusively for men I only include men in my replication of their methodology. I find that the estimates of wage gains at occupation transitions and employer transitions are quite similar, suggesting a large degree of overlap. I show that wage growth following occupation transitions varies substantially by destination and starting occupations, but in an asymmetric way: occupations which are good to enter need not be bad to leave.

To begin, I mimic Topel and Ward [1992] and estimate wage growth around transitions with the following equation:

$$\begin{aligned}\mathbb{E}[\omega_{t+1,k_1} - \omega_{t,k_0} | \omega_{t+2,k_1}, \omega_{t-1,k_0}] &= \omega_{t+2,k_1} - \omega_{t-1,k_0} \\ &-\mathbb{E}[\omega_{t+2,k_1} - \omega_{t+1,k_1} | \cdot] - \mathbb{E}[\omega_{t,k_0} - \omega_{t-1,k_0} | \cdot]\end{aligned} \tag{25}$$

Where $t > 0$ represents the year, $k_1 \neq k_0$ are states that could reflect either employer or occupation and ω is the log wage. The term $\omega_{t+2,k_1} - \omega_{t-1,k_0}$ represents wage gains over the four year period surrounding the change of state k. The term $-\mathbb{E}[\omega_{t+2,k_1} - \omega_{t+1,k_1} | \cdot] - \mathbb{E}[\omega_{t,k_0} - \omega_{t-1,k_0} | \cdot]$ is a correction term, it represents the counterfactual wage growth that would have occurred absent a change. To maintain comparability with the past literature I follow Topel and Ward [1992] and estimate this term via a mincer regression of experience and employer tenure on wages. The average wage change resulting from an occupation or employer switch is estimated by taking a simple mean of the right hand side over different subgroups.

Table 4 replicates the mean wage gains by experience at different transitions as in table 7 row 2 of Topel and Ward [1992]. Their estimates are repeated for convince in the first row, and my estimates of log daily wage changes at employer changes are in the second[26]. The third row extends their methodology and estimates wage gains at *occupational* transitions. As a point of comparison, I am not yet separating employer and occupation transitions, so rows 2 and 3 in my sample in principle share a large number of observations.

[26]The results from Topel and Ward [1992] are technically log changes in quarterly earnings, not daily wages. However, if the number of hours worked is constant before and after the change this will not affect the estimates. This seems likely as they and I both condition on full-time work status.

Inspection of table 4 reveals a few important facts. Comparing rows 1 and 2, the qualitative patterns of wage growth across job transitions are broadly consistent across my sample and that of Topel and Ward [1992]. Wage gains from employer transitions are highest in the first few years of experience, and then decline rapidly with potential experience. However, while my estimates for wage growth at the start of the life cycle are slightly (about 5%) higher than Topel and Ward [1992], my estimates for wage growth later in the life cycle are substantially lower. I estimate wage gains at job transitions around 5-10 years of experience being about half that of Topel and Ward [1992]. This is plausibly due to institutional differences between Germany and the US. As unionization rates are higher in Germany, it may be that pay is more equitable across employers, and thus the wage gains from switching may be lower. My estimates of wage gains at employer changes may also be lower because the SIAB only contains data on establishment and not firm. Hence the changes I identify may have less potential for wage growth than those identified by Topel and Ward [1992].

Another interesting pattern lies in the similarity of the estimates of wage growth at occupation and employer changes. Since this table does not separate these categories, and since these kinds of transitions often occur together, the estimates will mechanically be very similar. This demonstrates the importance of separating the two, as it is not clear where the gains in transitions are coming from without doing so.

I next examine wage changes around (unseparated) occupational transitions where, instead of taking means of 25 by experience level, I take means by different starting and destination occupations. For the purpose of presentation, I aggregate starting and destination occupations to the level of occupation segments as used in Busch [2020]. This gives me a total of 30 occupation categories to collapse on. I then sort starting and destination occupations by the average wage gain at a transition, and present them in table 5. The first half of the table presents results with means taken by starting occupation, and the second half presents results with means by destination (ending) occupation.

Perhaps the most striking feature of table 5 is that there is not a clear ordering among the 30 categories. Business people and bakers appear in the top 5 categories for both columns. Artists have the second highest gains associated with leaving the occupation, but also the sixth highest gains associated with entering the occupation. Furthermore, almost all kinds of switches appear to be associated with wage gains, with only the bottom 3-4 categories in either column being associated with any kind of significant wage loss.

The asymmetry in table 5 is consistent with a model of matching of skills to tasks. To see this, consider the specific case of artists. Artists are often highly skilled workers, but their skills are useful on a very specific subset of tasks like graphic design and painting. If not many occupations require those tasks be performed, artists will likely start out working in lower paying occupations that do not utilize their skills. They remain in those occupations until they “catch a break” and happen across a job opportunity that lets them apply their talents. Once this happens, they transition into the occupation labeled “artist” and are able to leverage their individual specific human capital, resulting in wage gains. Furthermore, once an artist *has* found a job in their field, only an extremely good offer would entice them to leave. Thus one should expect large wage gains upon leaving the artist occupation as well. This is also plausibly the case for engineers, salespeople, and technicians.

Despite this asymmetry table 5 reveals a pattern consistent with a hedonic Roy model a la Dickens and Lang [1985]. That is, occupations which one would expect to be associated with large positive non-pecuniary values such as social work, teaching and art are associated with a large pay premium for leaving them. Furthermore, occupations associated with null or negative wage gains for exiting them seem to be occupations which have an element of safety risk: e.g. mining, chemical work and construction. This pattern is somewhat supported when looking at destination occupations, however it is not as strong. Becoming an artist is still associated with a large wage gain, and becoming a construction worker is associated with only a modest wage gain. Thus while hedonics are likely part of the story behind wage gains at occupational mobility, they are unlikely to be the whole story.

Table 4: Average Wage Gains at Job Transitions for Different Experience Levels

Experience Interval	0-2.5	2.5-5	5-7.5	7.5-10
Topel Ward, Job Transitions:	0.145	0.099	0.064	0.046
	(0.015)	(0.016)	(0.015)	(0.016)
My Sample, Job Transitions:	0.153	0.071	0.031	0.018
	(0.003)	(0.002)	(0.002)	(0.002)
My Sample, Occupation Transitions:	0.152	0.071	0.034	0.031
	(0.004)	(0.002)	(0.002)	(0.002)

This table presents average log wage gains at different transitions in my sample and from Topel and Ward [1992] table 7 row 2. The sample consists of West German men born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. Standard errors in parenthesis.

Table 5: Log Wage Change Estimates for Different Starting and Ending Occupations

Rank	Starting Occupation	Mean Change	Standard Error	Rank	Destination Occupation	Mean Change	Standard Error
1	Social Workers, Teachers, Scientists	0.162	(0.013)	1	Engineers and Mathmeticians	0.156	(0.008)
2	Artists	0.114	(0.017)	2	Banking, Insurance and Tourism Specialists	0.089	(0.007)
3	Buissnesspeople	0.09	(0.004)	3	Technicians and Lab Assistants	0.087	(0.003)
4	Banking, Insurance and Tourism Specialists	0.089	(0.007)	4	Salespeople	0.081	(0.004)
5	Service Workers	0.088	(0.007)	5	Buissnesspeople	0.08	(0.003)
6	Salespeople	0.086	(0.004)	6	Artists	0.078	(0.018)
7	Agriculture Workers	0.083	(0.01)	7	Chemical Workers	0.064	(0.005)
8	Assistants	0.074	(0.005)	8	Metal Workers	0.059	(0.003)
9	Technicians and Lab Assistants	0.07	(0.005)	9	Paper Makers and Printers	0.053	(0.007)
10	Medical Workers	0.066	(0.014)	10	Assemblers	0.052	(0.004)
11	Electrical Fitters and Mechanics	0.066	(0.004)	11	Social Workers, Teachers, Scientists	0.05	(0.012)
12	Engineers and Mathmeticians	0.06	(0.009)	12	Miners	0.047	(0.008)
13	Food Workers	0.059	(0.006)	13	Ceramics Workers	0.033	(0.011)
14	Non-Electrical Fitters and Mechanics	0.043	(0.002)	14	Machinists	0.028	(0.004)
15	Security Workers and Servants	0.036	(0.009)	15	Goods Recievers, Examiners, Dispatachers	0.028	(0.004)
16	Goods Recievers, Examiners, Dispatachers	0.033	(0.004)	16	Medical Workers	0.024	(0.02)
17	Vehical Operators and Warehouse Workers	0.03	(0.003)	17	Painters	0.023	(0.007)
18	Textile Workers	0.027	(0.009)	18	Electrical Fitters and Mechanics	0.018	(0.005)
19	Paper Makers and Printers	0.019	(0.009)	19	Non-Electrical Fitters and Mechanics	0.017	(0.003)
20	Assemblers	0.018	(0.004)	20	Textile Workers	0.015	(0.011)
21	Carpenters	0.014	(0.006)	21	Wood Workers	0.011	(0.011)
22	Wood Workers	0.012	(0.009)	22	Building Modifiers	0.008	(0.007)
23	Ceramics Workers	0.011	(0.013)	23	Vehical Operators and Warehouse Workers	0.007	(0.003)
24	Chemical Workers	-0.003	(0.005)	24	Builders and Construction Workers	0.005	(0.004)
25	Machinists	-0.004	(0.005)	25	Assistants	0.003	(0.006)
26	Metal Workers	-0.004	(0.003)	26	Food Workers	-0.006	(0.008)
27	Painters	-0.006	(0.006)	27	Service Workers	-0.015	(0.007)
28	Building Modifiers	-0.015	(0.006)	28	Carpenters	-0.023	(0.008)
29	Builders and Construction Workers	-0.02	(0.004)	29	Security Workers and Servants	-0.026	(0.006)
30	Miners	-0.024	(0.006)	30	Agriculture Workers	-0.051	(0.011)

SIAB data, West German men ages 20-65 employed full-time. Sample ranges from 1975-2010. Standard errors in parenthesis. Wage gains using the methodology from Topel and Ward [1992] for occupation switchers by destination and starting occupation. The “Mean Change” column represents the mean change in log wages of switchers adjusting for a mincer regression designed to capture counterfactual wage growth.

C Decomposition by Education Groups

One may wonder about how the qualitative facts I have presented differ by education levels. In this section I separate workers by the *maximum* of the three possible education levels they attain in my data (no vocational training, vocational training and a university degree) and run the regression given by 2 separately for each level on my sample of men[27] controlling for lagged tenure and unemployment.

The results are presented in figures 11, 12 and 13. Figure 11 presents the results for those who have at most secondary schooling, figure 12 presents the results for those who have at most a vocational training certificate and figure 13 presents the results for those who have at most a university education.

The figures reveal (noisier) patterns that are qualitatively consistent with the primary specification. In all cases, excess wage growth at the year of the change ($t-1$ to t) is largest for simultaneous occupation-employer moves and declines monotonically with experience, flattening off at around 10 years of potential experience. Excess wage growth in the pre-period ($t-2$ to $t-1$) is often noisy, but broadly speaking workers who make occupation employer switches have the slowest ex-ante wage growth. Finally, there is positive excess wage growth in the years following a occupation-employer switch for all groups. [28]

Quantitatively speaking, the group with the *lowest* maximum educational attainment has the *largest* wage gains from occupation-employer changes. One explanation for why this group has such large gains from changing careers is that education provides information about worker specific skills. The market has less information about the skills of workers with low education levels, and so the gains from experimentation are greater for that group.

Wage growth at occupation-employer transitions is second highest for individuals who receive at most a university education, the greatest maximum education level in my data. As I am not controlling for the education level in these specifications, it is possible possible that the high levels of excess wage growth I observe for this group are driven by educational

[27] I am only able to perform this exercise for men due to disclosure restrictions.

[28] Individuals who receive at most a university education do have substantially noisier estimates, but visual inspection of figure 13 panel (c) reveals that individuals who make an occupation employer transition do have statistically significantly faster wage growth for most levels of potential experience.

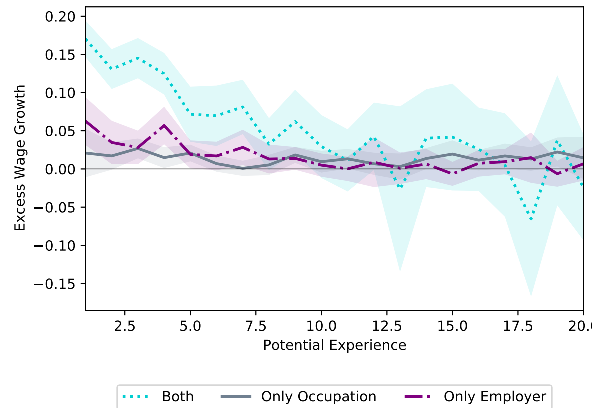
attainment. Yet it may also be that, in an imperfect labor market, these workers are not quickly matched to jobs which allow them to apply the skills they acquired in their education. Suppose someone with a degree in graphic design finds a job at a coffee shop to pay the bills after university, and after a year or two finds a job as a graphic designer. The wage gains following the occupation-employer change in this case are, in a sense, a result of improved matching of their skills to tasks. Thus, even if individuals are acquiring new skills from university, it is not clear that the high degree of excess wage growth for that group should be interpreted purely as gains from educational attainment and not as improvements in match quality.

Excess wage growth for occupation-employer switchers who attain at most a vocational degree (figure 12) is the lowest of all the educational groups. This likely means vocational degrees provide a precise signal about individual skill, and that individuals with a vocational degree start in jobs well matched to their skill-set. In this case initial match quality is high and well known and so the potential wage gains from occupation-employer transitions are low.

Figure 11: Excess Wage Growth By Experience, Men, Max Education: No Vocational Schooling

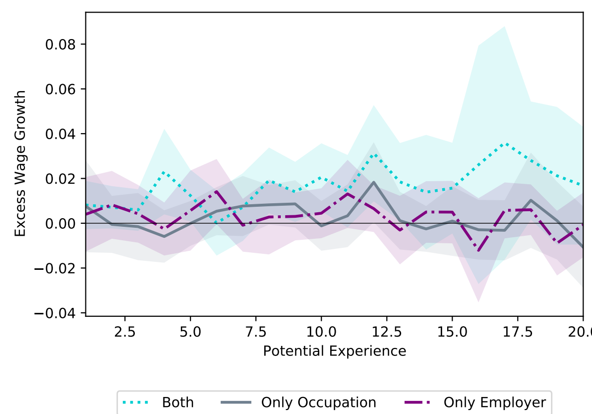
(a)

(b)



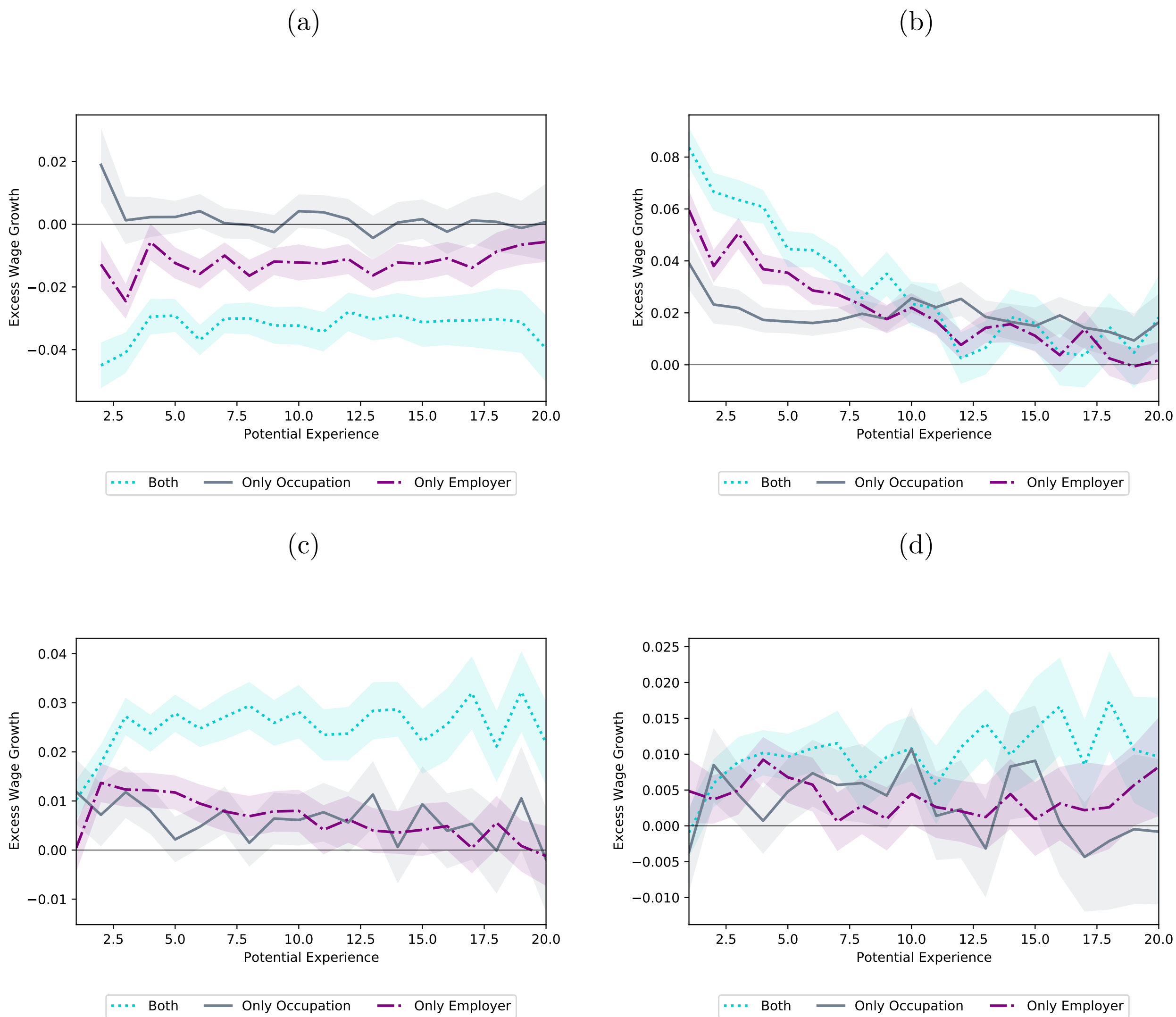
(c)

(d)



This figure gives the results from running the event study given by equation 2 for individuals who receive at most a secondary school certificate. The sample consists of West German men born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. Shaded areas represent a 95% confidence interval computed with standard errors clustered at the individual level.

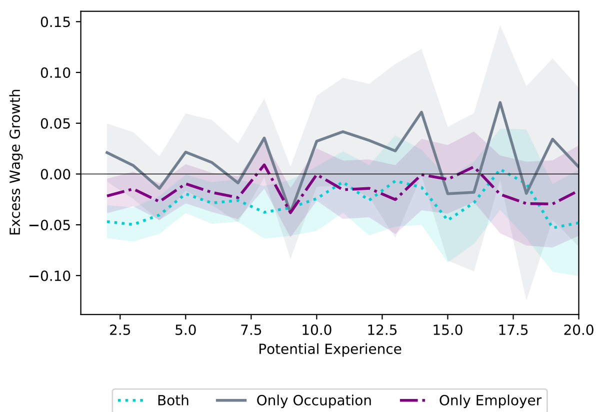
Figure 12: Excess Wage Growth By Experience, Men, Max Education: Vocational Schooling



This figure gives the results from running the event study given by equation 2 for individuals who receive at most vocational training. The sample consists of West German men born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. Shaded areas represent a 95% confidence interval computed with standard errors clustered at the individual level.

Figure 13: Excess Wage Growth By Experience, Men, Max Education: University Education

(a)



(b)

(c)

(d)

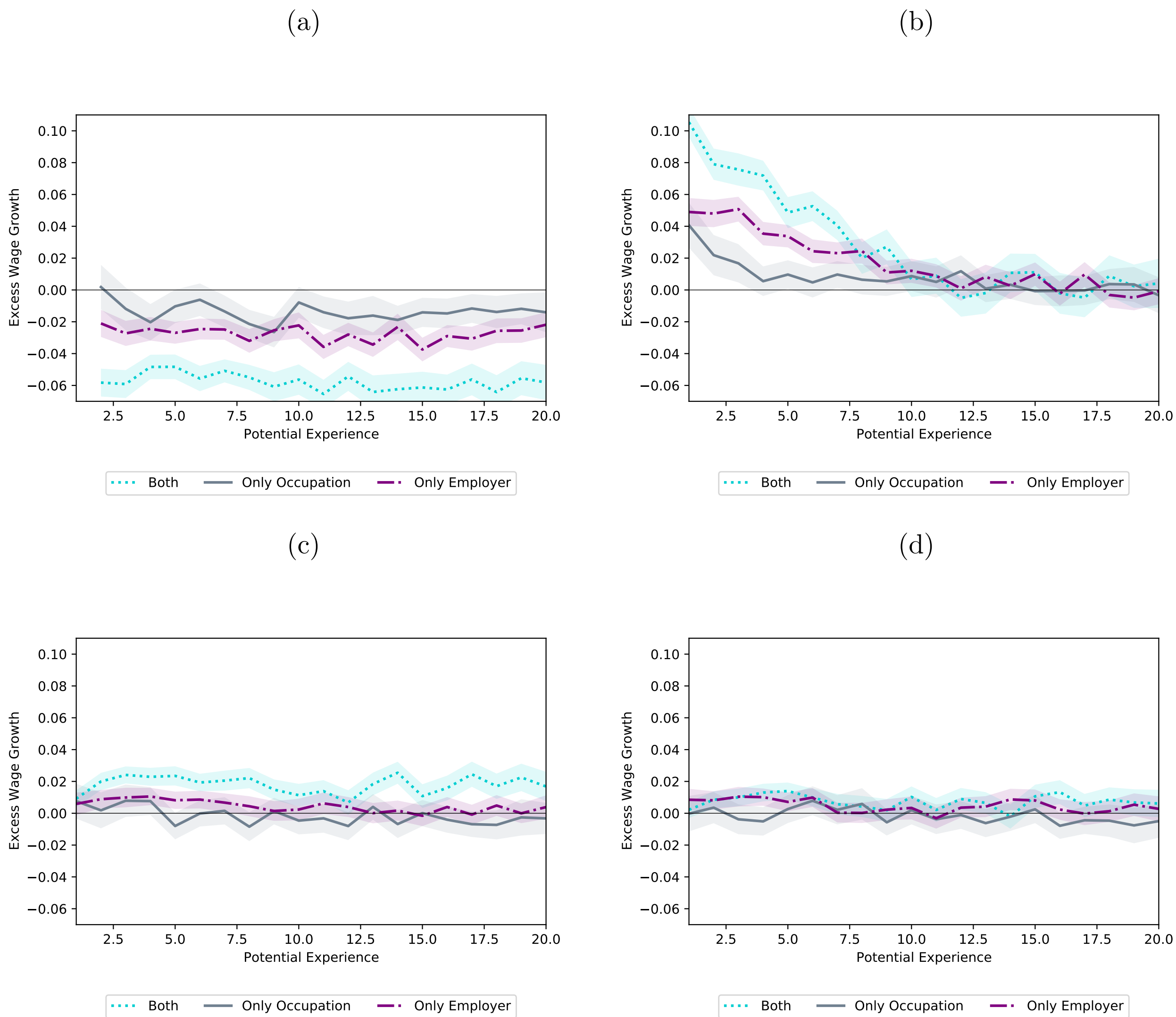
This figure gives the results from running the event study given by equation 2 for individuals who receive at most a university education. The sample consists of West German men born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. Shaded areas represent a 95% confidence interval computed with standard errors clustered at the individual level.

D Sample Period Robustness

It is possible the large wage gains I observe at occupation-employer mobility episodes are a result of my chosen sample period. Individuals who entered the labor market before 1990 saw large degrees of wage growth early in their careers. This pattern could plausibly drive the results on early career wage acceleration from simultaneous occupation-employer transitions if these early career wage gains are disproportionately among occupation and employer movers. Furthermore, the German reunification which occurred in 1991 caused substantial structural shifts and plausibly altered the returns to occupational mobility.

To address this I run my main event study after the reunification (post-1991) controlling for lagged tenure and unemployment. If sample period selection substantially alters my results, one should expect to see large changes in the wage acceleration that occurs following an occupation/employer move. Figure 14 shows the results from this exercise. The qualitative results are identical and there is very little quantitative difference. Wage growth is slightly (less than 1%) slower for movers in the period prior to a job switch when compared to the full sample. This could be a result of improving information dissemination. If workers and employers are learn about match quality faster due to improved management practices or information technology, then wages will grow relatively faster for job stayers than job switchers in the period before a switch. Never the less, the finding that job switchers receive a considerable improvement in their wages following an early career change remains robust. I thus conclude that my results are unlikely to be substantially affected by the choice of sample period.

Figure 14: Excess Wage Growth By Experience, Men Post 1991



This figure gives the results from running the event study given by equation 2 after 1991. The sample consists of West German men born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. Shaded areas represent a 95% confidence interval computed with standard errors clustered at the individual level.

E Occupation Fixed Effects: Changing Absolute Advantage

It may be that individuals are responding to changes in mean occupational wages. In this case a static model may underestimate wage gains due to changes in absolute advantage between occupations. To address this problem, I allow occupation fixed effects to time vary by including occupation specific time trends[29]. Symbolically, I run the following regression:

$$\omega_{it} = \eta_i + \gamma_k + \psi_j + \zeta_k t + X_{it}\beta + \varepsilon_{it} \tag{26}$$

In the case of a linear trend the gain in the occupation's absolute advantage can be written as:

$$\gamma_{k(i,t)} + \zeta_{k(i,t)} * t - [\gamma_{k(i,t-1)} + \zeta_{k(i,t)} * (t-1)] = \gamma_{k(i,t)} - \gamma_{k(i,t-1)} + (\zeta_{k(i,t)} - \zeta_{k(i,t-1)}) * t + \zeta_{k(i,t)} \tag{27}$$

Where I have used the fact that, in my data, an individual i's occupation k is purely a function of the year t. For occupation switchers, for whom $k(i,t) \neq k(i,t-1)$, this expression gives the gain in absolute advantage. Notice however, that absolute advantage occupations changes for stayers as well. Setting $k(i,t) = k(i,t-1)$ this becomes:

$$\gamma_{k(i,t)} + \zeta_{k(i,t)} * t - [\gamma_{k(i,t-1)} + \zeta_{k(i,t)} * (t-1)] = \zeta_{k(i,t)} = \zeta_{k(i,t-1)} \tag{28}$$

This is a problem as the comparison group in my event study is the set of non-movers. Allowing for fixed effects to trend means that, when one computes the gain in absolute advantage relative to occupation stayers, one should account for the counterfactual increase that would have occurred absent an occupation change. In order to adjust for this, I compute gains in the following expression:

$$\gamma_{k(i,t)} - \gamma_{k(i,t-1)} + (\zeta_{k(i,t)} - \zeta_{k(i,t-1)}) * t + \zeta_{k(i,t)} - \zeta_{k(i,t-1)} \tag{29}$$

The difference between equation 27 and equation 29 is that in the latter I subtract off the counterfactual gain in absolute advantage from the lagged occupation. This is not

[29] I prefer to estimate gains with occupation specific time trends instead of, say separately running my regressions for different time periods, because I do not have enough statistical power to compute the latter. The same is true for occupation year fixed effects.

the only way one could adjust for changing occupation absolute advantage of non-movers, one could equivalently remove time trend terms from destination occupations. However I choose to remove trends from starting occupations as it is more likely to work against my results. If workers leaving their occupation in response to technology shocks they should leave occupations with a low ζ_k in favor of those with a high ζ_k. Hence, under that hypothesis, the estimated gain in absolute advantage is largest given my choice of adjustment factor.

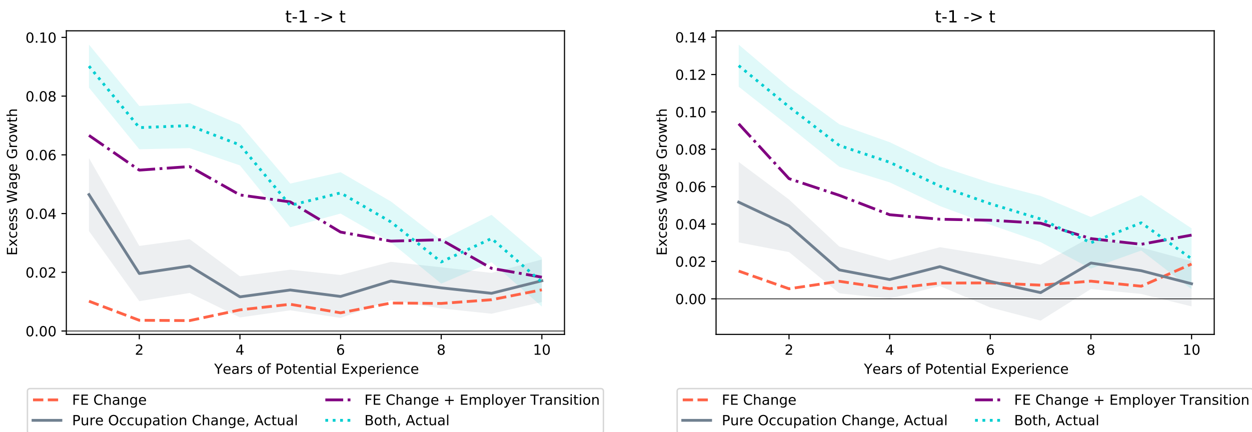
Figure 15 presents the results of this exercise for men and women. Again, the gains in absolute advantage for pure occupation movers and simultaneous occupation-employer movers are added to excess wage gains for non-movers. The qualitative result remains; gains in absolute advantage are unable to explain career wage gains for occupation moves.

One could also check for changing returns to occupation by running equation 13 separately for different time intervals, estimating changes in fixed effects within those intervals. I perform this exercise for men, breaking my sample period up into five year intervals and present the results in figure 16. The estimates are qualitatively similar, but the connected set of occupations within each 5 year sample period is small. Thus there is substantially more noise in my fixed effect estimates, and so less insight can be gained from their movements in this context.[30] Never the less, occupation fixed effect gains underestimate wage gains at most levels of experience using this methodology, and so I conclude that these results are consistent with my preferred empirical specification.

[30] While I could, in principle, perform this exercise for women the smaller sample size and lower occupation switching rate would make this problem of a disconnected set of occupations even more acute and so such an exercise would provide little insight.

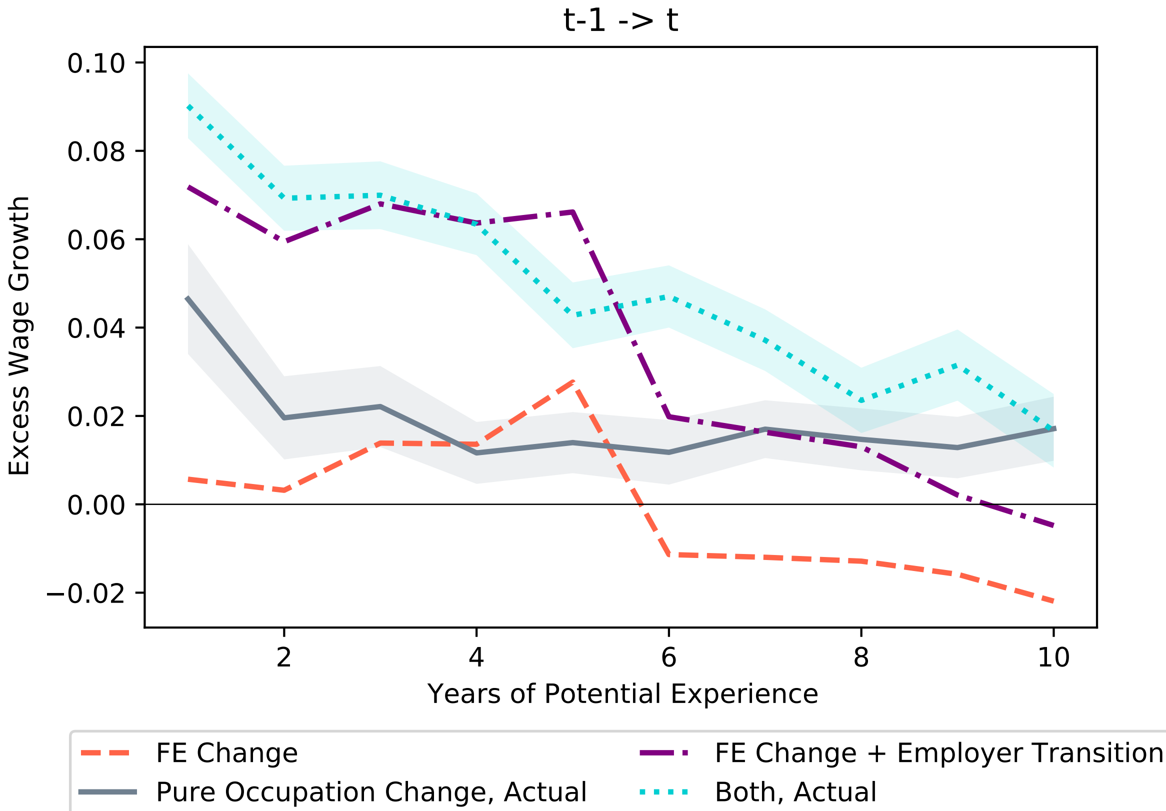
Figure 15: Average Occupation Fixed Effect Gain Above Counterfactual

(a) Men (b) Women



This figure shows the average change in the occupation fixed effect at occupational mobility episodes compared to actual wage gains at those episodes. The sample consists of West Germans born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010.

Figure 16: Average Fixed Effect Change at Occupation Changes, Men



This figure shows the average change in the occupational absolute advantage at occupational mobility episodes compared to actual wage gains at those episodes. Occupation fixed effects are estimated separately for different 5 year intervals. The shaded areas represent a 95% confidence interval.

F Transition Probabilities by Experience

Thus far I have only considered how wages change around transitions. However to get a full picture of the role different transitions play in the labor market it is important to understand their frequency as well. In pursuit of this I plot transition probabilities conditional on experience in figure 17. The figure plots

$$\begin{aligned} &P(B_{it} = 1 | x_{it} = x) \\ &P(E_{it} = 1 | x_{it} = x) \\ &P(O_{it} = 1 | x_{it} = x) \end{aligned} \tag{30}$$

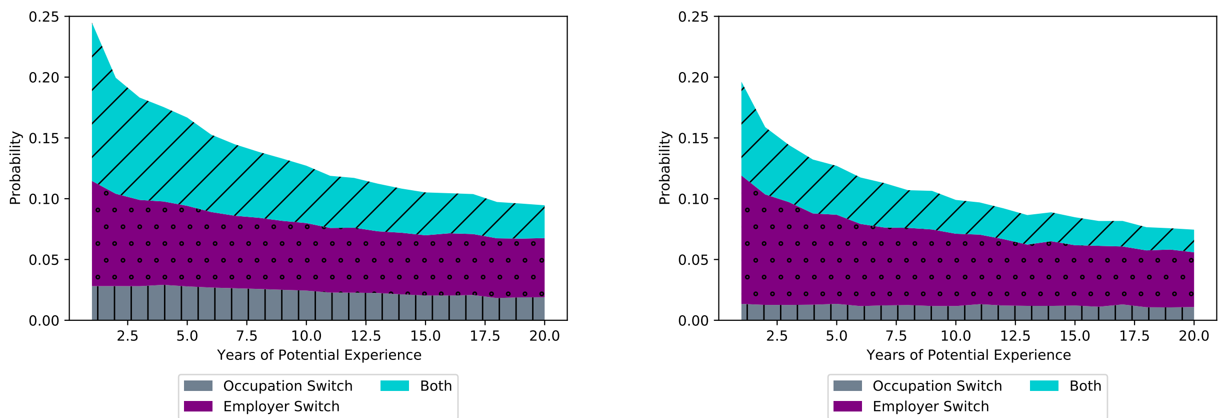
in a stacked area plot. Panel (a) plots mobility probabilities for men and panel (b) does the same for women. Note that 1 minus the y-axis gives $P(N_{it} = 1 | x_{it} = x)$. Figure 17 reveals three new and interesting facts. Firstly, most of the decline employer changes over the life cycle is driven by declines in occupation-employer transitions. This is in line with prior work by Neal [1999] who shows that, in a model where workers do not have the option to make pure occupation transitions, search for new careers (occupations) always precedes search for new employers. It is also in line with a model in which workers eventually learn their occupational comparative advantage and gradually settle in to occupations for which the are a good fit.

Secondly, the absolute probability of a pure occupation transition is relatively small and stable. This lends credence to Neal's assumption that workers do not generally have the option to change occupation within employer. Pure occupation transitions are also remarkably stable over the life cycle when compared to transitions that involve a change in employer. One possibility is that these transitions tend to reflect promotions which, since individuals are likely to accept them when they are offered, are primarily a employer decisions.

Thirdly, comparing panels (a) and (b) there are great differences in job movement probabilities across genders. Women are much more likely than men to make no transitions. This is entirely driven by women having lower occupation switching probabilities as, interestingly, they are slightly more likely to make pure employer transitions. One possible explanation for why women have larger pure employer switching probabilities is that gender pay gaps vary by employer. Another explanation is that non-pecuniary employer specific features are more variable for women than men. In either case these results suggest that extensive margin gender discrimination operates quite strongly along occupational lines. Women may be held to a higher standard of review for entry into desirable occupations than men, or men may have more opportunities to signal high levels of key skills than women.

Figure 17: Mobility Probabilities By Experience

(a) Men (b) Women



This figure plots the probability of changing occupation, employer or both by different experience levels and gender. The sample consists of West Germans born after 1955 with at least 7 years of experience in their first 10 years after labor market entry, with years ranging from 1975-2010. The vertical distance at a particular level of experience represents the probability of the change occurring. The 1 minus the top of the curve gives the probability of no transitions occurring.