Understanding the Decline in Occupational Mobility *

** WORK IN PROGRESS **

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Abstract

The process of workers switching from occupation to occupation is a vital part of career development and self-discovery. Using the CPS and SIPP I show that occupational switching rates have declined significantly over the past 25 years. This decline has been robust for each consecutive cohort and it is more pronounced for younger workers than older workers. The decline could imply that it is becoming more difficult/costly for workers to find better jobs (increases in switching costs), leaving people increasingly stuck in poorly-matched and unfulfilling careers. Paradoxically, it could also mean finding better jobs is becoming easier (due to advances in ICT), since workers in good matches are less likely to switch. This paper develops a dynamic discrete choice lifecycle model to separately identify and quantify how changes in switching costs and information over time contribute to the observed declines in occupation switching. The result is that increased switching costs drive about 72% of the decline while better information drives about 8%. The increases in switching costs have decreased average lifetime welfare for workers who enter the labor market in 2003 by roughly $35,000 per person. The total aggregate labor income loss due to high switching costs from 1993 to 2013 is $292 billion dollars[1].

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[1]All dollar amounts are in 2000 constant USD

1 Introduction

The process of workers switching from occupations to occupations is a vital part of career development and self-discovery. Switching occupations allows workers to search for the positions which best match their interests and abilities. Workers may switch occupations many times during the course of their career in order to find the position which fits the best[2]. However, this occupation switching rate has declined by 43% over the past 20 years[3].

This raises concerns for policy makers: The decline could mean that the economy is becoming less flexible due, perhaps, to regulatory environment changes. This would imply that it is growing more difficult/costly to switch to better matched occupations, so people are increasingly stuck in poorly-matched and unfulfilling careers. If the decline in switching rates is indeed associated with a less flexible economy, workers will tend to be more mismatched and will adjust more slowly to find appropriate occupations[4]. However, a possible opposite explanation is that workers increasingly do not need to switch occupations because the occupations they choose initially are better matches on average, reducing incentives for subsequent switches. So the drivers behind the decline in occupation switching rate may be benign or beneficial. Thus the appropriate policy response to observed declines in switching, and how these policies affect welfare, depends critically on the explanation for the decline. To this end, a careful analysis and exploration of what's driving the decline in switching rate is an important area of research.

In this paper I use data from the Current Population Survey (CPS) (Flood et al. (2015)) and the Survey of Income and Program Participation (SIPP) to document the decline in occupational switching rate (see Figure 1). The results are in line with the existing literature such as (Moscarini and Thomsson (2007)), and are robust to controlling for changes in worker demographics[5] and industry composition. I document a new feature of the decline: the decline in occupation switching rates over the past 20 years primarily affects young workers

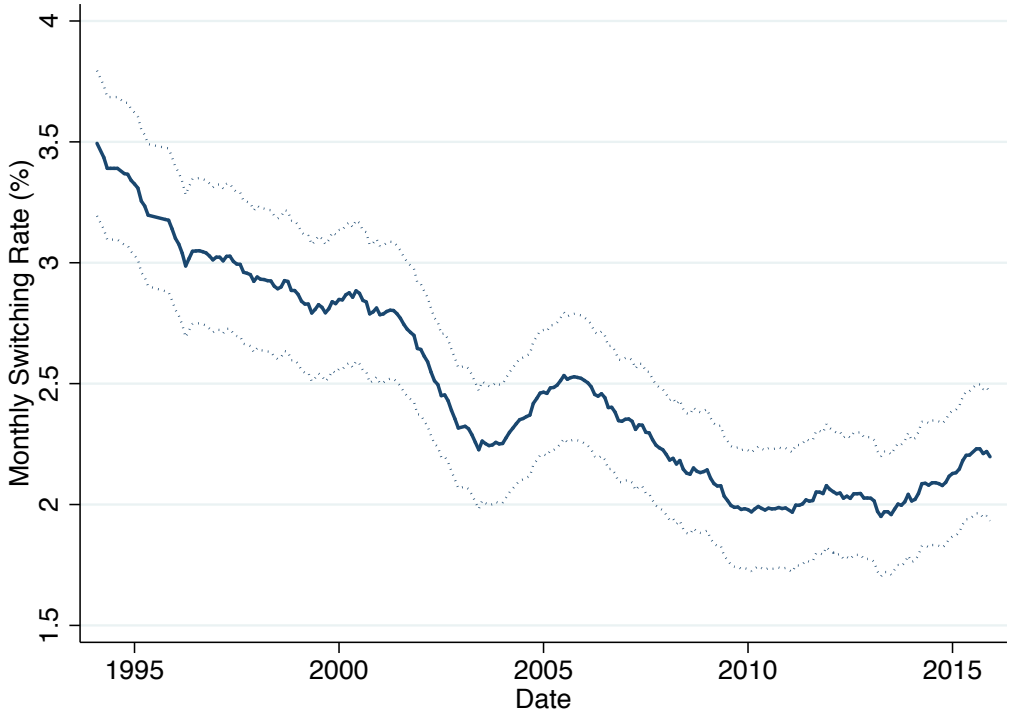
[2]Over 40% of high school graduates transition between white and blue collar occupations more than once between the ages of 18 and 28. Many workers make occupation transitions within one year of entering the labor force, with the average time until the first occupation switch being roughly 1.5 years (Gorry, Gorry and Trachter (2014))

[3]This number is calculated using SIPP data from 1993 to 2013. Details about the sample selection is introduced in the empirical section.

[4]A significant recent literature has identified job to job switching as an important indicator for labor market flexibility and fluidity (For example, Hyatt and Spletzer (2013) and Davis and Haltiwanger (2014)). Bowlus and Robin (2004) investigate workers lifetime earnings through labor market transitions; Flinn (2002) has also shown that high frequency of movements between labor market states leads to a more equitable distribution of lifetime welfare in the U.S..

[5]The controls are: gender, age, race, education

Figure 1: Monthly Occupation Switching Rate



relative to older workers (For example, see Figure 2). In fact, young worker occupation switching rates (at the 3 digit occupation level) dropped five times more than old workers in terms of population share. Furthermore, the occupation switching rates dropped when considering even very aggregated occupation codes, and these changes in switching rates differ considerably across occupation groups.

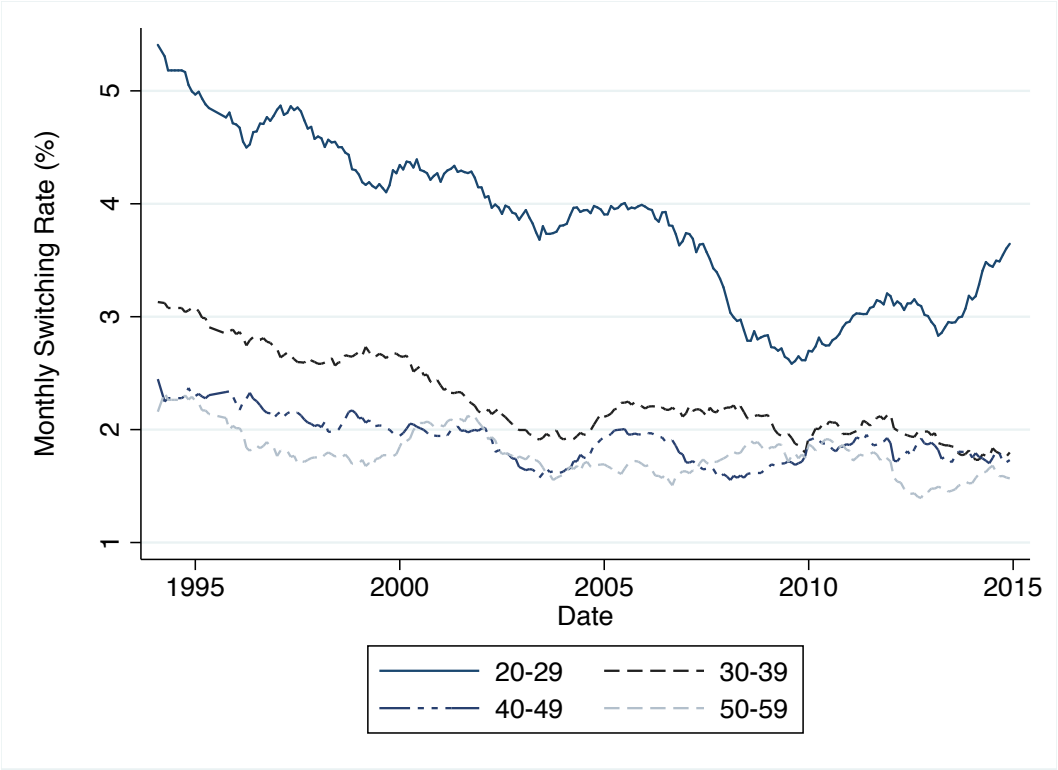
These empirical facts suggest that changes in young workers' switching patterns contributed significantly to the observed aggregate decline in switching rates. Young workers are often more mismatched than older workers because young workers have limited information about their match quality, so they will need more time to learn and discover about their true ability and interests (Gervais et al. (2016)). Furthermore, young workers are often more resource constrained than older and established workers. Thus, changes in young workers' information about their match quality as well as the switching frictions that they face may play a significant role in explaining the observed young workers', and therefore aggregate, switching rate decline. What may give workers more information about their match quality or the characteristics of a particular occupation? One possibility is the dramatic growth in information technology since the early-mid 1990s. ICT not only allows for workers to quickly

learn about the requirements and characteristics of different occupations, but may also improve education and self-knowledge, improving the precision with which students know how they might perform in different roles. There is some empirical evidence of this mechanism. Faberman and Kudlyak (2016) shows that workers are increasingly using online job search methods to look for jobs, and that the job finding rate is higher for workers who have access to the Internet at home. In the Baccalaureate and Beyond survey, new college graduate students are asked to answer the question: Do you consider the current occupation part of your long term career? 54.5% of students who graduated in 1993 and 83.99% of students who graduated in 2008 answered "strongly agree" or "somewhat agree" (Xu, 2016). Furthermore, Molloy et al. (2016) show an increase in average starting wages for young workers aged 22-34 from the early 90s to 2013. Hyatt and Spletzer (2016) shows the median years of tenure has increased from 3.5 to 4.5 between 1990 and 2012. Since better match quality is often associated with higher starting wages and longer tenure, these empirical findings motivate a more careful analysis of how information and match quality play a role in worker career choices. There is also significant evidence of increases in switching costs that workers are facing. For example, Cairo (2013) shows that the average employer training requirements have increased from 1983 to 2010. Gittleman, Klee and Kleiner (2015) and House (2015) show that occupational licensing has grown sharply over the past few decades, which along with possible increases in the costs of retraining may contribute to increases in switching costs. Using newly constructed data (in progress), Kleiner and Xu (2017) show that occupation licensing requirements have increased for all of the universally licensed occupations from the 1980s to 2016, and that this has significant negative effects on worker occupational switching rates.

To further test and examine these insights, I develop a dynamic discrete choice model featuring information frictions, learning about heterogeneous occupation-specific match quality, and occupational switching costs. Younger workers are unsure about their own occupation-specific ability and preferences, so they switch between occupations while learning about their ability and searching for their best match. If the young workers have better information about their match quality prior to entering the labor force, they will find their best matched occupations sooner and so switch less. Workers also face switching costs. If switching costs increase relative to the benefits of switching, workers will switch less. This switching costs could differ across occupations and individuals, which can lead to the heterogeneity in occupational switching rate across occupations and age groups.

This paper makes three contributions: first, using all waves of SIPP data from 1990 to

Figure 2: Monthly Occupation Switching Rate by Age Groups



2013, I construct pseudo cohort occupational switching rates, and establish a novel fact that the decline in occupational switching rate has increasingly affected each of the successive cohorts over the past 20 years. Secondly, I build a dynamic discrete choice model which I use to separately identify the effects of changes in information from changes in switching costs. Thirdly, I calibrate the model by fitting the model to all of the pseudo cohort data, then assemble the cross sectional agents using the simulated cohorts. I then compare the cross sectional agents in the simulation to those in the data (comparing apples to apples instead of assuming steady states), and use a newly constructed licensing data set (same data used in Kleiner and Xu (2017)) to run policy experiments. The result shows that these two mechanisms both contribute significantly to the total decline in occupational switching rate, and together they can account for up to 80% of the total aggregate decline. The improvements in initial information mainly affect the young, but the change in switching costs affects all workers. Therefore in aggregate, the switching costs have a much bigger effect on the decline in occupation switching rates than information. The switching costs alone contribute up to 72% of the total decline. I show that the increase in initial information increases workers income and welfare while the increase in switching costs has the opposite

effect on workers income and welfare. Improvements in information generates as much as a 0.04% increase in average worker annual income per worker per year. The switching costs decrease average worker annual income by as much as 0.53%. In terms of aggregates, this implies a total gain of roughly $22.1 billion from improved information over this period, but a total loss of nearly $292.5 billions from increased switching costs over the same period. Moreover, using compensating variation analysis, the model suggests that the total welfare change due to the two factors is much bigger than when just looking at workers lifetime income. This is because the compensating value includes monetary as well as non-pecuniary utility compensation. The average welfare cost from increasing switching friction for workers who enter the labor market in 2003 is about $35,000.

This paper proceeds as follows. In section two, I use CPS and SIPP to show the key features in the data. In section three, I present the model and discuss the main driving forces behind the decline in occupation switching rates. I then show the quantitative analysis in section four and five, and describe the estimation results and experiments. Lastly, I conclude in section six and discuss possible extensions.

2 Data and Empirical Evidence

I focus my analysis on working-age adults in civilian households during the past 20 years. In this section, I document the decline in occupation mobility using two different data sets: the Current Population Survey (CPS) (Flood et al. (2015)) and the Survey of Income and Program Participation (SIPP). The CPS is an important source of official U.S. labor market statistics. It is also the primary source of data used by many researchers to study worker flows across occupations, industries and employers. The CPS has very large nationally representative monthly cross sectional samples, as well as a very limited panel dimension. Therefore it is useful for analyzing high-frequency labor market movements and changes in aggregate variables, though not as much for looking at changes in particular individuals over time. Much of the literature on job and occupation mobility has used the CPS as a major source of evidence, including Fallick and Fleischman (2004), Nagypál (2008) and Moscarini and Vella (2008). I use it primarily for constructing and documenting the aggregate empirical facts. Due to the limited nature of its panel dimension and wage information, I do not use it for the model estimation. The SIPP is a household-based survey designed as a continuous series of national panels. Each panel features a nationally representative sample interviewed over a multi-year period lasting approximately four years. Compared with other panel data

surveys such as the PSID and NLSY, the SIPP has a relatively shorter panel, but much larger sample size ranging from approximately 14,000 to 52,000 interviewed households. This makes it suitable for aggregate analysis, and decreases worries about sampling error when measuring employment distributions across disaggregated cells, such as three-digit occupations (analysis which would be impossible with a smaller dataset such as the NLSY). Given the rich information about workers' work history, income, and demographics available in the SIPP, I use it as the primary data set for both the empirical evidence and the model estimation sections of this paper.

2.1 Declines in Occupational Mobility

I firstly explore the CPS monthly data from 1994 to 2016, using a similar cleaning process to Moscarini and Thomsson (2007)[6]. My primary sample for the CPS is working age (20-64) male workers who are employed between survey months 2 and 3.[7] Figure 1 shows that the monthly switching rate for this sample decreased consistently between 1994 and 2016, declining from about 3.5% to 2.2% . To put this 40% decline in switching rate in context, consider that in 1994, there were about 3.9 million workers switching occupations every month[8], and this number decreased to 2.8 million in 2016[9]. In the appendix/extension, I include the empirical evidence for employer switch rates. The conclusion from this graph is that the number of switchers has been reduced by 1.1 millions even though over the past 20 years, employment levels have gone up by 30 million. Moreover This decline is robust across different occupation classification methods. Using coarsely defined six occupation[10] classification, the decline in switching rate remains, and the graph can be found in the appendix.

Many studies have looked at labor market mobility and transition using the March CPS[11]. Using data on current occupation, and questions about previous occupations, one can cal-

[6]They carefully analyze the CPS occupation and employment data in order to develop their method for dealing with suspicious records and measurement error. I follow their procedure in order to maintain comparability with the rest of the literature

[7]Results including both males and females can be found in the appendix. Overall, the switching rate decline is robust with various sample selection methods. See appendix for details.

[8]Here occupation switch is defined at the 3-digit occupation code level

[9]An investigation of job or employer switches reveals the same trends

[10]The six occupations are: 1. Managerial and Professional 2. Technical, Sales and Administration Support 3. Service Occupations 4. Farming, Forestry, and Fishing 5. Precision Production, Craft and Repair 6. Operators, Fabricators and Laborers.

[11]for example, Bowlus and Robin (2004) uses the matched March CPS to analyze the lifetime inequality level through a labor transition frame work.

culate an "annual" occupational switching rate that has declined from about 10% in 1994 to 8% in 2015. From its peak in 1995 to the zenith in 2010, this rate nearly halved, though it has recovered some since the end of the Great Recession[12]. This supports the evidence for a declining switching rate, however the switching rate measured by this method may not represent the true annual mobility. Kambourov and Manovskii (2013) argue that the annual switching rate obtained using the historical questions in the March CPS is closer to the three to four-monthly switching rate, which is about 6 times smaller than the annual switching rate they obtain from the PSID. However, though the level (annual or not) may require more investigation, fact that this rate has been declining over time remains. I also look at the fraction of people who have held more than one job in the previous year[13]. The question specifically asks about multiple jobs held NOT at the same time. If multiple jobs are held at the same time, the CPS treats them as one job, so multiple job holders are essentially job switchers. Figure 3 shows that the fraction of multiple job holders has decreased significantly over the past 20 years, which further supports the observation that occupational mobility has been declining.

The SIPP panel is my primary data source. The SIPP interviews households every four months with a short recall period (monthly). Because the SIPP has a short panel structure, each individual panel is not really suitable for long time series analysis, however a comparison across panels shows that the average four month switching rate for the coarsest occupation classification (with just 6 occupation groups) has dropped from 5.65% to 3.24% between 1993 and 2013. I examine the four month switching rate rather than one month rate because the SIPP suffers from seam bias: the tendency for estimates of change estimated across a seam between two consecutive surveys to exceed changes measured within a single interview[14]. This result showing declines in the occupational switching rate is also robust for 3 digit occupation codes, 2 digits, and 1[15]. As further evidence, Hyatt and Spletzer (2013) use the Longitudinal Employer-Household Dynamics (LEHD) to confirm the decline of the job switching rate. Details about the SIPP sample selection can be found in appendix

Figure 3: Fraction of Workers with Multiple Jobs

2.2 Key Patterns of Occupational Switching

This subsection examines demographic and economic patterns in occupational mobility over the past 20 years. First of all, it is well recognized that occupational mobility declines with age. This is shown clearly in Figure 2 using the CPS data. Younger workers tend to switch job/occupation more often than elders. Therefore, one may expect that an aging population will likely drive occupational mobility down. It is certainly true that an aging population contributes to the overall decline of occupational mobility, but the magnitude is limited. Similarly, gender, occupational composition and educational composition may also play a role in the decline of switching rates. Figures 5, 6 and 7 show that occupational mobility decline appears in all gender, education and occupation groups. [16]. However, changes in the distribution of these groups over time can only account for a very small fraction of the change in switching rates. Figure 8 plots an accounting decomposition of the switching rates by these

[12]https://www.stlouisfed.org/on-the-economy/2015/august/occupational-switching-occurring-less-often
[13]Many paper have used this as an indicator of occupation or job switching including Hyatt (2015)
[14]https://www.census.gov/srd/papers/pdf/rsm2008-03.pdf
[15]The occupation categories follows the occupational classification in Dorn (2009)
[16]The occupation groups used are defined in Figure 7.

Figure 4: Occupation Switching Rate by Education Level

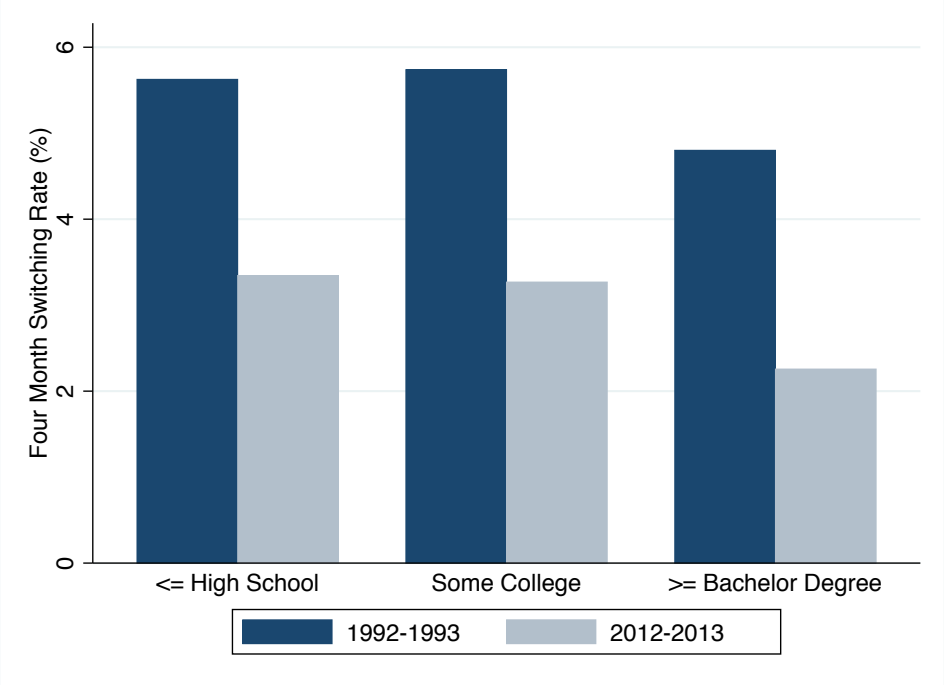


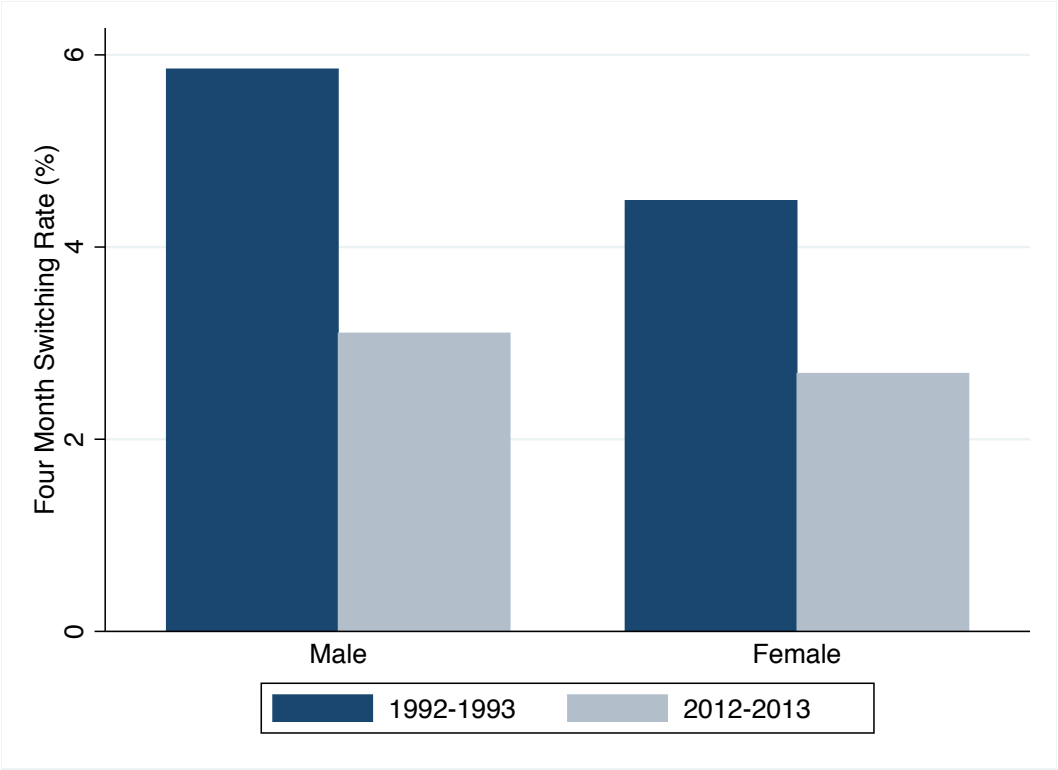
Figure 5

different factors. When fixing the age, education, and race distributions at their early 90s level and allowing the group-specific switching rates to change over time as observed in the data, most of the decline remains.[17] Figure 9 shows the decomposition when holding industry distribution and occupation distribution constant[18]. The result shows clearly that neither of these factors contribute much to the total occupational switching rate decline. Clearly then the change in switching behavior is a change in group-specific switching rates rather than a change in group composition (such as aging baby boomers). This result is in line with the literature on declining job mobility: for example Hyatt and Spletzer use LEHD data to show that firm size and age can't explain much of the decline. In fact, similar to my own findings,

[17]The age groups 20-24, 25-29, 30-34, ... 60-64. The education groups are: less or equal to high school, some college or associate degrees, greater or equal to bachelor degree. The race groups are white and none-white.

[18]The industry groups are: 1. Agriculture, Forestry and Fisheries 2. Mining 3. Construction 4. Manufacturing 5. Transportation, Communications, and Other Public Utilities 6. Wholesale Trade 7, Retail Trade 8 Finance, Insurance and Real Estate 9. Business and Repair Services 10. Personal Services 11. Entertainment and Recreation Services 12. Professional and Related Services 13. Public Administration. The occupation groups are: 1. Managerial and Professional 2. Technical sales and Administration Support 3. Service Occupations 4. Farming Forestry and Fishing 5. Precision Production, Craft and Repair 6 Operators Fabricators and Laborers

Figure 6: Occupation Switching Rate by Gender

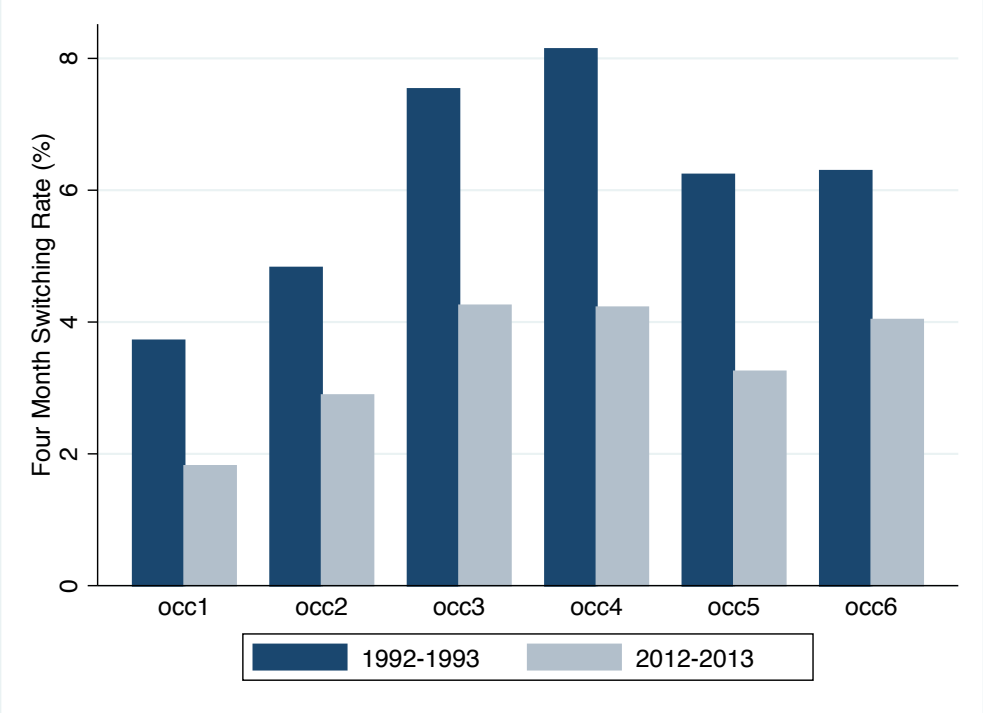


they find that all the distributional effects they consider combined can explain at most 30% of the total decline of the job mobility, with the majority still remaining unexplained. My focus in this paper is then to consider two primary factors which may account for the unexplained majority of this decline.

There are two key features that I aim to capture in the data. The first one is that the occupational switching rate declined for all age groups but more prominently for young and new workers. This fact is illustrated in figures (10). The top line in figure (10) shows the occupational switching rate by age in 1992 to 1993 at the coarsely defined occupation level with six major occupation groups as defined before, while the bottom line shows the occupational switching rate by age in 2012 to 2013. I used these years in the empirical and model analysis because they bound the maximum period I can look at using the SIPP while still keeping the survey questions and design comparable over time[19]. Over the 20 years in question, the occupational switching rate dropped from about 14% to 7.5% for the 20

[19]While there may be concern that my earlier period is close to the recession in 1991, recall that I am restricting my analysis to job-to-job flows of occupation switches. To the extent that job-to-job occupation switches are probably lower during recessions (as opposed to work-unemployment-work churn which may grow), this timing would only make my result stronger.

Figure 7: Occupation Switching Rate by Major Occupation group



The occupation groups are:
occ1: Managerial and Professional occ2: Technical Sales and Admin Support occ3: Service Occupations
occ4: Farming Forestry an Fishing occ5: Precision Production Craft and Repair occ6: Operators Fabricators and Laborers

years old workers, which is a 46% decline in switching. Older workers also saw a decrease in switching, but to a much lesser degree - the average switching rate for 60 year olds only dropped by 1.3 percentage points, a change from 2.8% to 1.5% over 20 years. The result holds for all occupation classifications and groupings. In the appendix Figure (**??**) shows the result holds for more finely defined groups using the 1990 census occupation classification, the relative magnitudes remain very similar - younger workers are much less occupationally mobile than they used to be. Any attempt to explain the decline in mobility must account for this fact. My model thus will be able to reproduce this age-specific dynamics in switching rates. The second feature is that the occupational switching rates declined for all occupation groups, but there are clear cross-occupation differences. This will allow me to examine directly the switching frictions which may be common across occupations, but also possibly occupation-specific changes in relative switching costs or information frictions.

One concern about comparing two segment of the cross section data is that this way may not truly capture the full trend of the data. Without showing the full picture in the past 20 years, it is possible that the two segment periods of choice is only a special case and is not representative of what is happening from the early 90s until now. The time series of the

Figure 8: Occupation Switching Rate Decomposition

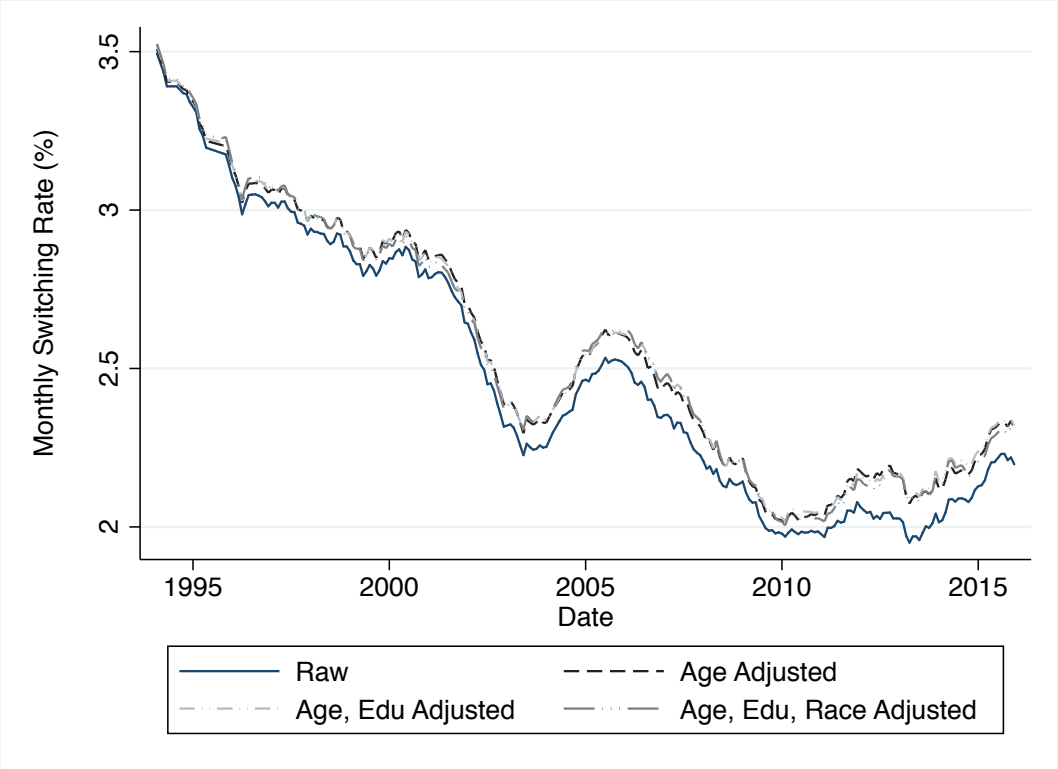
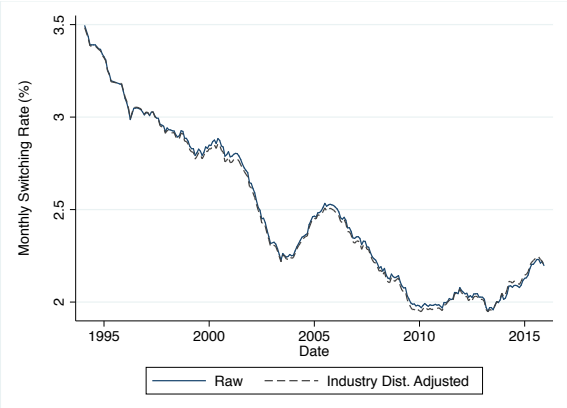
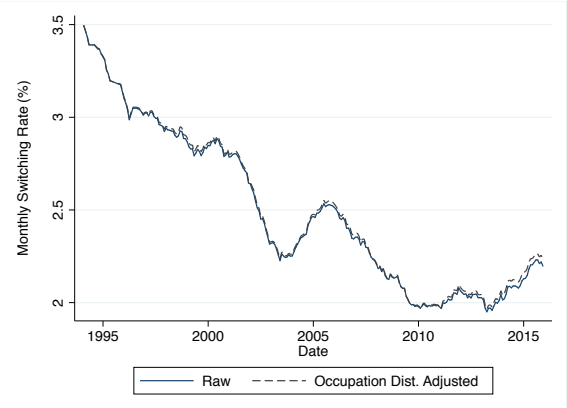


Figure 9: Occupation Switching Rate Decomposition

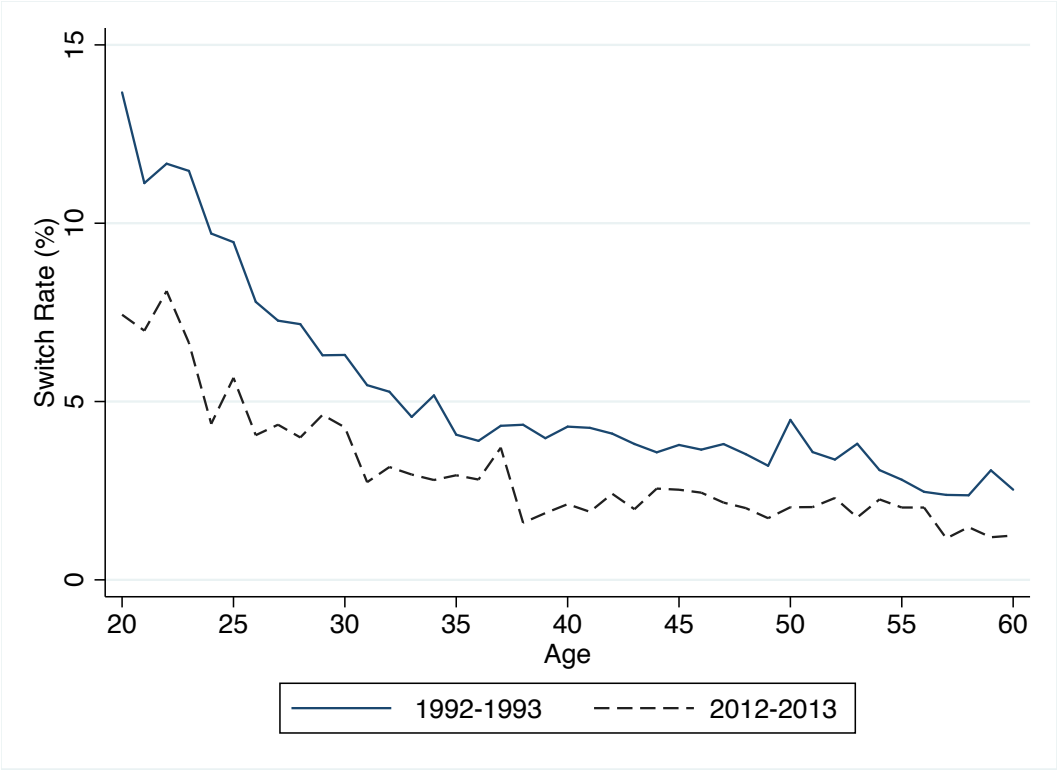


Adjusted by Industry Distribution



Adjusted by Occupation Distribution

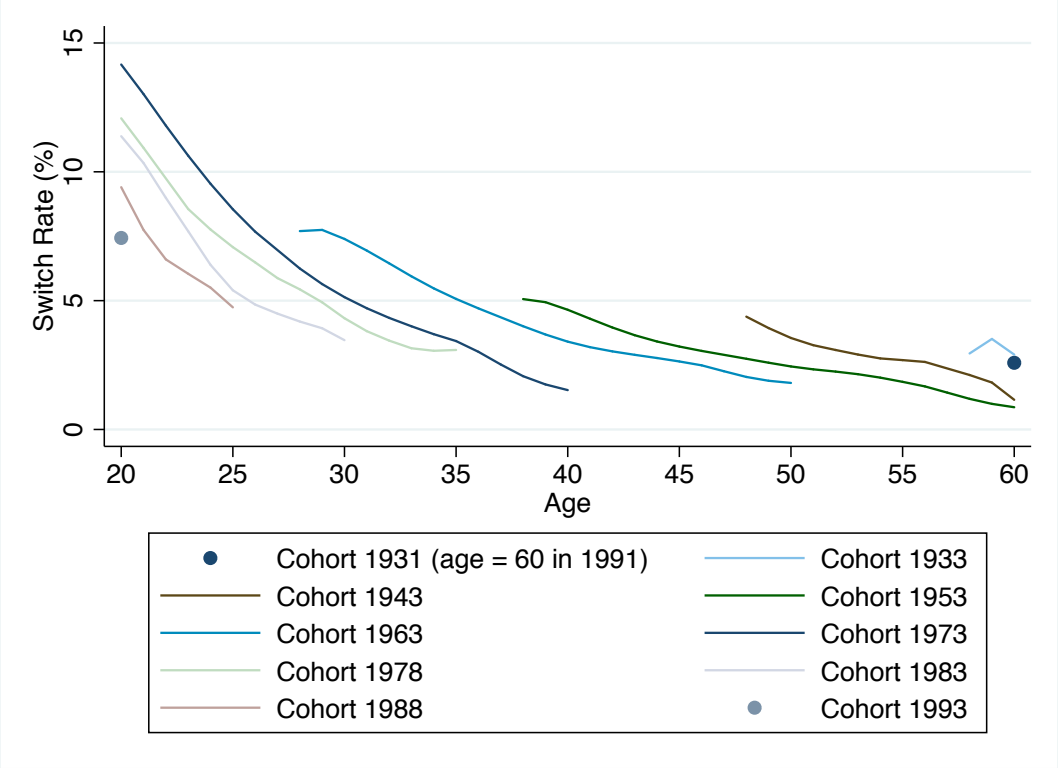
Figure 10: Occupation Switching Rate by Age



switching rate in CPS is an indirect way to address this issue. More directly, I use all the data available from SIPP from 1991 to 2013, and constructed the pseudo cohort occupational switching rate. Specifically, I take workers from the same cohort, and construct their average life cycle occupational switching rates. For example, I calculate agents mean occupational switching rates for 20 years olds in 1993 then 21 years olds in 1994 and so on. I calculate the switching rate all the way to 40 years olds in 2013, and that is one pseudo cohort partial life cycle occupational switching rate I constructed. The reason I construct pseudo cohort is that even though SIPP has a short panel structure, it only follows agents for up to 3 years. It is not enough data for works life cycle analysis. Furthermore, I am only interested in the aggregate trend and statistics in the labor market. Therefore even if the pseudo cohorts I constructed are not really following the same agents lifecycle, it still captures the aggregate trend of the same cohorts. Figure 11 shows the result of the pseudo cohort (partial) lifecycle occupational switching rate[20]. The graph, from the left to right, plot all the cohorts (by birth year) partial life cycle occupational switching rate age profile in between 1991 and 2013. Starting from the very left is the most recent cohort who enters the labor market

[20]This plot is smoothed by locally weighted regression method.

Figure 11: Occupation Switching Rate by Age (Pseudo Cohort)



in 2013. Given the available SIPP data, this cohort is only observed once, therefore a dot. Moving to the right, the next cohort I show enters the labor market in 2008 (at age 20). Given the data frame, I observe them from 20 to 25 years old. As we move to the older cohorts, I observe some for more years: for example, I observe cohort 1973 (20 years old in 1993) for 20 years (all the way until they are 40 years old in 2013). The very earliest cohort I see in this time frame, is the workers who retire in 1992, so I only observe them once in 1991. This pseudo cohorts graph shows a novel fact: the decline in occupational switching rate has increasingly affected each of the successive cohorts over the past 20 years. Furthermore, this graph also confirms the previous observation: the gap of the switching rate between cohorts is much bigger for young workers than older workers.

3 Model

The empirical findings show that the occupational switching rate has declined for all age groups, especially for young workers. I also observe common as well as heterogeneous changes

in occupational switching. Guided by these empirical findings, I construct a dynamic discrete model of occupation choice with two key mechanisms that can drive changes in the occupational switching rate: changes in information technology/pre-career education and changes in occupational switching costs. As mentioned in the introduction, these two factors may both contribute to the decline of the overall switching rate. However they have very different implications. Increases in information technology and improved education will increase young workers' information about their own abilities and the characteristics of different occupations or jobs before they even enter the labor market. This tends to lead to better initial matches between workers and occupations, and higher incomes/welfare, meaning workers have less incentive to subsequently switch occupations. At the same time, if switching rates are declining because retraining is more costly, or occupational licensing becomes stricter, then workers will be worse off.

I model occupational choice as an optimal dynamic search process. The basic assumption is that individuals use wages as a signal to learn about their occupation-specific ability or match quality. Self learning and discovery throughout their career drives workers to switch occupations, especially for the young who are relatively uncertain of their abilities or proclivities. There are many papers which have investigated the effect of learning on occupational switching. For example, Guvenen et al. (2015) proposed that learning is an important aspect of a worker's experience in the labor market, and switching occupation is part of this process. Several recent papers including Kennan and Walker (2011) and Kaplan and Schulhofer-Wohl (2012) have also looked at the effect of knowledge and learning on migration rates, finding that information plays an important role. Switching costs in my model can vary by age, time and occupation-specific characteristics.

In this model, the key feature is that workers are endowed with an individual-occupation specific level of ability about which they are uncertain. In each period they choose the occupation which they believe can give them the highest discounted lifetime utility. The initial information available to workers prior to entering the labor force (referred to throughout as the education signal) gives workers their first clue about their own ability. Throughout their career, they learn about their occupation-specific ability by working in that occupation, using wages as a signal. When a worker decides to switch, they face occupational switching costs. The cost is different across time, age, and occupational characteristics, potentially including an occupation-pair specific fixed cost (it may be more difficult to switch from garbage collector to professor than to janitor, even conditional on individual ability)[21]. The model is

[21]Several recent papers investigate these directional pair-specific switching costs. See Traiberman (2016)

intended to describe the partial equilibrium response of labor supply to wages (which workers take as exogenous), switching costs and the information structure across occupations. Firm decisions certainly play a critical role in determining supply of vacancies across occupations, labor market characteristics and wages. While I do not model this directly, it can be partially captured by the occupational switching cost structure in the model, since workers take these cost into account when they move from occupation to occupation, and I allow these costs to evolve over time. A simple assumption here is that if a worker pays the applicable switching cost, he/she can become qualified to perform any occupation. A complete equilibrium analysis would of course be much more difficult, but my model can be viewed as a building-block toward an equilibrium analysis of occupational choice and mobility.

3.1 Model setup

Environment

The economy consists of heterogeneous agents who live for T discrete periods, and differ in their match quality to different occupations. Individuals choose between J occupations: $j \in \{1, 2, ..., J\}$. When first entering the labor market, individuals draw a permanent match quality for each occupation: $\nu^j \sim \mathbb{N}(0, \sigma_\nu)$, which can be thought of as a productivity term since it will enter into the wage. Individuals do not observe their true match quality, instead they make their occupational choices based on their beliefs about their match quality for each occupation. While working in occupation j, individuals receive wages w^j, which both enters into utility and acts as a signal of their match quality for occupation j. Individuals update their beliefs about their true match quality in a Bayesian fashion. Those who decide to leave their occupation (j) and switch to a different occupation (k) in the next period pay a switching cost conditional on their own state as well as occupation k's specific characteristics.

Preferences

Individuals are risk-neutral and choose a sequence of occupations to maximize the expected discounted lifetime utility:

$$\mathbb{E} \sum_{t=1}^{T} \beta^{t-1} \Big(\underbrace{w_t - \kappa_t}_{u_t} + \zeta_t \Big)$$

for a recent application and overview of the literature.

where w_t is the wage the individual receives in period t, κ_t is the potential switching cost that individual pays in period t, and ζ_t represents a random preference component which will depend on occupation. Both the wage and switching cost depends on the individual state vector (the state vector includes the individual's current occupation, beliefs and precision about the matching quality of each occupation, the individual's age and wage information, as discussed below). The preference shock ζ is a J-vector random variable that is assumed to be independently and identically distributed (i.i.d.) across occupations (1 to J) and across time periods, independent of the state vector.

The Recursive Problem

Given vector of state variables x, which includes age, work history and beliefs over match quality, the period utility for an individual who chooses occupation j is:

$$u(x, j) + \zeta^j$$

where $u(x, j) = w(x, j) - \kappa(x, j)$. The individual's decision problem in recursive form is

$$W(x, \zeta) = \max_j \Big(u(x, j) + \zeta^j + \beta \sum_{x'} p(x'|x, j) \mathbb{E}_\zeta W(x', \zeta) \Big) \tag{1}$$

Here $p(x'|x, j)$ represents the transition probability from state x to state x' when occupation j is chosen, and $\mathbb{E}_\zeta$ denotes the expectation with respect to the distribution of the J-vector ζ with components ζ^j. Let $\rho(x, j)$ denote the probability of choosing occupation j given state vector x. We can re-write the value function as

$$W(x, \zeta) = \max_j (V(x, j) + \zeta^j)$$

where

$$\begin{aligned} V(x, j) =& u(x, j) + \beta \sum_{x'} p(x'|x, j) \mathbb{E}_\zeta W(x', \zeta) \\ =& u(x, j) + \beta \sum_{x'} p(x'|x, j) \rho(x', j') V(x', j') \end{aligned}$$

I assume ζ^j is drawn from a type I extreme value distribution. In this case, following Rust(1987), the probability of choosing occupation j in state x is

$$\rho(x,j) = \frac{\exp(V(x,j))}{\sum_{k=1}^{J} \exp(V(x,k))}$$

This is convenient, since it allows me to integrate out over the preference shock and greatly simplifies the solution to the worker's problem[22].

Information and Wages

Recall that each individual has a J-vector ν of match quality terms: $\nu = (\nu^1, \nu^2, ..., \nu^J)$, one for each occupation, which is fixed over time. Individuals do not know these match qualities and must learn about them over time, making decisions which depend on these beliefs, and their relative level of uncertainty. Prior to entering the labor force, each individual's prior belief about their vector of match qualities is equal to the true population distribution of quality: $\nu^j \sim \mathbb{N}(0, \sigma_\nu)$. Before individuals start their first job, they receive a signal about their true ability for each occupation. I refer to this as the educational signal, though it could represent any occupation-specific knowledge gained prior to the labor market, perhaps from the media, internet, school or other sources. The accuracy of this signal may be affected by changes in factors such as the availability of information technology (the Internet), or quality/level of schooling. The educational signal for each occupation e^j is normally distributed and centered around the true match quality: $e^j \sim \mathbb{N}(\nu^j, \frac{1}{\tau_e})$. τ_e represents the precision of the educational signal: the higher the precision, the lower the variance of the noise, so the more information it contains regarding the true match quality. After receiving the educational signal and before choosing their first occupation, the individual's belief and precision about his match quality for occupation j can be written as:

$$m_0^j = \frac{\tau_e^2 e^j}{1/\sigma_\nu^2 + \tau_e^2} \tag{2}$$

$$(\tau_0^j)^2 = 1/\sigma_\nu^2 + \tau_e^2 \tag{3}$$

Where m denotes the mean of the belief and τ denotes the precision. The subscript 0 means that the individual has worked at occupation j zero times, so this is the individual's prior

[22] I compute the individual's problem via value function iteration on $V(x,j)$. At age $T+1$, $V = 0$, so I compute the value function using backward induction. Taking advantage of this property of the type I extreme value distribution and iterating over value V rather than W, the problem is much simplified since the probability of choosing certain occupations can be described analytically once the state is specified.

for each occupation.

Individuals choose their occupations based on their beliefs. When an occupation j is chosen, the individual receives wage $w(x, j)$:

$$\log w(x, j) = \psi(a, j) + \underbrace{\nu^j + \varepsilon^j}_{\theta^j} \tag{4}$$

where ψ is an age and occupation specific life cycle component of wage, ν^j is the individual and occupation specific match quality, and ε is wage innovation, which is independently and identically distributed across occupations and individual states, drawn from a random normal distribution: $\varepsilon^j \sim \mathbb{N}(0, \sigma_\varepsilon)$. Individuals don't know their true match quality ν^j, but do know the structure of wages, and so use wages as a signal to infer the matching quality ν_j and update their current beliefs. Specifically, they know the life cycle component ψ, and therefore they can observe $\theta^j = \nu^j + \varepsilon^j$. Using θ^j as a signal, individuals update their believes about occupation j using Bayesian learning. In the baseline setting of the model, the match quality ν^js are independent from each other. So learning about occupation j only happens when individuals are working at j. However, in the extension of the model, I allow ν^js to be correlated with each other. In that setting, learning about one occupation can happen whether or not individuals are working at this occupation. The amount/speed of learning will be depending on the correlation between the νs.

Because both the match quality and the innovation are normally distributed, the signal θ is also normally distributed. Furthermore, since both the prior and the signal are normally distributed, the posterior distribution after any number of signals will also be normally distributed. The posterior distribution of belief of occupation j after receiving n signals (of j) can be completely described by its mean m_n^j and variance $\frac{1}{\tau_n^j}$. Using Bayes' theorem and the definitions of normal densities, one can write how the belief and precision evolves:

$$m_n^j = \begin{cases} \frac{(\tau_{n-1}^j)^2 m_{n-1}^j + \frac{1}{\sigma_\varepsilon^2}\theta_n^j}{(\tau_0^j)^2 + n\frac{1}{\sigma_\varepsilon^2}} & \text{if occupation j is chosen this period} \\ m_{n-1}^j & \text{if occupation j is NOT chosen this period} \end{cases}$$

$$(\tau_n^j)^2 = \begin{cases} (\tau_{n-1}^j)^2 + \frac{1}{\sigma_\varepsilon^2} \\ = (\tau_0^j)^2 + n\frac{1}{\sigma_\varepsilon^2} & \text{if occupation j is chosen this period} \\ \\ (\tau_{n-1}^j)^2 & \text{if occupation j is NOT chosen this period} \end{cases}$$

The conditional distribution of the time t signal for occupation j, θ_t^j, given the information available at the end of period t-1 (beginning of period t), is normally distributed with a mean and variance given by

$$\mathbb{E}\left[\theta_t^j \mid j, m_t^j, n_t^j\right] = m_t^j \tag{5}$$

$$Var\left[\theta_t^j \mid j, m_t^j, n_t^j\right] = \sigma_\varepsilon^2 + \frac{1}{(\tau_n^j)^2} \tag{6}$$

Notice that the precision term τ, which is the inverse of the variance of the belief, can be exactly derived once n (the number of periods one works at occupation) is known, so I take n as my state variable instead of the variance of the signal. This is easier for computation purposes.

To sum up, the individual's state x_t at the begining of period t (end of period t-1) is

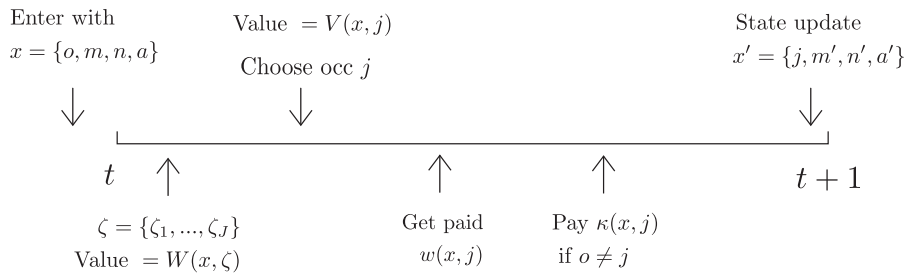
$$x_t = \{o_t, m_t^1, ..., m_t^J, n_t^1, ...n_t^J, a\}$$

and individuals choose occupation j_t for period t at the end of period $t-1$. It is worth stressing that o_t is the occupation that the individual worked at in period $t-1$. The time line of the worker's problem is shown in figure (12). Specifically: 1. The individual enters period t with the state x_t. 2. The individual observes their preference shock vector $\zeta = \{\zeta^1, \zeta^2, ...\zeta^J\}$. 3. Given the realized preference shocks and current state, he chooses an occupation that he wishes to work at in period t. 4. The individual receives a wage and uses it as a signal to update his belief about j. 5. The individual pays the switching cost if he decided to switch occupations.

Switching Costs

Let $\kappa(x, j)$ denote the switching cost. The switching cost has three components. The first component is an age varying component, denoted $\kappa(a)$. Individuals in different ages may

Figure 12: Time Line



face different switching cost. For example, older workers may have more social resources or be more experienced in searching jobs so they are facing lower costs; or maybe older workers have more family restrictions or are learning relatively slower so they are facing higher switching costs. Allowing the switching cost to vary by age makes the framework much more flexible than assuming the same switching cost for all. The second component in the switching cost is a occupational skill distance component. let $\Delta(o, j)$ denote the distance from occupation o to occupation j, defined in task space. It is natural to measure the distance between occupations using the task and skill requirements (for example Poletaev and Robinson (2008), Robinson (2017) and Stinebrickner, Stinebrickner and Sullivan (2017)). Specifically, I map the occupational skill requirement data (from O'NET) to three dimensional task space (cognitive skills, manual skills and interpersonal skills) using the method of Principal Component Analysis (PCA). I then measure the distance between the occupations in this task space to decide to what degree occupational skill requirements differ from each other. The intuition behind this approach is that occupations which require very different mixes or levels of skill will be more difficult/costly to switch between compared to occupations which use very similar skills. For example: typically it is much easier to switch from mathematician to economist than from waiter to economist, simply because the skills re-

quired for the former are more similar than for the latter. This sort of specification has been recently used in many papers including Lindenlaub (2014), Lise and Postel-Vinay (2015), Traiberman (2016) and Cortes and Gallipoli (2014). The third component is an destination occupation specific component. This captures that some occupations have higher entrance cost than others. For example, some occupations require much more strict and expensive licensing than other occupations. Everyone who is entering these occupations are required to pay the cost regardless of age and previous occupation. Furthermore, Note that one only pays the occupational switching cost when occupation switches actually happen, which is represented by the indicator function $\mathbf{1}_{o\neq j}$. Put together, the occupational switching cost is specified as:

$$\kappa(x,j) = (\kappa(a) + \alpha\Delta(o,j) + \gamma\mathbf{1}_j)\mathbf{1}_{o\neq j}$$

Finally, the average occupational switching cost varies by time. This captures the generic (average) switching cost changes across time that affects all occupations and age groups.

3.2 Model Mechanisms

What may lead an individual to switch occupations? Firstly, a low realization of the wage signal θ may cause a worker to switch occupations. The low realization causes an individual to lower his match quality belief for his current occupation, and re-rank his occupations in terms of expected future income. This means his beliefs over other occupations are revised relatively upward (the individual's belief about other occupations don't change, but relative to the current occupation, the belief about them increases). If this change in belief is large enough to overcome the associated switching costs, the individual will switch occupations. Secondly, a low realization of the exogenous preference shock ζ in the current occupation relative to the other occupations can lead an individual to switch, if the individual does not already value one significantly greater than the other. Thirdly, the individual may switch to explore his options. In the model, individuals make the occupational choice before the realization of the wage, so decisions are made by comparing expected wages. When one is uncertain about an occupation's match quality, due to the exponential functional form his expected wage for occupations he's uncertain about can be high even when his (mean) belief about his ability in the occupation is comparatively low. Thus workers may perceive high value in visiting occupations about which they are highly uncertain.

So what may have changed over time so that workers increasingly decide to switch less often than before? The dramatic increase in information technology between the early 90s

and today may have increased the precision of worker's educational signal τ_e. If so, individuals will have a better and more accurate idea about what occupations suit their ability and interests. This reduces the likelihood of seeing low wage signals (since match quality enters directly into the wage function), and therefore the likelihood of switching via the first mechanism above. Furthermore, increasing information also reduces the probability of switching for exploration, as it decreases (average) uncertainty for all occupations. Increases in switching costs can also contribute to the reduction in occupational switching. When a low wage realization or a low preference shock occurs, a worker who would like to switch might increasingly find it too costly to do so, decreasing switching rates and possibly overall matching rates. The next section will focus on these two mechanisms (changes in information technology/education and switching costs) and quantify their effect on the aggregate as well as different age group's occupational switching rates.

4 Quantitative Analysis

This section shows the strategy used to quantify the effect of the proposed mechanisms on the declining occupational mobility rate.

A key problem in examining changes in switching rates over time is in modeling and estimating how conditions change as new cohorts of workers enter the labor force. A particular switching rate or information structure in 1995 will affect younger workers differently than older workers, and younger workers in year 1995 will face different switching rates than those in year 2010. Because both the aggregate and life cycle switching rates are changing over time, possibly in response to economic conditions which also change over time, any model which investigates this issue will benefit from using individual-level data across multiple cohorts.

This paper uses the SIPP survey as the primary data source to estimate the model and quantify the parameters. The SIPP has several advantages over other data sets for the purpose of the analysis in this paper: The SIPP covers the entire time period of interest (early 90s to early 2010s); It has a large nationally representative sample size; The short panel structure and rich variables allows one to track agent's occupational movements and wage changes, which is the key to identification in this paper; and it has data for many cohorts, which is crucial in capturing the changes of the information as well as the changes in switching costs. Comparatively, other available public data sets would not be sufficient

for the analysis in this paper.[23]

However, the SIPP does have one key limitation–the panel structure in the SIPP is very short, so one can not keep track of agents for more than three years. A typical strategy to analyze questions related to age or cohort is using cross sectional data (with or without short panel structure) is to assume steady states. The idea is to assume that everyone prior to a particular period faced a certain set of parameters/conditions, while everyone after faced a different set of conditions. This assumption is very restrictive, and given the time frame of the interest to this paper, this assumption can not be applied. The reason is the following: this paper is interested in the changes in occupational mobility over the past 20 years. Many agents who show up in the cross section of switching rates today also show up in the switching rate cross section from 20 years ago. For example, people who are 20 years old in 1993 are 40 years old in 2013. It is not reasonable to assume two different steady states across these 20 years, since one would have to assume that the same agent faced two different sets of parameters in the two steady states analysis. The 40 year olds in the 2013 cross section faced the same initial conditions as the 20 year olds in the 1993 cross section.

To overcome this issue, I construct pseudo cohorts statistics as shown in the empirical session (figure 11). I then assume that the time varying parameters follow a growth path (details are shown in the next subsection). Given a set of estimated parameter growth paths, agents life cycle problems are calculated for all the cohorts in the years between 1991 and 2013[24]. I then calibrate the model to the pseudo cohort statistics. The following subsection shows a summary of all the parameters and the assumptions made in the calibration.

4.1 Parameters and Assumptions

The agent's problem over time can be characterized by the following sets of parameters:

1. τ_e – the precision of the educational signal.
2. $\kappa(x, j)$ – the occupational switching cost.
3. σ_ε – the standard deviation of the innovation in wages.

[23]Both the PSID and NLSY have a much better panel structure than the SIPP, but the small sample size and the limitated of number of cohorts/waves makes them not as useful as the SIPP. Monthly CPS data has a higher interview frequency, however the wage information is limited.

[24]To be specific, there are 58 cohorts in total assuming agents enter the labor market at age 20 and retire at 55. Starting from people who are 55 years old in 1991 (the earliest cohort I observe in the data) to people who are 20 years old in 2013 (the latest cohort I observe in the data), in total 58 cohorts.

4. $\psi(a, j)$ – life cycle component of wages.

5. σ_ν – the standard deviation of the initial match quality.

6. β – discount rate.

Besides the agent's discount rate β, which I choose following the literature[25], all of the other sets of parameters are estimated within the model. The model is estimated using all the cross section data with a short panel structure from 1991 to 2013, with the purpose to capture the trend in changes. Therefore the first four sets of parameters are all time variant. The fifth set – the standard deviation of the initial match quality, is assumed to be invariant for simplicity since there isn't clear evidence or theory suggesting that people's initial match quality or ability is becoming more or less dispersed. I assume that each of the other time varying parameters follows a piecewise linear growth path. For simplicity, I assume the growth rate for each set of parameters can (but doesn't have to) differ before 1995 and after 1995. The reason that the year 1995 is chosen is because that the interest of this paper is to see the labor market changes in the past 20 years (from 1993 to 2013). It is then appropriate to allow changes to happen in the beginning of this 20 years time period. In the appendix, I show that the results for letting the potential change in growth rate happen in 1994 and 1996 are basically the same.

In theory the switching cost κ and the wage life cycle component ψ both vary with occupation. This increases the number of the parameters that is to be estimated. For simplicity, in the baseline model, both sets of parameters are restricted to vary with age and time only. I explore the possibility of occupation varying parameters in the extension of the model. After this simplification, there are in total 18 parameters to be estimated:

$$
\begin{aligned}
&\tau_e = \tau_0 + \tau_1 year_{<95} + \tau_2 year_{>95} \\
&\kappa = \kappa_0 + \kappa_{01} year_{<95} + \kappa_{02} year_{>95} + \kappa_1 age + \kappa_2 age^2 \\
&\psi = \psi_0 + \psi_1 age + \psi_2 age^2 + \psi_3 year + \psi_4 year^2 + \psi_5 age * year \\
&\sigma_\varepsilon = \sigma_0 + \sigma_1 year_{<95} + \sigma_2 year_{>95} \\
&\sigma_\nu
\end{aligned}
$$

The structure of the average life cycle wage component follows Kambourov and Manovskii (2005). The simplification of the problem by reducing the estimated parameters as discussed

[25] $\beta = 0.986$, which is equivalent to an annual discount rate of 0.96.

above doesn't change the two key drivers that I want to examine in the model. A simplified approach will also still allow me to capture one of the key features in the data: that occupational mobility dropped largely for the young workers but much less so for the old. In the setting without occupational changing parameters, the heterogeneous occupational differences will not be analyzed, instead, the model captures the average change in the economy. For example, if half of the occupations experience an increase in the switching costs, then I'll see an increase in κ_0 in the calibration (as an average increase in the costs). In the extension of the baseline model, I relax the assumption so both κ and ψ vary by age and occupation.

I estimate the 18 parameters using Simulated Method of Moments (SMM). The computational burden is heavy, given that each cohort is already facing a large state space[26] and there are 58 cohort problems which need to be solved for each guess of the parameters. These computational burdens are overcome using MPI and the assistance of several hundred cpu cores. Despite the heavy computational burden, there are obvious advantages to calibrating the model to all of the pseudo cohorts as opposed to applying the traditional steady state assumption. I am able to calibrate the model without assuming steady states, which is very restrictive and not reasonable to the analysis in this paper. Additionally I can fully utilize all the data that is available in the public data set, and capture the general trend of changes in the past 20 years with this large amount of data; Furthermore, I can construct cross section economy using simulated cohorts. The cross section economy in the data is consist with agents coming from different cohorts, so I can compare the cross section agents in the data directly to the cross section agents in the simulated data (apples to apples), and run policy experiments. When comparing the two time period (1993 vs 2013), one natural concern that may be raised is about the timing in the first period. The NBER defined recession ends in April 1991, so it that may affect the switching rate cyclically (causing the observed switching rate to be higher or lower than its natural rate). However, the data I use is averaged over 1992 to 1993 which is long after the end of the recession. Further, if the recession has any effect on the switching rate, it likely drives it down rather than up. So the observed decline in switching rates across the time periods might be under-estimated, but probably not over-estimated.

In the following subsection I will discuss the identification and then show the estimation results for this baseline model and the counter-factual experiments in the next section.

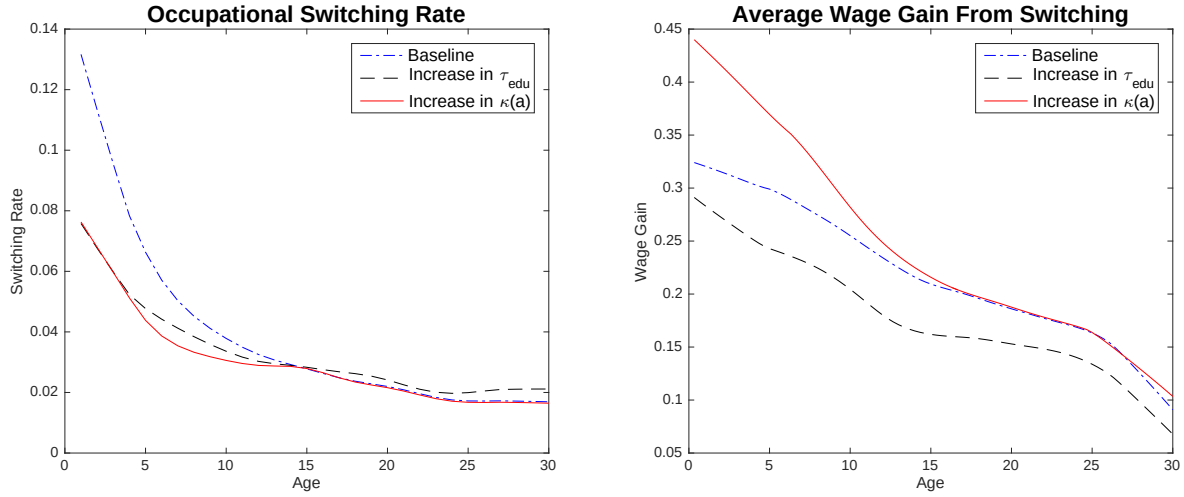
[26]The state space under 3 occupations, 5 grid points of beliefs, and 35 years of working life is: $3 \times 5^3 \times 35^3 = 16,078,125$

4.2 Identification

The five sets of parameters that need to be estimated are: $\{\tau_e,\ \kappa,\ \psi,\ \sigma_\varepsilon,\ \sigma_\nu\}$. Of the five sets, τ_e and κ are the focus of the paper's interest: How much can the occupational switching rate decline be attributed to the improvement in information v.s. the increase in switching costs? Therefore the key to identification is to separately identify these two factors. If the switching cost κ is not age dependent, then the two factors can be easily separated: the information improvement mainly affects the young workers, while older workers are barely affected. If the switching cost doesn't vary by age, then the slope of the switching rate age profile will be sufficient to separate the two factors apart. However, when the switching cost varies by age, the occupational switching rate age profile itself will not be enough for the identification – as shown in the left panel in Figure 13. The left panel of Figure 13 shows the model generated occupational switching rate age profile. The increase in precision case is shown in the dashed black line while the increase in age varying switching cost case is shown in the solid red line. Both the increase in the information precision and switching cost have similar effect on the occupational switching rate — they can generate similar tilting pattern from the baseline switching rate age profile. This makes the identification more challenging. However, the right panel of Figure 13 shows the solution to this problem. When we look at the wage change associated with the occupation switching, the increase in information precision and switching cost drives the wage change to the opposite direction comparing to the baseline. This is intuitive: an increase in switching cost leads to an increase in wage gain conditional on switching. This is because only switchers who expect a higher wage gain would decide to switch. The higher wage gain can be interpreted as a compensation of the high switching costs. On the other hand, an increase in information precision leads to an decrease in observed wage gain conditional on switching. This is because workers switch occupations as they learn about their true match quality in their career. When information is precise, people who were wrong about their match quality but later on discovers and decide to switch are "less wrong" in comparing to the limited information case. As a result when they make the correction in their current occupation, they don't gain as much.

The information structure and Bayesian learning in the model makes a full analytical proof of identification very difficult. However, I can provide an analytical proof in a similar but much simplied setting in order to build intuition about identification in the full model. Assume the following simple case: Agents work for only two periods and choose from only two occupations a and b. Agents draw their match quality from a distribution $\nu^j \sim \mathbb{N}(0, \sigma_\nu),\ \ j \in \{a, b\}$, and receive educational signal $e^j = \nu^j + \eta^j,\ \ \eta^j \sim \mathbb{N}(0, \frac{1}{\tau_e}),\ \ j \in \{a, b\}$. Agents choose

Figure 13: Identification



their first period occupation j after receiving the educational signal, and then receive a wage from the occupation they chose: $w^j = \nu^j$. There is no preference shock, and agents learn fully about the match qualities of both occupations in the second period. This is a direct simplification of the full model, where agents learn over time. However, it's not too different given the 2-period nature of the simplified model, since workers in the full model do eventually know their true match qualities. So one could think of the 2 periods as representing the first and second half of a worker's career, where in the second half they have realized their match qualities. The probability of switching is the following:

$$\begin{aligned} \Pr(a \to b) = &\ \Pr(e^a > e^b \ \& \ \nu^a < \nu^b - \kappa) \\ = &\ \Pr(\kappa < \nu^b - \nu^a < \eta^a - \eta^b) \end{aligned}$$

Note that $\Pr(a \to b) = \Pr(b \to a)$ due to the symmetry of the problem. The probability of switching from a to b is then the joint probability that workers choose occupation a in period one (when their signal of a is better) and then switch to occupation b in period two (after their realization of true match quality). Since ν^a, ν^b, η^a, η^b are individually identically normally distributed, we have:

$$\nu^b - \nu^a \sim \mathbb{N}(0, \sqrt{2}\sigma_\nu), \quad \eta^a - \eta^b \sim \mathbb{N}(0, \frac{\sqrt{2}}{\tau_e})$$

From the expression of the probability above, it is clear to see that this probability decreases when κ increases. Furthermore, when τ_e increases, the standard deviation of the η difference

decreases, which also reduces the probability of switching given $\kappa > 0$. Therefore, as the example shows above, both increases in switching costs and improvements in information decrease the switching probability. This corresponds to the result from the example above: the improvement in information and increases in switching costs affect the occupational switching rate in the same direction.

To demonstrate identification, one will need to examine the average wage gains associated with switching. What I am interested in is the following:

$$\begin{aligned}
&\mathbb{E}\Big[\ \nu^b - \nu^a \ \Big|\ \mathbb{E}(w_1^b < w_1^a),\ \mathbb{E}(w_2^b > w_2^a)\Big] \\
&= \mathbb{E}\Big[\ \nu^b - \nu^a \ \Big|\ e^b < e^a,\ \nu^b - \kappa \geq \nu^a\Big] \\
&= \mathbb{E}\Big[\ \nu^b - \nu^a \ \Big|\kappa < \nu^b - \nu^a < \eta^a - \eta^b\Big]
\end{aligned}$$

When κ increases, this conditional expectation increases (since the distribution of wage increases which satisfy the inequality is truncated on the left). When the standard deviation of the η difference decreases due to improved information, the conditional expectation decreases. This means that the mean wage gain of switchers conditional on switching increases with the switching costs, but decreases with the information precision. Therefore, using both the level of occupation switching rates and the gains from occupation switching, one can separately identify information precision from switching costs, even when switching costs are flexible and vary by age. When moving from the simplified setting to the full model, the problem becomes much more complicated and identification can only be shown numerically. This is true even for a small modification to the simple setting: suppose there is still full learning, but only for occupations which are actually chosen by the worker. i.e. if workers choose occupation a, their knowledge about occupation b does not improve. Once this assumption is imposed, the problem becomes difficult to solve analytically. The identification in this case is shown in the appendix via a numerical example.

Identification of the other parameters is straightforward. ψ, σ_ε and σ_ν all directly enter the wage. By targeting the age profiles of the average wage and wage variance, these parameters can be pinned down. In the next section, I show the estimation results and model fit, then show the results from various experiments.

5 Estimation Results and Experiments

This section presents some model results from the basic calibration as described above. I also discuss the counter-factual exercises I run using the calibrated model.

5.1 Calibration and Model Fit

Recall the key parameters of interest are the information precision τ_e and the switching costs κ. This paper is interested in their level as well as trend over time. The piecewise linear trend allows but does not require this trend to be different before and after 1995. The model setting also stays flexible, which allows the trend of parameters to be increasing, decreasing, and allows the possibility of negative switching costs (switching compensation). The calibrated parameter growth paths for τ_e and κ is shown in Figure 14 and Figure 15. The calibrated values of switching cost are quite reasonable. Switching costs increase from about \$1500 to \$1800 over the past 20 years on average (an increase from about 60% of the average monthly wage to 65% of the average monthly wage). This is comparable in magnitude to the occupational licensing cost change. For example, average initial licensing costs have increased by \$117 from 1995 to 2013[27]. The \$300 increase in average switching costs that is backed out from the model includes not only this initial licensing cost, but also changes in educational requirements, examination fees, retraining costs, etc. The effects of licensing changes are discussed in further detail in section 5.5.

The other calibrated parameters are summarized in Table 1. Using the calibrated parameters, the simulated model matches the data well. Figure 16 shows the model generated cohort occupational switching rates compared to the pseudo cohort switching rates in the data. Similar with the graph in the empirical section, from the left to the right the graph presents occupational switching rates for cohort 2013 (20 years old in 2013), cohort 2008, 2003, 1998, 1993, 1983, 1973, 1963 and 1956 (the dot on the right, 55 years old in 1991). The solid line is the same as the graph in the empirical section while the red dashed line shows the model's fit. The model fits the slope of the switching rate as well as the value reasonably well for all the successive cohorts.

Taking the simulated agents from 58 consecutive cohorts, I then construct successive annual cross sections of the simulated economy, and compare the with the cross sectional data. Figure 17 shows the comparison: Overall the model is able to replicate the key features

[27]This estimation of licensing cost is very preliminary, the details are introduced in section 5.5.

Figure 14: Information Precision Growth Path

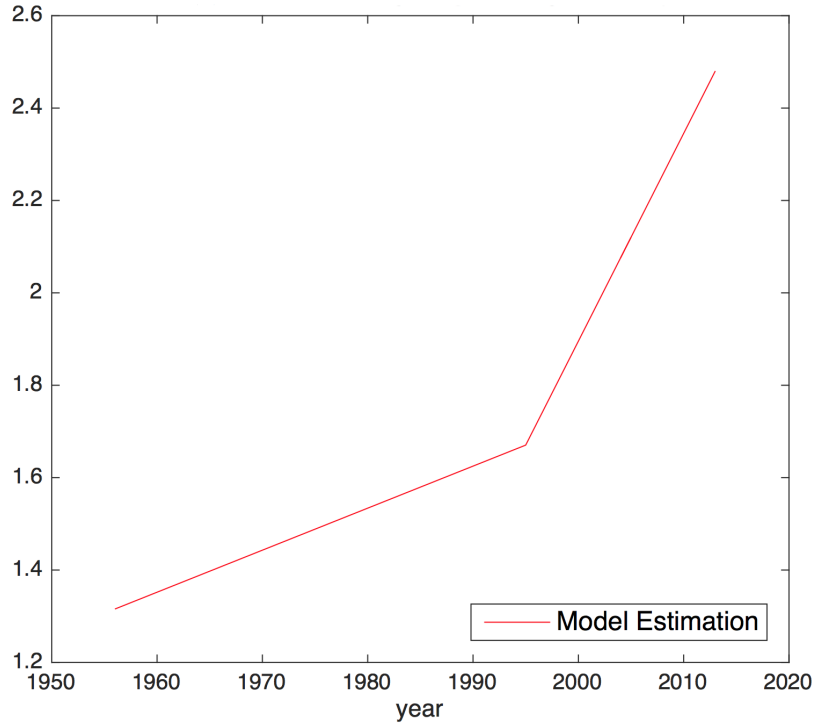


Figure 15: Switching Costs Growth Path

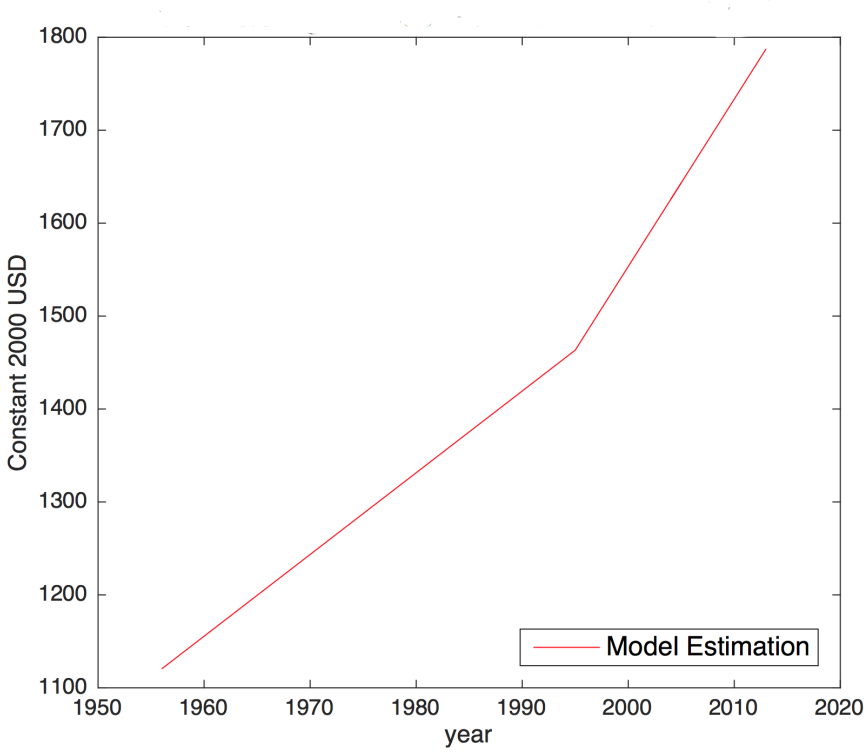


Table 1: Calibrated Parameters

κ_1	κ_2	σ_ν	σ_0	σ_1	σ_2
0.007657	0.000003	3.286007	1.572388	0.022078	0.019409
ψ_0	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5
6.209692	0.023704	-.000141	0.006962	-.000062	-.000022

Figure 16: Occupation Switching Rate by Pseudo Cohorts Age Profile

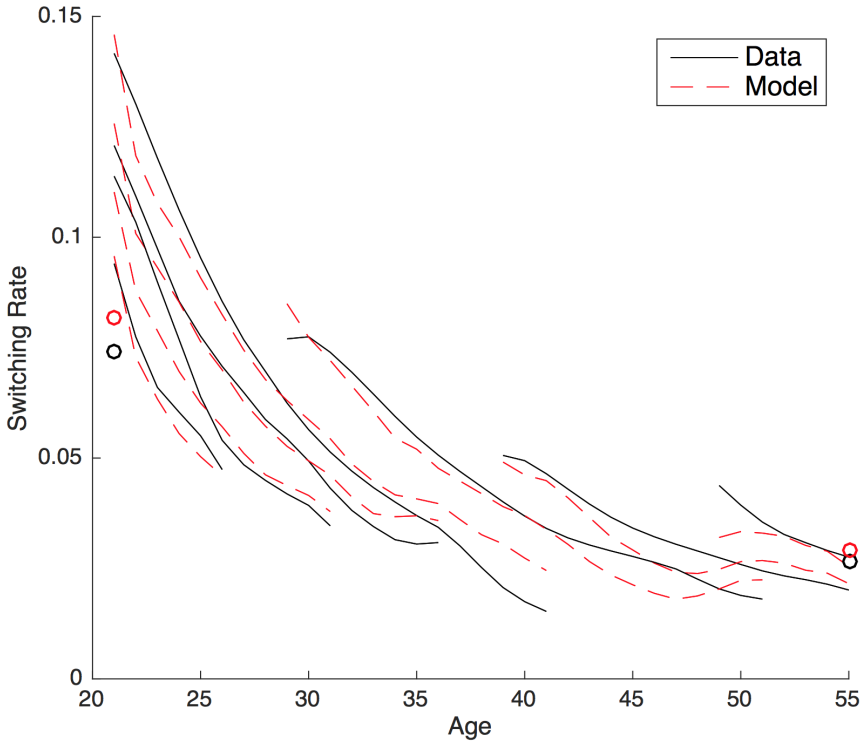
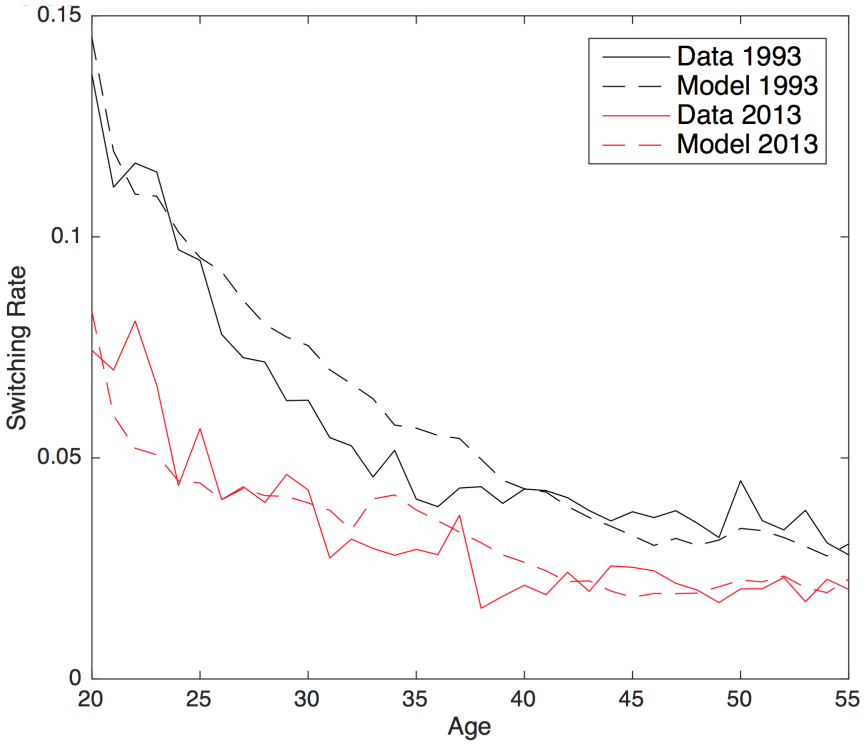


Figure 17: Occupation Switching Rates Cross Section Comparison

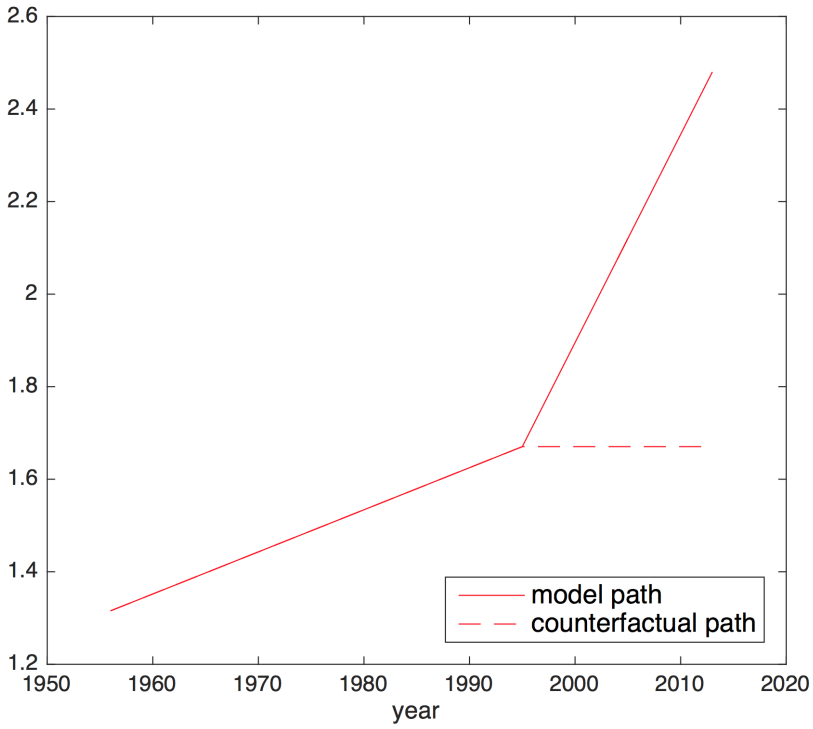


of the cross section data - that early workers in 1993 have higher switching rates than later workers in 2013 in every age. This also gives a clearer picture of the relatively large decline in the switching rate for young workers compared to older workers.

5.2 Counter-factual Experiments and Switching Rate Changes

The counter-factual exercises use the model to measure the contribution of initial information and switching costs to changes in occupation switching rates and workers welfare. The exercises can all be seen as structural decompositions. For each factor, I do the following: I hold that factor at its 1995 level while allowing all other factors to shift to their 2013 level. I then hold both the information and switching cost at the 1995 level and allow others to progress. The counterfactual experiments with respect to the information precision and switching costs are shown in Figure 18 and Figure 19 respectively. This counterfactual experiments shows an upper bound of the effects of the two factors: suppose starting 1995, neither (either) information nor (or) switching cost has changed at all, what would the switching rates and worker welfare be in 2013? In the appendix, I perform a similar experiment where

Figure 18: Counter-factual Growth Path: Information Precision



I while hold the parameter growth rates at their pre-1995 levels. In this subsection, I show the result for the switching rate effects. In the following subsections, I show the result for workers welfare changes.

Holding the information precision at 1995 level, the information effect on switching rate can be shown in Figure 20. The solid lines are the same as the model values in Figure 17. The red dashed line shows the occupational switching rate age profile in the counterfactual. The area between the blue dashed line and the red solid line (shaded blue) shows the effect of the change in information over time. Information changes predominantly affect young worker switching behavior, and it has no effect on cohorts who enter the labor market prior to 1995. Compared to the information effect, the effects of increased switching costs is much more prominent. The switching cost effect on occupational switching rates by age is shown in Figure (21), where as in the figure for changes in information, the red dashed lines are the counter-factual switching rate for each age if kappa were held at the 1995 level and all else progressed to the 2013 level as in the calibrated economy. The switching cost effect is represented by the red shaded area. Unlike the information experiment, the change in switching costs affects all workers in the economy, and the effect is large. Furthermore, the change in information in 1995 not only affects workers in 2013 but also all workers in

Figure 19: Counter-factual Growth Path:Switching Costs

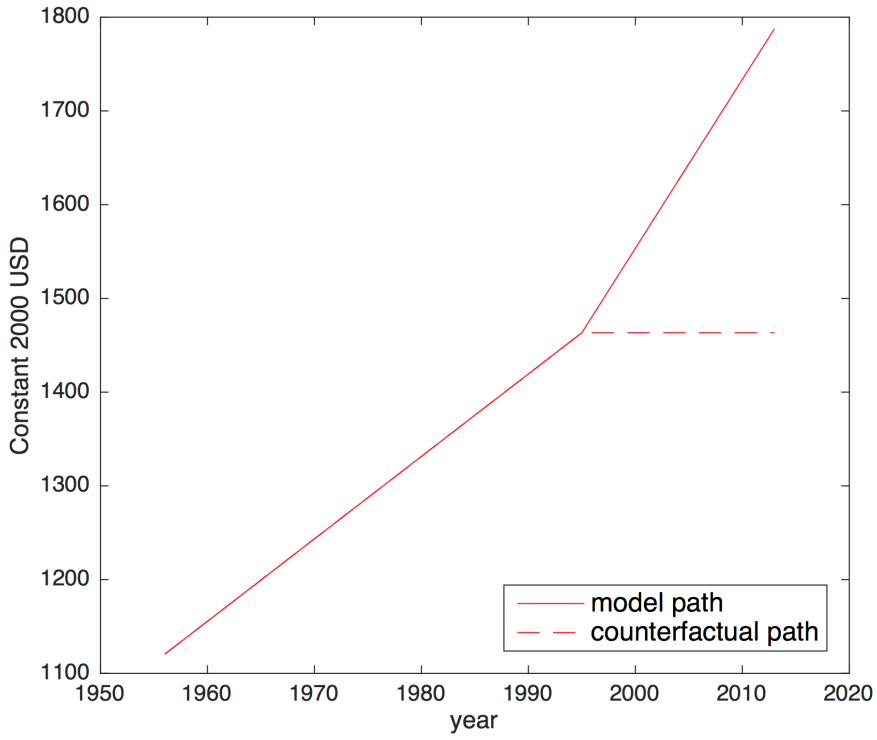


Figure 20: Occupation Switching Rates by Age (Information Effect)

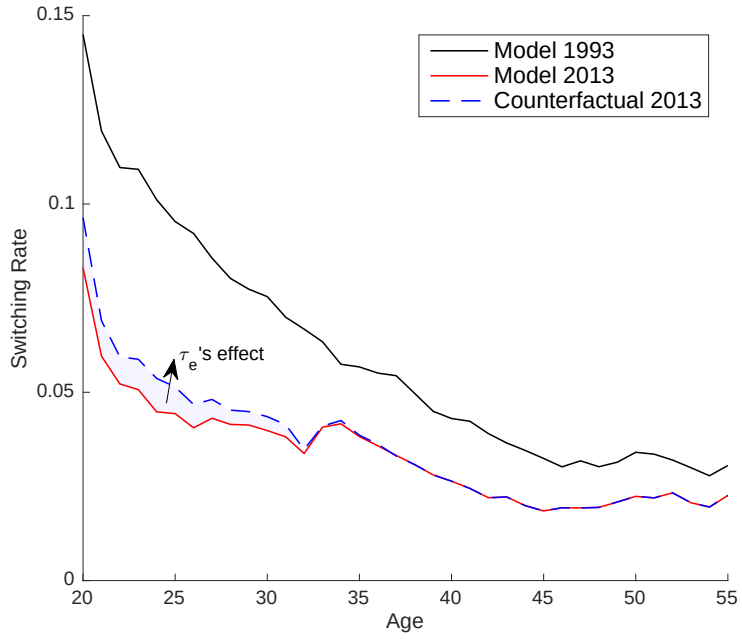
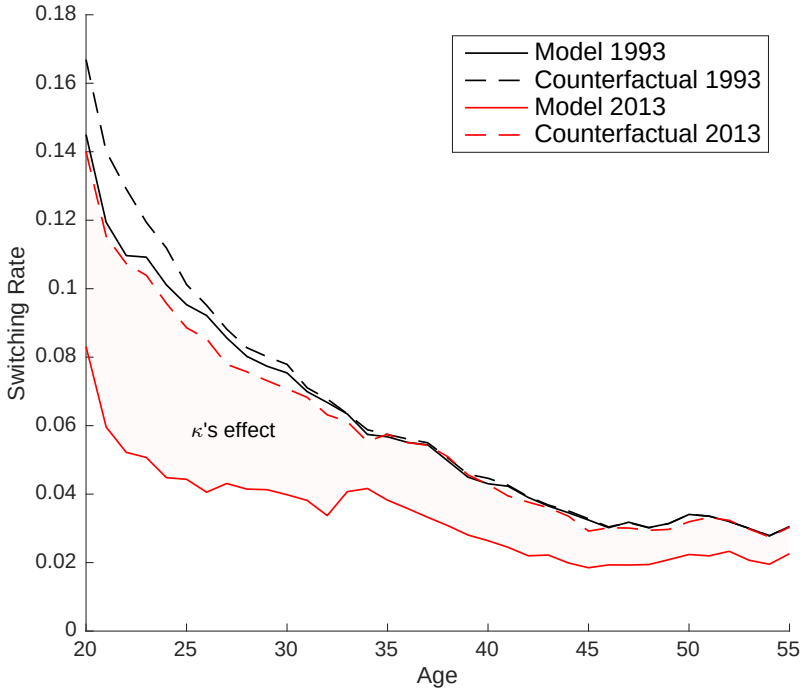


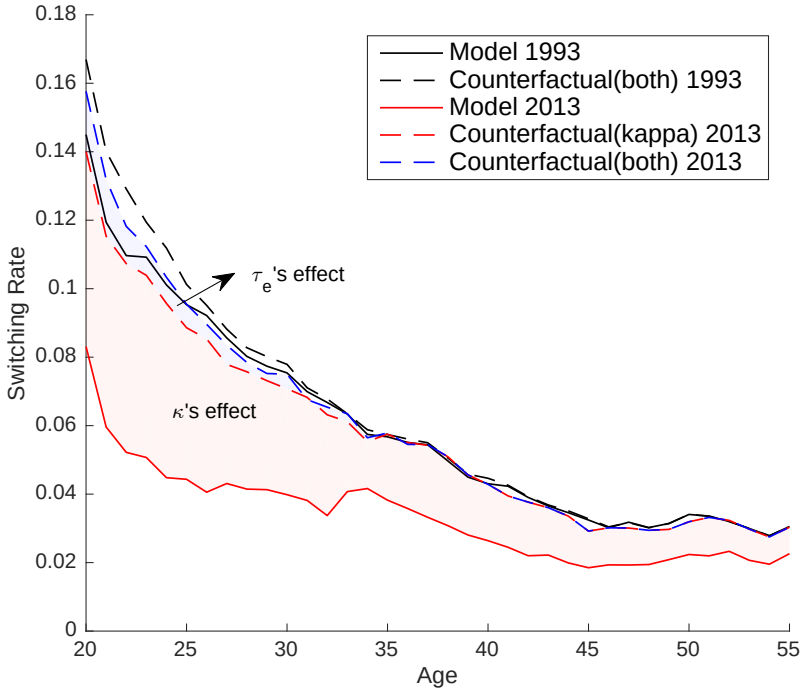
Figure 21: Occupation Switching Rates by Age (Switching Costs Effect)



1993 regardless of entry data/cohort. The black dashed line in Figure (21) represents this effect: Workers in 1993 anticipate a change in switching costs in the future, and therefore alter their behavior. Thus we see the counter-factual 1993 switching rate shifts up relative to the switching rate in the data. For example, 20 year olds in 1993, knowing that in 2 years the switching cost will be flattened, will choose to switch more often then they would if they anticipated continued future growth in switching costs.

The last counter-factual exercise examines the joint effect of switching costs and information. The effects of both on switching rates by age is shown in Figure 22. The dashed blue line shows the joint effect, while the dashed red line shows the switching cost effect as in Figure 21. In the appendix, I show decomposing the joint effect in the opposite order (information first, then switching cost) doesn't change the result much. Comparing the two factors, switching costs account for a much bigger effect and affect agents of all ages. Information also accounts for a significant amount of the decline but the effect is considerably smaller than the switching cost effect since it only affects the young. The effect of the two factors (separate or together) on the aggregate switching rate is shown in table (2). The first column shows the data for each year, which is calculated from the respective (population

Figure 22: Occupation Switching Rates by Age (Both Factors Effect)



representative) SIPP panels. The second column shows the same statistics calculated using the simulated data from the calibrated model. Each of these variables in the top panel is constructed using the simulated worker panel along with demographic shares from the US Census Bureau. For example, to calculate the aggregate switching rate in the calibrated model for 1993, I select random subsamples of the simulated worker panel according to the census population shares for 1993 and calculate the switching rate from this new representative cross-section. The expected lifetime income is calculated as the mean total lifetime income for the entire simulated panel (I will discuss more about this in the next section). Columns three through five are the main counter-factual exercises, which I describe above.

The first three rows examines the aggregate switching rate. The first thing to notice is that the results from the calibrated model are very close to the data, despite not targeting these moments directly, and despite the parsimonious nature of this exercise. The switching rates in the first time period is slightly higher than in the data, but the second period matches fairly well. Column three shows the information counter-factual exercise, τ_e. This column examines the contribution of changes in the precision of the education signal, τ_e. Here the switching rate in the 1993 counterfactual is 6.11%, which is the same as in the model

column. This is because that in the counterfactual exercise where I hold the information precision at 1995 level while allow other things to progress to 2013 level, the agents in 1993 will not be affected (this is not the case in the switching cost counter-factual, as it is shown below). However, the counter-factual switching rate in 2013 is 3.5%, which is 0.21 percentage points higher than it is in the estimated model. This implies that the change in information precision can account for 7.6%[28] of the total occupation switching rate decline. Column four of Table (2) describes the corresponding counter-factual exercise for the switching cost, κ. This calibration suggests that most of the decline in switching rates is due to the increase in switching costs, which is 71.8%[29] of the total decline. As mentioned, the switching cost counter-factual experiment is different than the information experiment: in the counter-factual when I hold the switching cost in 2013 at the 1995 level, this not only affects agents in the 2013 cross section, but also those in 1993. This is because of the same reason mentioned above: agents in 1993 anticipate this upcoming change in switching costs, so they change their behavior accordingly. The first number 6.41% in this column shows this effect–anticipating the coming decline in switching costs relative to the estimated economy, workers in 1993 will switch more often (6.41% instead of 6.11%). The final counter-factual (τ, κ, column five) examines the joint effect of the increase in signal quality and switching costs vs the effects of changes in the income process. Here we can see that the joint effect accounts for up to 80.2% of the total change in occupation switching. Notice that both the increase in information and switching cost changes the switching rate in the same direction, so the joint effect can account for most of the decline in occupational mobility rates.

These results suggest that as predicted, both changes in switching costs and changes in initial information played an important role in the observed decrease in switching rates, while changes in demographics played almost no role at all.

5.3 Aggregate Welfare Implications

The counter-factual exercises above shows how the changes in information precision and switching cost affect workers occupational switching rates. However, the real question of importance is how these two effects have affected welfare. Workers switch occupations to find a better match, which implies improved productivity, wages and welfare. This section shows the effect of information and switching cost on worker wages and welfare.

[28] $7.6\% = 1 - \frac{6.11-3.5}{6.11-3.29}$

[29] $71.8\% = 1 - \frac{6.41-5.62}{6.11-3.29}$

Table 2: Calibration Results and Counter-factuals

		Data	Model	Counterfactual		
				τ_e	κ	τ_e, κ
Switching Rate	1993	5.65%	6.11%	6.11%	6.41%	6.41%
	2013	3.24%	3.29%	3.5%	5.62%	5.85%
				(7.6%)	(71.8%)	(80.2%)
Mean Income	1993	\$2498	\$2495			
	2013	\$2676	\$2745	\$2743	\$2770	\$2765
Mean Annual Income			\$31,871	\$31,858	\$32,042	\$32,018
(Averaged over 1993-2013)				(-0.04%)	(0.53%)	(0.46%)
Lifetime Income	1993		\$1.177M	\$1.177M	\$1.182M	\$1.182M
	2003		\$1.207M	\$1.205M	\$1.216M	\$1.214M
	2013		\$1.224M	\$1.223M	\$1.234M	\$1.233M

Note: *Income is measured in constant 2000 USD. Mean Income is the mean of one month income.*

The main calibration and counter-factual results are in table (2). I focus on three key aggregate measures of interest: the mean monthly income (rows four and five), mean annual income across the 20 year period (rows six and seven); and expected lifetime income (the bottom panel, rows eight to ten). For the first measure I compare the value of data, model, and counterfactual experiments in 1993 and 2013. The mean incomes in the estimated model fit the data very well. In the data, we see a modest increase in average monthly income, with a change of \$2,498 to \$2,676, and we see a similar change in the model from \$2,495 to \$2745. Similar with the aggregate switching rate results, the counter-factual results for mean income is shown in column three to five. The effect of the counterfactual decrease in information is shown in column Counterfactual τ_e. Even though the change in magnitude is small (the mean income decreased only by 2 dollars when information is not as precise), the effect is clear: High information precision is welfare improving. Also, while the effect on mean wages is small, the effect on a particular individual can be quite significant, since most agents in 2013 didn't benefit from the increased initial information signal post-1995. On the other hand, the declines in switching due to increased switching costs tends to decrease welfare. When switching costs are held at the lower counterfactual level (1995 level), we see an increase in the mean monthly income in column Counterfactual κ. The switching cost effect on income is bigger than the information effect: on aggregate this decrease in switching costs can lead to a \$25 gain in mean monthly income from 1993 to 2013. Unlike the joint effect on the switching rate where both factors have effects in the same direction,

they have opposite effects on welfare. The increase in information since 1995 has increased welfare while increased switching costs have decreased welfare. Jointly, we see an increase (decrease) in mean income in the counterfactual (data) relative to the data (counterfactual). This is because the switching costs effect is much bigger than the information effect so it dominates the direction of the welfare change. The magnitude may seem small, but this is only a mean income averaged across all agents in the economy. The effect is much bigger if we aggregate the effect up to annual income, and aggregate across all agents in the economy. The next two rows (Mean Annual Income) shows a clearer aggregate effect.

The Mean Annual Income variable is very similar with the previous monthly income variable. Here I take the mean annual income for each year, then average over the entire time period between 1993 to 2013. The value shows the mean effect on annual income for this period. This calculation gives a sense of the potential GDP loss from the mismatch: suppose worker wages reflect the productivity in the match, then what is the loss or gain in output when people are more mismatched (τ_e counterfactual) vs less mismatched (κ counterfactual). The income gain/loss is coming from the productivity increase/decrease when people are better/worse matched since people can move more/less freely in a low switching cost/low information precision environment. For example, the number in the "Model" column shows that the mean annual income for workers aged 20 through 55 during the period 1993 through 2013 was \$31,871. Under the first counterfactual, the mean annual income over this period would be \$13 lower. This number seems small, but aggregated up over 20 years, over the entire prime aged (20-55) full time workers, this amounts to about \$22.1 billion in lost wages from lower information, disproportionately affecting young workers (ie: the measured increase in information quality led to a gain of \$22.1 billion for younger workers over this period). The kappa counterfactual suggests that increased switching costs have cost workers a total of nearly \$292.5 billion over this period. This aggregate effect can be shown in Figure 23 and Figure 24. In the table, I show the mean annual income from 1993 to 2013, while Figure 23 shows the average annual income difference between the estimated economy and kappa counter-factual case year by year. For example, in 2013, the mean annual income when switching cost is low is 300 dollars higher than in the calibrated economy when switching cost is high, and this difference can be interpreted as the switching cost effect. Multiplying the total employment by the difference in the two economies (calibrated and counter-factual), Figure 24 shows the wage loss every year that is due to the growth in switching costs. In 2013, this loss is about 0.2% of real GDP[30].

[30]The total employment here is workers who are 20 to 54 years old, full time (>35 hours) workers. The time series of employment can be found in appendix.

Figure 23: Mean Annual Wage Difference

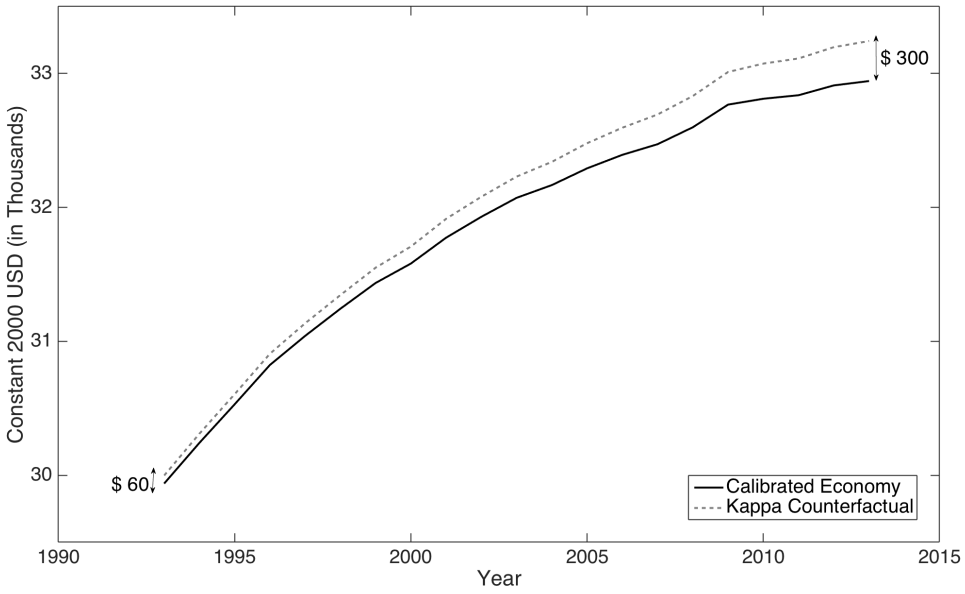
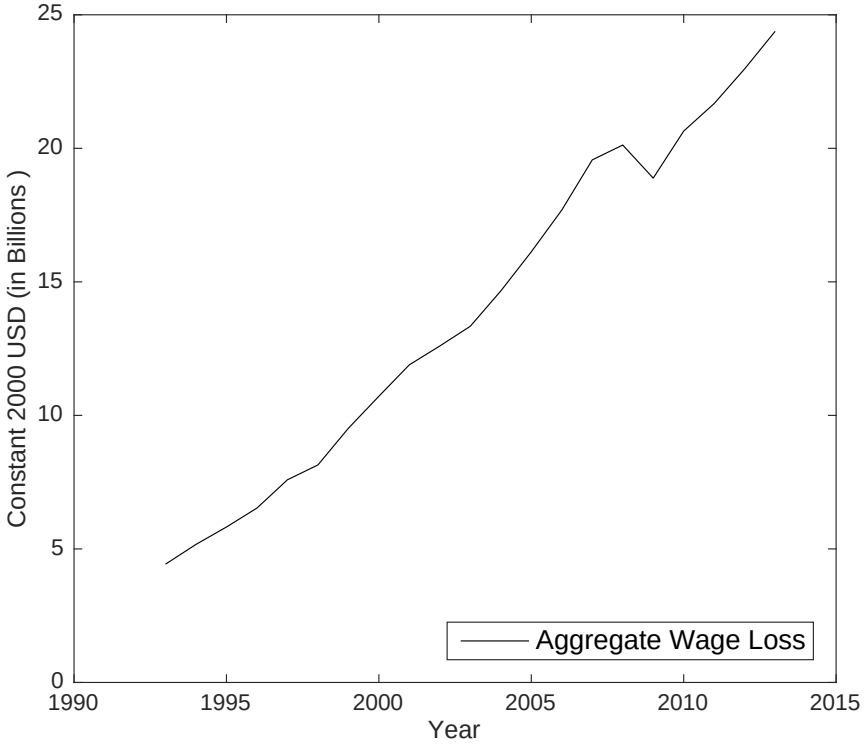


Figure 24: Aggregate Wage Loss from High Switching Costs



To sum up, increases in information provided modest improvements in average income and welfare, above and beyond the changes in the income process between those two periods. This implies that policies which target information frictions such as those faced by workers early in their career can play an important role in both improving welfare and mitigating productivity-sapping labor misallocation. Furthermore the increase in switching costs has a much bigger negative effect on average income and welfare, so policies which target the decrease in switching cost (for example, a decrease in the licensing costs) can help workers to find more productive occupation matches, increase their wages and welfare. A careful analysis using the licensing cost change data is shown in section 5.5.

5.4 Lifetime Welfare Analysis

This section investigate workers lifetime welfare effects. The last panel in Table 2 shows the individual's lifetime income implications. In the second column, I show the calibrated model generated cohort expected lifetime income, where the years are the labor market entrance year accordingly. This individual's lifetime income analysis shows the similar result as the aggregate analysis: better information increases workers' welfare while high switching costs does the opposite. Taking workers who enter labor market in 2003 as an example, if information hadn't improved, each worker would see a $2000 lifetime income loss on average. If the switching costs hadn't risen, workers would have a $9000 lifetime income gain on average. I've shown this seemingly small number can adds up to large aggregate income gains/losses. Furthermore, even on an individual level, this number is merely an average: this is a total loss averaged over all agents in the economy. However, it is straightforward that some individuals are not affected by these environment change: the change in switching costs does not bind for many workers in the economy. Therefore there is no real income loss for agents whose behavior are not actually affected by the change in labor market environment. If we only look at the loss among workers who are actually affected by the changes and therefore change behavior and potentially lose or gain, the lifetime income loss is close to $20,000 per person conditional on the loss.

The lifetime income calculation in the previous experiments captures workers monetary utility change. However, workers switch occupations for monetary reasons as well as other non-pecuniary preference reasons. The non-pecuniary utility is the part of workers' welfare which we can not directly observe in the data. However, we see workers' occupational choices and realized wages, and these realized decisions and outcomes depend on the non-observed

preferences. By applying compensating variation analysis using the estimated model, I can back out the monetary value of the total welfare effect of the two factors when taking both the monetary and the non-pecuniary utility into account.

Take the switching cost change as an example. The intuition behind the exercise is simple: in the counterfactual experiment where switching costs are held at the 1995 level, workers are facing lower costs when switching. As a result they can move more freely, making more income (shown in the previous subsection) and have higher utility. How much would workers facing the higher switching costs have to be compensated in order for them to achieve the same level of utility as under the lower switching costs? Agents entering the labor market at different times are compensated differently. Workers who retire before 1995 will not be affected by this switching cost change, so the compensation value will be zero. As worker enter later and later in time, they will be affected for longer in their career and face higher average costs so the compensation will be bigger. Figure 25 shows the compensating value by the year of entry in labor market. For workers who enter the labor market. On average, the compensating value for workers who enter the labor market in 2003 is $35,000 over their life time. In other words, the expected welfare cost for workers who start to work in 2003 and face the high switching cost growth path is $35,000 in constant 2000 dollar values, which is equivalent to losing one year of mean annual wages over this period.

The average compensating value shows the mean effect of the switching cost change. When there is a change in switching cost, some workers will be affected while some will not. For example, people who are in their well matched occupation may not change occupation regardless of the switching cost being high or low. And for those who are affected by this switching cost change, the magnitude can be very different. Taking a look at the distribution in the compensating values of workers who start to work in 2003 and lose due to the high switching cost, the 95th percentile of the life time utility loss is $144,381 dollars. Figure 26 shows the mean compensating value for workers by the year of entry in labor market conditional on losing. Note that the black solid line is the same as the value in Figure 25, which calculates the mean value over all workers. The red dash doted line calculates the mean compensating value of those who actually lose due to the high switching cost. For those who actually lose, the mean loss of lifetime welfare for workers who enter the labor market in 2003 is about $60,000 in constant 2000 dollars.

Figure 25: Lifetime Welfare Cost (Mean) by Cohort

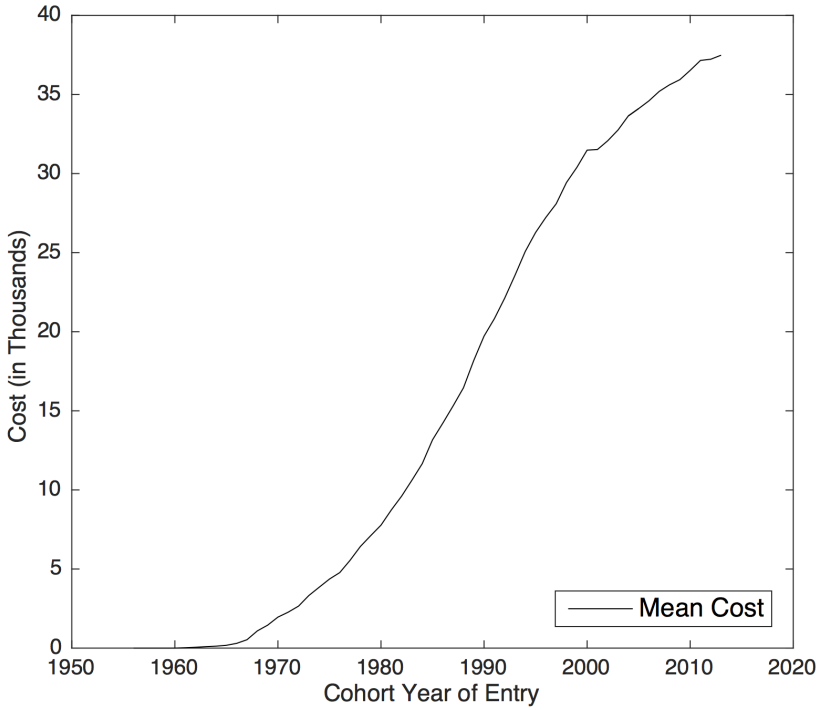
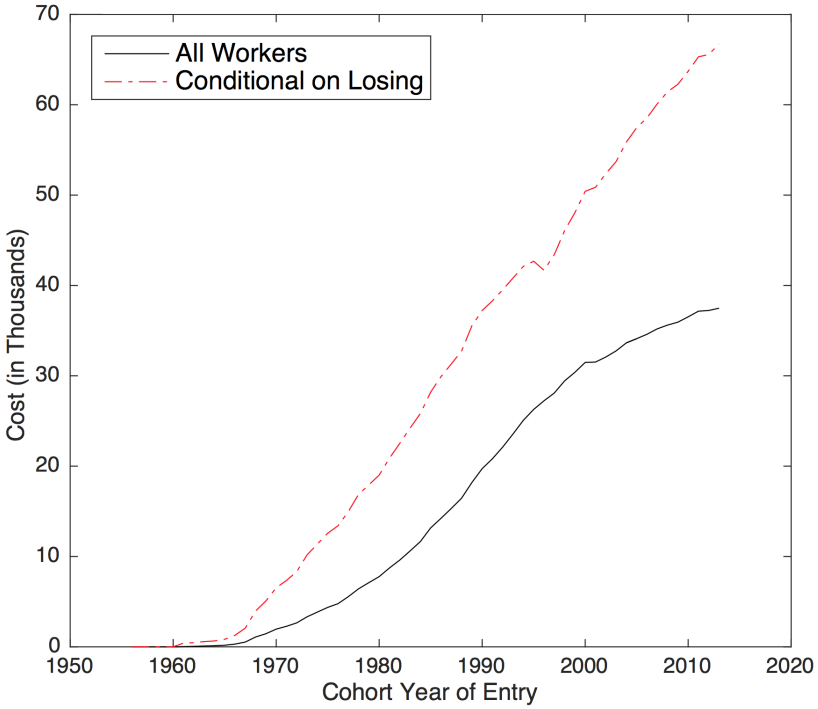


Figure 26: Lifetime Welfare Cost (Mean) by Cohort (Conditional on Losing)



5.5 Occupational Licensing Effects

One basic form of occupational switching cost is the need to obtain an occupational license. An occupational license is official permission from the government allowing someone to work in a particular field. Workers may obtain such a license via one or more of several typical paths: earn a certain quantity or type of education, complete some particular specialized training, write (and pass) a standardized exam, pay fees, and more. According to Carpenter et al. (2012), only one in 20 U.S. workers in the 1950s needed the governments permission to pursue their chosen occupation. Today, that figure has grown to almost one third. Many licensing schemes may not be necessary[31], and the onerous requirements may reflect the lobbying prowess of practitioners in securing laws to shut out competition rather than any characteristics of the occupations themselves (Carpenter et al. (2012)).

From early 1980s to 2012, the proportion of occupations that are licensed generically (universally) across the country has increased for all coarsely defined occupation groups: for example, in Management and Professional occupations, the proportion has increased from 34% to 46%; In Service occupations, the proportion of occupations licensed has increased from 18% to 25%. In total, this proportion has increased almost 10 percentage point, from 17% to 26% (Redbird (2017)). Not only have the proportion of workers that are licensed and the proportion of occupations that are licensed increased, but also many of the already licensed occupations have experienced a ratcheting-up of licensing requirements (Han and Kleiner (2016)).

Using newly collected data on occupational licensing, I observe a more complete pattern for changes in licensing requirements, and can measure changes in the aggregate/average requirements over time. The data set is constructed from a variety of government documents and online databases[32]: for example, LexisNexis[33] is particularly useful for finding administrative law changes. Careeronestop Credentials Center[34], which is sponsored by the U.S. Department of Labor, provides information about licenses required for different occupations. The collected data includes 45 universally licensed occupations across all 50

[31]The difficulty of becoming licensed often does not reflect the public health or safety risks involved in the occupation. For example, 66 occupations have greater average licensure burdens than emergency medical technicians. The average cosmetologist spends 372 days in training; the average EMT only 33 (Carpenter et al. (2012)).

[32]The online databases for collecting the occupational licensing requirements include: WestlawNext, LexisNexis, HeinOnline, Careeronestop-Credential Center, ABA Collateral Consequences, Way Back Machine, and Council for Higher Education Accreditation.

[33]https://www.lexisnexis.com/en-us/gateway.page

[34]https://www.careeronestop.org/credentials/toolkit/find-licenses.aspx

states and the District of Columbia[35]. The data include the following occupational licensure requirements: minimum education requirement, hours of training, year of initial licensure, experience, required exams, continuing education, initial licensing fee, and the cost of license renewal. The data also records information such as whether or not there exist licensing restrictions for former convicts, the composition of licensing boards, etc. All the requirements are collected from 1980 to 2015. This data set provides thorough and detailed information about occupation licensing requirement levels and changes, which allow me to investigate the licensing effects on worker switching behavior and welfare changes.

Table 3: Occupation Licensing Requirement Changes

Occupation	Education (yrs)		Initial Cost		Renewal Cost	
	'95	'13	'95	%Δ ('13)	'95	%Δ ('13)
Engineer	3.7	4.0	\$124	55%	\$46	101%
Land Surveyor	0.8	4.1	\$82	42%	\$86	24%
Massage Therapist	0.0	0.0	\$89	67%	\$42	138%
Psychologist	5.8	6.0	\$263	33%	\$169	56%
Nurse	2.0	2.0	\$36	124%	\$26	142%
Teacher	2.3	3.7	\$19	177%	\$16	188%
Veterinarian	6.0	6.0	\$23	512%	\$23	468%
Total (Mean)	3.22	4.9	**\$101**	**116%**	\$83	106%

Years of Education: 2 is High School, 4 is Assoc., 6 is Bachelor, 8 is Post-Grad

As of the time of this draft, the data set is half complete. I present some summary statistics from the data collected thus far in Table 3[36]. The table suggests that occupational licensing requirements have increased from 1995 to 2013, which corresponds to the time span of the counter-factual experiments in the previous sections. This will allow me to use my estimated model to directly run policy experiments with the observed licensing requirement changes (see below). The first column of the table lists seven of the universally licensed occupations. The second (Education) column shows the change in education requirements for each occupation from 1995 to 2013. For example, on average (across states) workers only needed to have a high school degree or less to become a land surveyor in 1995. In 2013, the average requirement was an associates' degree. The third (Initial Cost) column shows the change in initial licensing costs from 1995 to 2013. The same land surveyor had to pay \$82

[35]The full list of occupations can be found in the Appendix

[36]These statistics are calculated using the current subset of the data containing 20 occupations and 30 states. Because the data is not yet complete, this table shouldn't be taken as anything but suggestive evidence at this point.

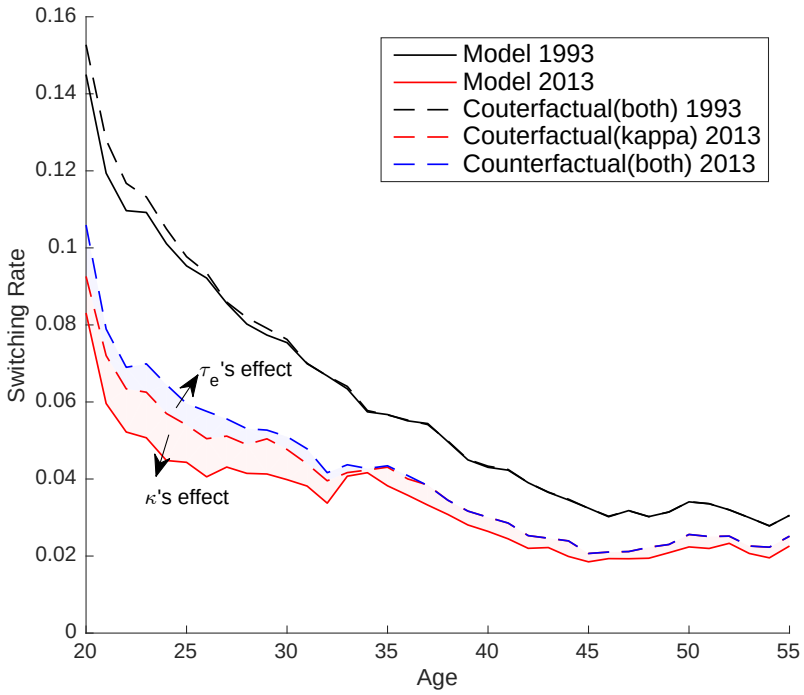
dollars to obtain an license in 1995. This number increased 42%, to $116 dollars in 2013[37]. The initial fee typically includes initial application fees, exam fees, and other initial costs. The fourth (Renewal Cost) column shows the cbanges in the cost of licensing renewal from 1995 to 2013. For land surveyors, the renewal fee increased by 24% from $86 dollars to $106 dollars. Licensing requirements and changes display a large degree of heterogeneity across occupations. For example, massage therapy does not require any degree in both the 90s and today. However, the renewal costs for massage therapists have doubled over the past 20 years. On average, the total initial cost of licensing has doubled from $101 dollars to $218 dollars[38].

I use this observed increase in average initial licensing costs directly to run a policy experiment. The experiment is the following: If the average initial licensing cost was fixed at its 1995 level, how would workers have behaved over the past 20 years, and how would wages/welfare have differed? Note that this increase in initial licensing cost is a very preliminary estimation: it both over and under-estimates the true changes in licensing costs. On one hand, the initial cost of getting a license is merely a small part of the total licensing requirements. The really burdensome and costly part is the required exams, hours of training, and education requirement changes (Carpenter et al. (2012)). Therefore using the initial costs as an indicator underestimates the licensing costs. However, the average cost changes here are only calculated over the set of fully licensed occupations for which I currently have data. Only about one third of the total workforce are licensed, so this estimated change in costs also overestimates total (average) switching cost changes due to licensing in the economy. Despite the limited nature of the incomplete data and this preliminary exercise, it is still informative for policy makers: how would holding licensing costs at their 1995 level (a total decrease of $117 dollars relative to 2016) change the labor market and worker welfare? Figure 27 shows the effect of this decrease in licensing fees on aggregate occupational switching rates by age. In aggregate, if average licensing fees had not increased since 1995, the aggregate switching rate in the economy would have been 4.57% (as opposed to 3.29%). Thus the changes in licensing costs can account for 35% of the total decline in the aggregate occupation switching rate from 1993 to 2013. This work is ongoing as the data is still being completed, the related results and experiments will be updated as more data becomes available.

[37] All dollars are in 2000 constant dollars

[38] The average is over all 20 occupations in the current data, not just the seven occupations that are shown as an example in the table.

Figure 27: The Increasing Initial Licensing Costs Effects



6 Conclusion

This paper joins the growing literature (for example, Molloy et al. (2016)) which documents the aggregate decline in the occupation switching rate over the past few decades in the US. It is clear that demographic changes including age distribution, gender, and educational composition can explain only a small portion of this decline, with the remaining portion as of yet unexplained. Further scrutiny using public data (CPS and SIPP) reveals that the decline in occupational switching over the past 20 years is much more prominent among young workers than for the old. This is observation appears new to the literature, and also suggests a new potential mechanism driving the aggregate decline.

Guided by the empirical findings, I use a dynamic discrete choice model to examine two potential driving forces for the decline in switching rates. Are workers facing higher switching costs than before, so the labor market has become less flexible? Alternately, do workers now have more information on their own occupational match quality and so are better matched than before and have less incentive to switch? An estimation using SIPP data shows that both factors are very important in driving the decline of the total mobility rate. Together

they can account for up to 80% of the total decline. While the precision of the pre-labor market information signal appears to change significantly, it only drives about 8% of the change in aggregate switching since it mainly affects the young. The estimated change in switching costs are relatively modest, but because all workers are affected equally, this has a larger effect on the decline - roughly 72% is a result of this change in switching costs. Still, the increase in initial information dramatically affects matching in the model, which may have significant unmeasured productivity and welfare implications. In the model, it generates as much as a 0.04% of increase in average worker income. The switching costs decrease mean worker income by as much as 0.53%. In terms of aggregates, this implies a total gain of roughly $22.1 billion from improved information over this period, but a total loss of nearly $292.5 billion from increased switching costs over the same period. Moreover, using compensating variation analysis, the model suggests that the total welfare changes (which include monetary as well as non-pecuniary utility) due to the two factors is much bigger than when just looking at lifetime income. The average welfare cost for workers who enter the labor market in 2003 is about $35,000.

There are several relevant policies which a government may use to improve worker matching and welfare by increasing information access and transparency. However, such policies will mainly assist young workers in finding better matches. For older workers, efforts to decrease occupational associated switching costs may be most beneficial. For example, a decrease in licensing fees can encourage older workers to switch occupations when they feel it necessary. Using a newly constructed occupational licensing requirement change data set, I show that an average increase of $117 dollars in initial licensing fees can account for up to 35% of the aggregate decline in occupational switching rates.

My future work extends this analysis to a much larger set of occupations. By mapping occupations to task space, the computational burden will be less of an issue despite the larger number of occupations. I am also working on including the firm (labor demand) side in the analysis. Occupational mobility is not a unilateral decision. For every economist who wants to become a pilot, there must be a firm who wants to hire a former economist as a pilot. Declines in occupational mobility may thus depend critically on factors such as labor market tightness and firm dynamism. Several papers show that job training gives workers more incentive to stay in an occupation or job rather than hopping between firms. For this extension, I'll further explore the firm's hiring and firing decisions and extend my analysis into a general equilibrium framework so that the effects on consumer welfare of various policies affecting switching rates can be appropriately considered.

References

Bowlus, Audra J, and Jean-Marc Robin. 2004. "Twenty years of rising inequality in US lifetime labour income values." *The Review of Economic Studies*, 71(3): 709–742.

Cairo, Isabel. 2013. "The slowdown in business employment dynamics: The role of changing skill demands." *Unpublished manuscript, Universitat Pompeu Fabra.*

Carpenter, Dick M, Lisa Knepper, Angela C Erickson, and John K Ross. 2012. "License to work: A national study of burdens from occupational licensing." *Institute for Social Justice.*

Cortes, Guido Matias, and Giovanni Gallipoli. 2014. "The Barriers to Occupational Mobility: An Aggregate Analysis."

Davis, Steven J, and John Haltiwanger. 2014. "Labor market fluidity and economic performance." National Bureau of Economic Research.

Dorn, David. 2009. "Essays on inequality, spatial interaction, and the demand for skills." PhD diss. University of St. Gallen.

Faberman, Jason, and Marianna Kudlyak. 2016. "What does online job search tell us about the labor market?" *FRB Chicago Economic Perspectives*, 40(1).

Fallick, Bruce, and Charles A Fleischman. 2004. "Employer-to-employer flows in the US labor market: The complete picture of gross worker flows."

Flinn, Christopher J. 2002. "Labour market structure and inequality: A comparison of Italy and the US." *The Review of Economic Studies*, 69(3): 611–645.

Flood, Sarah, Miriam King, Steven Ruggles, and Robert Warren. 2015. "Integrated Public Use Microdata Series, Current Population Survey: Version 4.0.[dataset]. Minneapolis: University of Minnesota." http://doi.org/10.18128/D030.V4.0.

Gervais, Martin, Nir Jaimovich, Henry E Siu, and Yaniv Yedid-Levi. 2016. "What should I be when I grow up? Occupations and unemployment over the life cycle." *Journal of Monetary Economics*, 83: 54–70.

Gittleman, Maury, Mark A Klee, and Morris M Kleiner. 2015. "Analyzing the labor market outcomes of occupational licensing." National Bureau of Economic Research.

Gorry, Aspen, Devon Gorry, and Nicholas Trachter. 2014. "Learning and life cycle patterns of occupational transitions."

Guvenen, Fatih, Burhanettin Kuruscu, Satoshi Tanaka, and David Wiczer. 2015. "Multidimensional Skill Mismatch." National Bureau of Economic Research.

Han, Suyoun, and Morris M Kleiner. 2016. "Analyzing the Influence of Occupational Licensing Duration on Labor Market Outcomes." National Bureau of Economic Research.

House, White. 2015. "Occupational Licensing: A Framework for Policymakers." *Report prepared by the Department of the Treasury Office of Economic Policy, the Council of Economic Advisers and the Department of Labor*, 7.

Hyatt, Henry R. 2015. "The decline in job-to-job flows." *IZA World of Labor*.

Hyatt, Henry R, and James R Spletzer. 2013. "The recent decline in employment dynamics." *IZA Journal of Labor Economics*, 2(1): 1–21.

Hyatt, Henry R, and James R Spletzer. 2016. "The shifting job tenure distribution." *Labour Economics*.

Kambourov, Gueorgui, and Iourii Manovskii. 2005. "Accounting for the changing life-cycle profile of earnings." *University of Pennsylvania. Mimeo*.

Kambourov, Gueorgui, and Iourii Manovskii. 2013. "A cautionary note on using (march) current population survey and panel study of income dynamics data to study worker mobility." *Macroeconomic Dynamics*, 17(01): 172–194.

Kaplan, Greg, and Sam Schulhofer-Wohl. 2012. "Understanding the long-run decline in interstate migration." National Bureau of Economic Research.

Kennan, John, and James R Walker. 2011. "The effect of expected income on individual migration decisions." *Econometrica*, 79(1): 211–251.

Kleiner, Morris, and Ming Xu. 2017. "Occupational Licensing and Labor Market Fluidity." *Manuscript, University of Minnesota*.

Lindenlaub, Ilse. 2014. "Sorting multidimensional types: theory and application." *Preprint*.

Lise, Jeremy, and Fabien Postel-Vinay. 2015. "Multidimensional Skills, Sorting, and Human Capital Accumulation." Society for Economic Dynamics.

Molloy, Raven, Christopher L Smith, Riccardo Trezzi, and Abigail Wozniak. 2016. "Understanding declining fluidity in the US labor market."

Moscarini, Giuseppe, and Francis G Vella. 2008. "Occupational mobility and the business cycle." National Bureau of Economic Research.

Moscarini, Giuseppe, and Kaj Thomsson. 2007. "Occupational and Job Mobility in the US." *The Scandinavian Journal of Economics*, 109(4): 807–836.

Nagypál, Éva. 2008. "Worker reallocation over the business cycle: The importance of employer-to-employer transitions." *Manuscript, Northwestern Univ*.

Poletaev, Maxim, and Chris Robinson. 2008. "Human capital specificity: evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000." *Journal of Labor Economics*, 26(3): 387–420.

Redbird, Beth. 2017. "The New Closed Shop? The Economic and Structural Effects of Occupational Licensure." *American Sociological Review*, 82(3): 600–624.

Robinson, Chris. 2017. "Occupational mobility, occupation distance and specific human capital." *Journal of Human Resources*, 0814–6556R2.

Stinebrickner, Ralph, Todd R Stinebrickner, and Paul Sullivan. 2017. "Job Tasks, Time Allocation, and Wages."

Traiberman, Sharon. 2016. "Occupations and Import Competition Evidence from Danish Matched Employee-Employer Data."

Xu, Ming. 2016. "Student Loans and Early Employment Outcomes." *Manuscript, University of Minnesota*.

Appendix

Universally licensed Occupations

The following occupations are universally licensed (licensed in all 50 states and the District of Columbia) in the country. There are many occupations that are partially licensed in some states but not the others. For example, security guards are licensed in 37 out of 51 states, while bartenders are licensed in 13 states. These occupations are beyond the scope of the licensing data that I use in the paper.

- Accountant/auditor
- Architect(except landscape or naval)
- Barber
- Bus driver(municipal)
- Chiropractor
- Cosmetologist
- Dental hygienist
- Dentist
- Emergency medical technician
- Engineer
- Funeral director
- Hearing aid dispenser
- Insurance agent
- Land surveyor
- Insurance adjusters
- Lawyer
- Practical/vocational nurse

- Medical and health service manager
- Mortgage loan originator
- Registered nurse
- Nursing assistant
- Occupational therapist
- Occupational therapy assistant
- Optometrist
- Osteopath
- Pesticide applicator
- Pharmacist
- Physical therapist
- Physical therapy assistant
- Physician assistant
- Physician/Surgeon
- Podiatrist
- Psychologist
- Real estate agent
- Real estate broker
- Real estate appraiser/assesor
- School bus driver
- School Counselor
- Securities, commodities and financial service agent
- Social worker

- Speech language pathologist
- Truck driver
- Veterinarian
- Veterinarian technician/assistant
- Teachers

CPS Sample Selection

The Current Population Survey (CPS) is a monthly survey of about 50,000 households, which has been conducted by the Bureau of the Census for the Bureau of Labor Statistics. The CPS sample selection in this paper closely follows Moscarini and Vella (2008). I focus on workers who are in their first four months of the sample, and i study their occupation changes between month two and month three. I restrict the sample to male workers who are 20 to 60 years old, and working in both month two and month three. I cleaned the suspicious occupation switches using the ANY3 and FLAG filter as introduced in Moscarini and Vella (2008). The decline of occupation switching rate using the 1990 census occupation classification is significant as it is shown in the main text. The result for more coarsely defined (the six groups are introduced in the main text of the paper) occupation group's monthly switching rate is shown in Figure 28. It is clear that the magnitude of the switching rate is smaller when using a coarsely defined groups of occupations, however, the declining pattern remains.

The occupation switching rate pattern holds when the sample selection includes both male and female workers. Including both genders in the sample, and decomposing the demographic effects as done in the paper, the decline remains. The result for monthly occupation switching rate for both male and female workers can be seen in Figure 29 and the decomposition is shown in Figure 30.

Lastly, in Figure 31 I compare the total occupation switching rate versus the job switching rate. The top solid line represents any type of job switching (occupation switching, employer switching, or both). The bottom dashed line shows the occupation switching rate as shown in Figure 29. The occupation switching rate time series mimics the series for any type of job switching, and can account for more than 70% of the total switching throughout the past 20 years. This provide confidence that occupation switching accounts for the majority of

Figure 28: Monthly Occupation Switching Rate (6 Occupations)

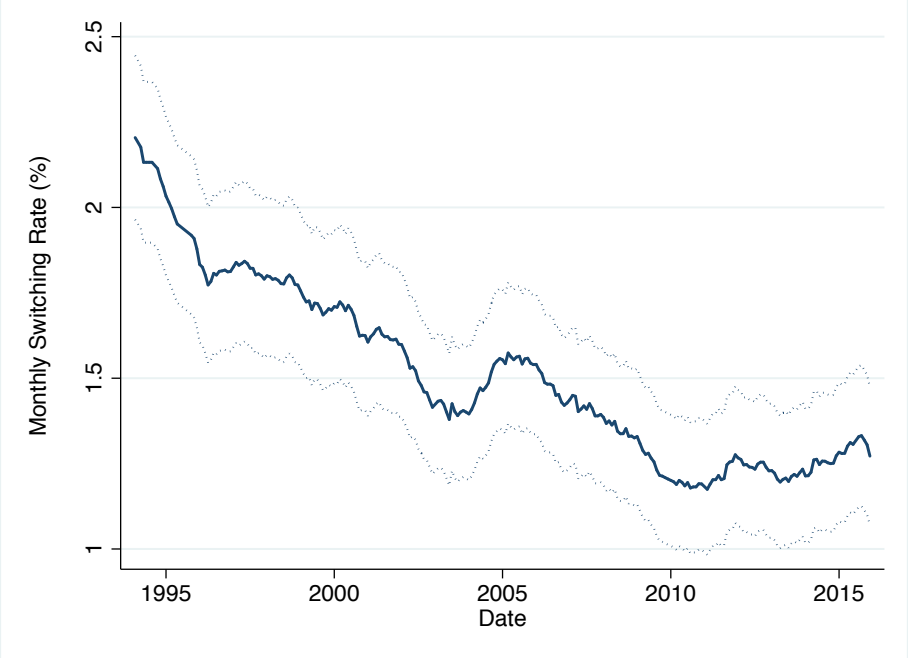


Figure 29: Monthly Occupation Switching Rate (Both Genders)

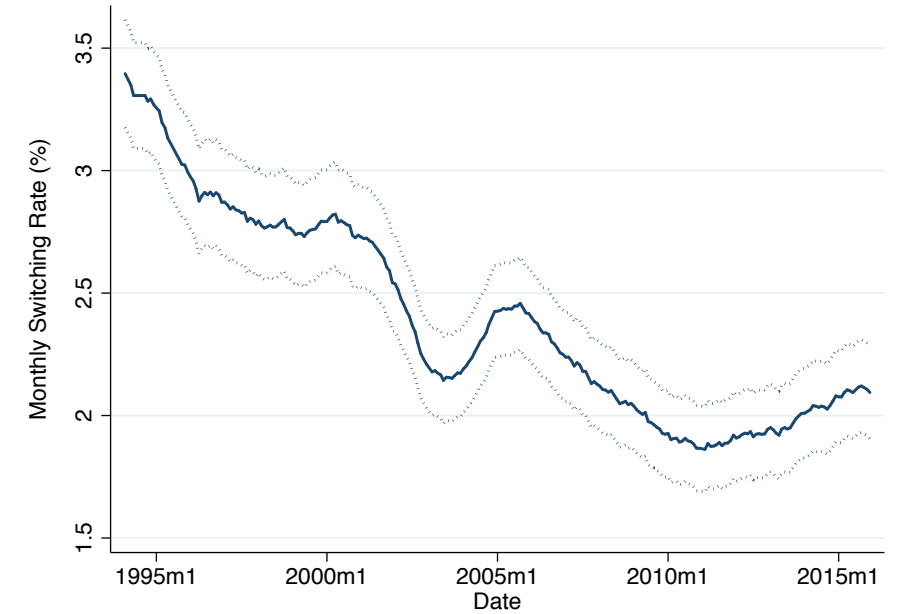
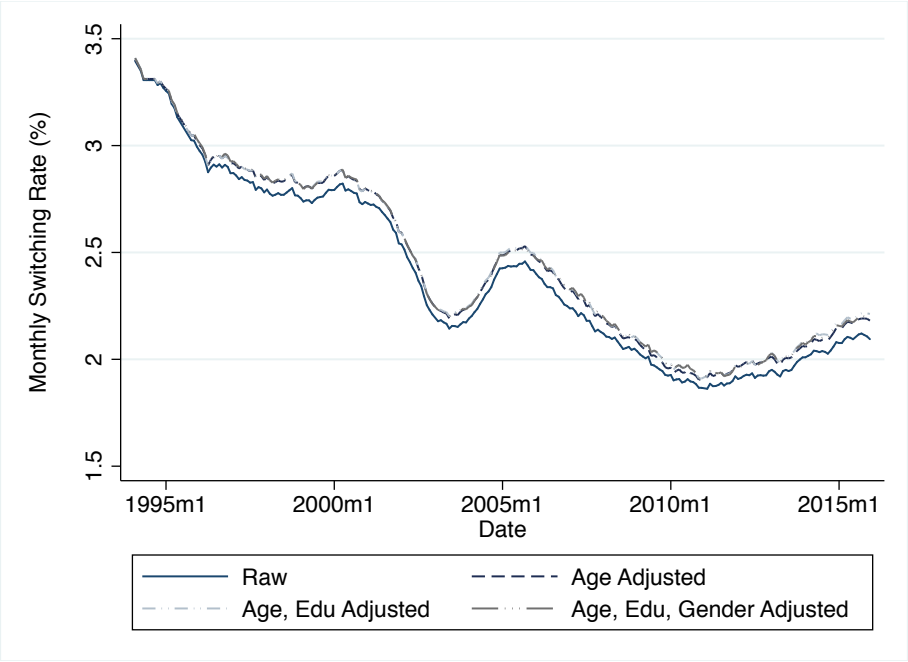


Figure 30: Decomposition of Occupation Switching Rate (Both Genders)



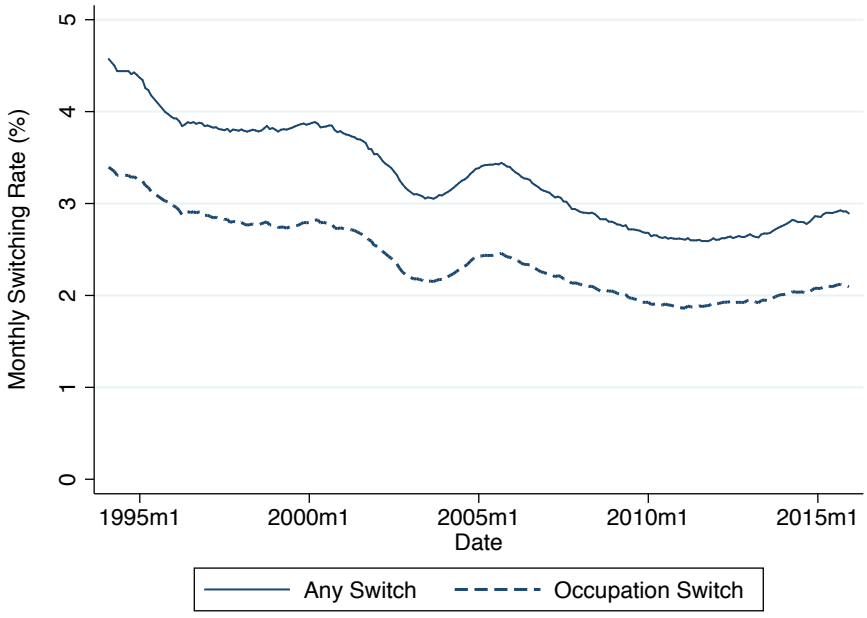
job switching, and thus the story of decreasing job switching cannot be purely an employer switching story. The bottom line is that while the employer switching rate has also declined over this period and is another important area of research worth exploring, this does not reduce the importance of the occupational switching rate decline. Both types of switching are worthy topics for research and increased attention.

Identification Example

This is an simple extension of the example of identification presented in the paper. Here I relax the learning assumption so that it is closer to the set up in the full model. Workers learn about their occupation match quality only after working at that occupation. Their knowledge about other occupations remains unchanged. Under this slightly modified setting, to examine the average wage gain associated with switching, one is interested in the following[39]:

[39]Here I present the case when agents firstly choose occupation b, then switch to a in the second period. This represents the average switch gain, since all the distributions are symmetric and people who switch from a to b are facing the same problem.

Figure 31: Job Switch and Occupation Switch

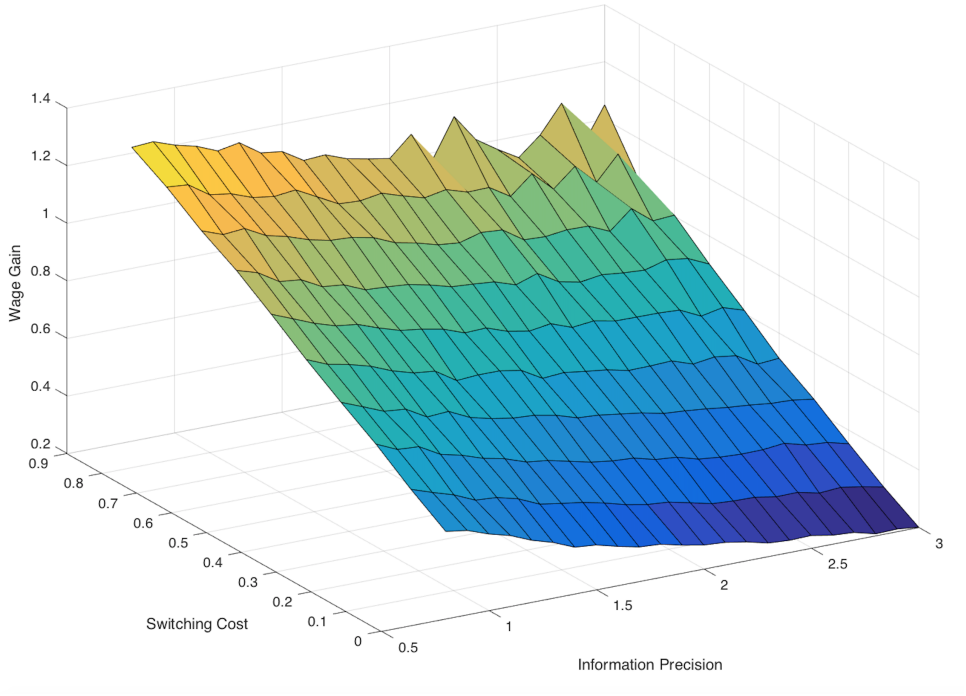


$$
\begin{aligned}
&\mathbb{E}\Big[\ \nu^a-\nu^b\ \Big|\ \mathbb{E}(w_1^a<w_1^b),\ \mathbb{E}(w_2^a>w_2^b)\Big]\\
=&\mathbb{E}\Big[\ \nu^a-\nu^b\ \Big|\ e^a<e^b,\ \frac{\tau_e^2}{\tau_e^2+1/\sigma_\nu^2}e^a-\kappa\geq\nu^b\Big]\\
=&\mathbb{E}\Big[\ \nu^a-\nu^b\ \Big|\ \nu^a-\nu^b<\eta^b-\eta^a\ \&\ \frac{\tau_e^2}{\tau_e^2+1/\sigma_\nu^2}\nu^a-\nu^b\geq\kappa-\frac{\tau_e^2}{\tau_e^2+1/\sigma_\nu^2}\eta^a\Big]
\end{aligned}
$$

In the first line, the subscripts 1 and 2 denote the time periods. From the third line of the expression it is clear that when κ increases, the conditional expectation also increases, so the mean of switcher's wage gain increases with the switching costs conditional on switching. However, the effect of increases in information precision τ_e is much less clear. The switching gain can be written as follows:

$$
\begin{aligned}
&\frac{\partial\mathbb{E}\Big[\ \nu^a-\nu^b\ \Big|\ \nu^a-\nu^b<\eta^b-\eta^a\ \&\ \frac{\tau_e^2}{\tau_e^2+1/\sigma_\nu^2}\nu^a-\nu^b\geq\kappa-\frac{\tau_e^2}{\tau_e^2+1/\sigma_\nu^2}\eta^a\Big]}{\partial\tau_e}\qquad \eta^a,\eta^b\sim\mathbb{N}(0,\frac{1}{\tau_e})\\
=&\frac{\partial\frac{\tau_e^2}{4\pi^2\sigma_\nu^2}\int\int\int\int_{\frac{\tau_e^2+1/\sigma_\nu^2}{\tau_e^2}(\nu^b+\kappa)-\eta^a}^{\eta^b-\eta^a+\nu^b}(\nu^a-\nu^b)e^{-\frac{\nu_a^2}{2\sigma_\nu^2}}d\nu^a e^{-\frac{\nu_b^2}{2\sigma_\nu^2}}d\nu^b e^{-\frac{\eta_a^2}{2(1/\tau_e)^2}}d\eta^a e^{-\frac{\eta_b^2}{2(1/\tau_e)^2}}d\eta^b}{\partial\tau_e}
\end{aligned}
$$

Figure 32: Occupation Switching Wage Gain: Numerical Example



It is difficult to sign this analytical expression even in the simplified setting, but one can check the relationship between the conditional expectation and the information precision easily using numerical methods. As shown in Figure 32, the value of the mean of the wage gain conditional on switching is clearly increasing in switching costs, and decreasing in information[40].

[40]In the numerical example, I normalize $\sigma_\nu = 1$. I allow $1/\tau_e$ to vary from 0.33 to 1.25 (so τ_e is ranging from 0.8 to 3), so the educational signal is mostly more precise than the information in the population distribution. I let κ vary from 0 to 1, so the switching cost is comparable to the wage level. When both κ and τ_e are big there are very few switchers (high cost, precise information), so the surface plot has jumps and is not as smooth as other parts.