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Kingston, Ontario, Canada

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Did Canada Experience a Reversal in the Demand for Skill and Cognitive Tasks?

Author:

Samuel Gyetvay

Supervisor:

Prof. Charles Beach

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Abstract

I use monthly microdata from the Canadian Labour Force Survey to investigate whether the demand for skill and cognitive tasks underwent a reversal during the period 1990-2012. I show that cognitive task prices and the growth in the employment share of skilled labour stalled or decreased from the late 1990s until around 2005, but that both wage and employment growth resumed in the period after 2005. I also show that college graduates graduating in the early 2000s that lower rates of accession into high-skill occupations and lower wages. Using the panel dimension of the survey, I show that, after 2000, workers separated from jobs in high-skill occupations were jobless for a longer period of time and transitioned to lower-skilled occupations, which suggest a relatively slack market for skilled labour. I conclude that there was a short-term decrease in the demand for skill and cognitive tasks followed by a recovery. This stands in contrast to the United States, where recent empirical work has suggested a more long-term or permanent reversal.

Contents

1 Introduction

It is often taken for granted that advanced economies are in the process of transitioning towards a "knowledge economy," with an increasing portion of their labour forces employed in occupations consisting of cognitive tasks requiring abstract thought and post-secondary education, rather than in primary production or manufacturing occupations. Implicit in this transition is a sustained future increase in the demand for such tasks. Under the identifying assumption that concurrent increases in wage and employment are largely caused by demand shifts, the demand for such skilled labour increased consistently throughout the second half of the 20th century. The most common view among labour economists has been that the secular increase in demand was the result of skill-biased technical change (SBTC) that complemented skilled labour and substituted certains types of unskilled labour (Katz and Autor, 1999).

Has this trend continued into the 21st century? What are the effects on wage inequality if the increase in demand stalls or reverses? Beaudry, Green and Sand (2013) show that in the United States the demand for cognitive tasks underwent a reversal beginning in the year 2000. They also suggest that this process affected not only skilled workers but workers across the wage distribution, as underemployed highly educated workers move down the occupational ladder, displacing less skilled workers and pushing down wages.

Berman, Bound and Machin (1998) use international comparisons to identify whether changes in the wage distribution are driven by technological or institutional factors. They argue that changes common to all advanced economies may be attributed to technology, whereas those that differ between countries may be attributed to institutional differences. Beaudry, Green and Sand (2013) offer a technological explanation, showing that the reversal in demand and the ensuing "deskilling" process described above are well explained in a model where cognitive tasks accumulate to form a stock and the diffusion of skill-biased technological change leads to a boom-and-bust cycle. The purpose of the present paper is to look North for fresh evidence of trends in the demand for cognitive tasks, and to replicate the empirical exercises of Beaudry, Green and Sand (2013, 2014) using microdata from the Canadian Labour Force Survey (LFS) from 1990-2012. I also take advantage of the panel dimension of the LFS to test predictions of the decline-in-demand hypothesis on flows in and out of employment and across occupations.

I find mixed evidence for a decline in the demand for skill and cognitive tasks in Canada. While there is some indication that cognitive employment stalled, it appears to have come mostly from a decline in the share of management positions. Furthermore, the timing is not as decisive as the reversal that Beaudry, Green and Sand (2013) show occuring around the year 2000 in the United States. In the Canadian data, the trend appears to begin earlier, yet is much less strong. I also find some evidence that the cognitive labour market became more slack after 2000, with unemployed workers searching for longer periods of time and settling for lower-skilled jobs.

Another contribution of the present paper is to investigate whether the reversal in demand is temporary or permanent. If we observe a temporary reversal in demand in Canada followed by a rebound, this could suggest that the reversal observed in the U.S.. is temporary as well. I find that this is the case. For example, the rate at which college graduates enter into cognitive employment in their first years after college crashes around 2000. This is consistent with the result in Beaudry, Green and Sand (2014). However, unlike in the U.S.., the Canadian rate recovers back to its mid-90's level by the end of the series.

The rest of the paper is structured as follows. Section 2 presents an overview of the literature on tasks and skills and their relation to technology and the wage distribution in the U.S. and Canada, as well as an in-depth summary of the theoretical and empirical results in Beaudry, Green and Sand (2013) (herein BGS). Section 3 describes the data used, with a particular focus on differences between the LFS and the Current Population Survey (CPS) used by BGS, and provides preliminary descriptive statistics. Section 4 presents the main empirical results of the paper, and Section 5 concludes.

2 Literature Review

The present section is divided into two parts. First, to provide context and precision about what is meant by terms such as "cognitive tasks," "routine tasks" and "skills," a brief summary of the literature on skill-biased technical change (SBTC) is given. In the second part, I give a more thorough summary of the theoretical and empirical methods used in BGS.

Skills, Tasks, Technology

The literature on skill-biased technical change emerged as economists attempted to explain increases in wage inequality beginning in the 1970's. Persistent increases in the relative wage of college versus high-school educated workers (the college wage premium) alongside increasing rates of college attendance for both men and women led economists to conclude that technology had differentially affected skilled workers. Katz and Murphy (1992) show that movements in the college wage premium from 1963-1987 can be explained by movements in the supply of college-educated workers in a model with a posited secular increase in the demand for skilled. Autor, Katz and Krueger (1998) show that the rate of computerization within industries predicts increasing wage differentials and skill-upgrading. Juhn, Murphy and Pierce (1993) show that residual wage inequality, the portion of wage inequality not accounted for by changes in observable variables such as education and experience, also increased, suggesting that the returns to unobserved skill had increased. For Canada, Boubarbat, Lemieux and Riddell (2010) show that the economic returns to higher education have also increased significantly for men and women since 1980.

However, limitations of the explanatory power of the SBTC hypothesis eventually became apparent. Lemieux (2006) showed that the majority of the increase in residual inequality documented by Juhn, Murphy and Pierce (1993) was attributable to measurement error and a composition effect.[1] Card and DiNardo (2002) highlight several other problems, including that wage inequality stabilized in the 1990's, despite rapid computerization in many sectors of the economy.

The theoretical models underpinning early investigations of skill-biased technical change relied on models with two groups of workers, college and high school educated, who provide skilled or unskilled labour, respectively, as distinct inputs into production. The more recent tasks and skills literature, surveyed by Acemoglu and Autor (2010) takes a more general approach. Workers are endowed with *skills*: capabilities for performing various *tasks* which are themselves inputs to production. For example: I am endowed with

[1]Since the variance in wages among college-educated workers is greater than that of less educated workers, as the proportion of college-educated workers in the labour force increases, so does residual wage inequality. Using a reweighting approach to hold the composition of the labour force artificially constant, Lemieux (2006) showed that residual inequality only increased in the 1980's, which is inconsistent with SBTC since computerization increased throughout the 1990's as well.

the skills of reading comprehension and knowledge of statistical software, which I apply to the task of writing an MA essay.

This richer and more nuanced framework make it possible to overcome the aforementioned limitations of the simpler SBTC framework. Autor, Levy and Murname (2004) present a model where tasks can be either cognitive or manual, and either routine or non-routine. Routine tasks are well-defined by a set of simple and well-defined rules, and are easily automated or performed by a computer. That is, they are *substitutes* for computer capital, robotics and information technology (IT). An example of a routine cognitive tasks is calculation. Examples of non-routine manual tasks include sorting or assembly. Non-routine cognitive tasks are *complemented* by computerization: an econometrician with a computer can produce more research papers than one without. By contrast, non-routine manual tasks, which feature heavily in most low-skill service jobs, are neither complemented nor substituted for by computerization. Technology therefore pushes down wages and employment in routine sectors and increases the wages of highly skilled workers in cognitive tasks-intensive occupations. Since workers in routine occupations are typically not highly educated, they flow into non-routine manual low-skill service jobs. This creates employment polarization: positive employment growth in high and low-paid occupations, and negative growth in the middle.

A number of studies confirm the pattern of employment polarization using the following graphical method. First, rank all occupations in a base year on the horizontal axis according to some continuous measure of skill. A commonly used measure (and the one that will be used in this paper) is the average wage in a base year, which is typically chosen to be the first year in the series under consideration. Median occuptional wage or average years of education are also often used.[2] Then plot the change in employment shares between two periods on the vertical axis. Employment polarization in this context gives a U-shaped curve: an increasing share of employment in occupations with low- and high-skill occupations, and a decreasing employment share in middle-skill occupations. Goos and Manning (2007) shows employment polarized in the United Kingdom during the 80's and 90's; Autor, Katz and Kearney (2006) and Autor and Dorn (2013) show the same pattern in the United States. Green and Sand (2014) show a similar pattern for Canada.

Reversal in Demand for Cognitive Tasks

Since the goal of the current paper is to test the hypothesis that the demand for cognitive tasks has been decreasing since 2000 as documented in BGS for the U.S., I now give a more thorough summary of their theoretical model and empirical results.

BGS first present a stylized formal model to show how both the increase

[2]Goos and Manning (2007) have shown that their results are robust to which measure is used.

in demand for cognitive tasks seen in the 1990s and the subsequent decrease after 2000 can be explained in a unified framework. The model has two types of workers: high-skill and low-skill. Workers can supply their labour to perform a cognitive task, a routine task, or home production. Home production in the model serves as a wage-floor in order to generate unemployment: the measure of workers whose marginal productivity (and hence wage) in the market sector is below that of the home sector constitutes the unemployment rate. High-skill workers are, on average, more productive in both cognitive and routine tasks.

BGS depart from standard models of skill biased technical change that treat cognitive tasks purely as a flow by assuming that they accumulate to form a stock that depreciates at rate δ. The authors refer to this stock as organizational capital. Organizational capital complements cognitive tasks and is a substitute for routine tasks. At $t = 0$, the economy perfectly anticipates a permament organizational capital-augmenting technology shock at $t = \tau$. In order to take advantage of the technology, the economy begins to accumulate organizational capital by increasing the demand for cognitive tasks. Wages paid to cognitive tasks increase and workers of both skill types increase their supply of cognitive tasks. Routine sector wages also increase to draw in workers from the home production sector. So both average wages and overall employment increase during this boom period. Furthermore, there is skill-upgrading: a higher fraction of workers of both skill levels employed in the cognitive sector.

The boom is followed by a bust. Once the economy has enough organizational capital to take advantage of the increase in technology, it only needs to employ enough cognitive task to offset depreciation. While there will be a higher fraction of workers employed in the cognitive sector in the new steady state relative to $t = 0$, there is lower demand relative to the boom. The decrease in demand for cognitive tasks causes high-skill workers to accept routine-sector jobs. This creates a crowd-out effect: low-skill workers also move out of the cognitive sector, but there they have to compete with other high-skill workers. So more low-skill workers are forced to move into home-production. Relative to the boom, the bust features a lower over-all employment level, skill-downgrading, and a lower fraction of low-skill workers in routine tasks.

While this model may sound abstract, the process it describes is a familiar one. The best way to grasp the intuition is with a simple example. Consider a grocery store that hires an IT technician to automate its inventory database. Rather than being recorded manually (a routine cognitive task), changes in inventory due to sales will now be recorded automatically every time an item is purchased by a computer connected to each cash register. This makes it easier for the manager to predict shortfalls in supply (a non-routine cognitive task). The manager's productivity will increase permanently, but the IT technician will only be employed for as long as it takes her to install the computer system (the organizational capital), as well as the occasional return to fix glitches in the system (depreciation).

BGS are themselves agnostic about the exact mechanism that brings about these effects, stating that they "see several alternative avenues for explaining the patterns presented in this paper" such as a model with two separate shocks for the boom and bust period, but that "[i]t is not clear that the data patterns ... can differentiate between such a model and the one described here." In order to show that the empirical trends they present are consistent with a general demand shock, they use a simple supply and demand framework with an added non-routine manual sector to illustrate the main trends.

1. During the 1990's:

    - Exogenous outward shift of demand in non-routine cognitive sector. Wages and employment increase.
    - Inward shift of demand (due to substitution by technology) and supply (due to selection into cognitive sector) in the routine sector. Wages and employment decrease.
    - Outward shift of demand in non-routine manual sector.[3] Wages and possibly employment increase.

[3]Non-routine manual labour is neither substituted for nor complemented by technology. As wages and employment in the cognitive sector increase, demand for goods produced by the non-routine manual sector increase.

- Inward shift of supply in home production sector (selection due to higher wages in market sector).

2. After 2000:

    - Exogenous inward shift of demand in cognitive sector. Wages and employment decrease.
    - Inward shift of demand and outward shift of supply in routine sector as workers leaving cognitive sector flow in. Wages decrease, ambiguous small effect on employment.
    - Outward shift of supply in non-routine manual sector: as demand in routine and cognitive sector decreases, workers who can no longer find work in those sectors move down the occupational ladder.
    - Outward shift of supply in home production sector: as workers who cannot find work at prevailing in non-routine manual sector leave the market.

BGS then attempt to show that the data fit all of these patterns. One of the main empirical difficulties they face is accounting for composition effects. The average age, the educational attainment of women and the share of college-educated workers as a whole are all increasing over the sample frame. Since the supply shifts listed above do not correspond to compositional changes but to responses to changes in task prices, it is necessary to control for compositional shifts. To do this, BGS use a reweighting approach based on Dinardo, Fortin and Lemieux (1996) and Lemieux (2006). They create an indicator variable equal to 1 for individuals sampled in a base year of 1989, and run a logit regression on education, age, and indicators for gender and non-white ethnicity, as well as interactions of every variable with age and gender. They then use the model's predicted values to form counterfactual weights. These counterfactual weights put less weight on observations that were more unlikely to be in the labour force in the base year, relative to those that were more likely to be observed in the base year. For example, if there are twice as many university-educated non-white young women in the U.S. labour force in the year 2010 as there were in 1989, and assuming the reasons why are unrelated to task prices, an unweighted time series of average cognitive task may be increasing regardless of underlying movements in demand. The counterfactual weights would *downweight* university-educated non-white young women in the labour force in 2010 by half, thereby keeping the composition of the labour force constant at 1989 levels.

3 Data Source and Variables of Analysis

All of the empirical results documented in section 4 of this study are produced using the master file of the Canadian Labour Force Survey (LFS), a nationally representative household-level survey used to create Statistics Canada's official employment estimates. I restrict the sample to all individuals aged 18-65 and focus on the period 1990-2012.[4] The LFS has a rolling panel structure, where each member of surveyed households are interviewed once a month for six consecutive months, and a new rotation enters every months. All calculations are produced using weights provided by Statistics Canada. Real wages are calculated using Statistics Canada's yearly Consumer Price Index.[5]

Since the LFS is a household-level survey it does not include an individual identifier that tracks individuals across periods while they are in the sample. To match individuals across periods, I constructed an individual identifier by concatenating dwelling, household, and individual-within-household codes. Following Madrian and Lefgren (1999) and Skuterud and Su (2010), I use age and gender identifiers to limit the number of overidentified respondents. The resulting identifer uniquely identifies 99.2 % of all observations in the sample. Those that are not uniquely identified are dropped.

I use every month from January 1990 to December 2012. Yearly data are

[4] I choose the period 1990-2012 for two reasons. First, the period 1990-1999 corresponds to the peak of the boom in demand for cognitive tasks in BGS' model, while the period post-2000 corresponds to the bust. Second, the LFS' occupational variable is only consistently defined from 1987 onwards. Rather than construct cross-walks to create a consistent occupational classification over a longer period, I focus on the period containing the reversal documented by BGS. 2012 is the last year that LFS Master File data was available at the time this paper was written.

[5] Accessed at: http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/econ46a-eng.htm

aggregated up from monthly data. In the cross-sectional analysis, I use data from each individual respondent's first month surveyed. In cross-sectional analysis, I use every month that the individual was surveyed for.

The variable `soc4` records respondents' occupations consistently throughout the period under consideration, according to the NOC-S 2006 (National Occupational Classification for Statistics 2006.) The NOC-S 2006 classifies all jobs into 520 occupational categories. Statistics Canada provides a concordance between the NOC-S 2006 and the NOC 2006. The Department of Human Resources and Skills Development Canada (HRSDC) classifies occupations by skill type and skill level within the NOC 2006. Skill type refers to the kind of work performed in an occupation, and is related to the educational field of study required rather than the level of education. Examples of skill types include management, natural sciences and services. skill level refers to the level of educational attainment typically required to hold the occupation. In the analysis that follows I will use skill levels as a discrete measure of the skill content of occupations. The skill levels, along with definitions from the HRSDC are[6]

- 0 - management
- A - Occupations usually require university education
- B - Occupations usually require college or vocational education or ap-

[6]Accessed at http://www30.hrsdc.gc.ca/NOC/English/NOC/2006/Tutorial.aspx#8

prenticeship training

- C - Occupations usually require secondary school and/or occupation-specific training

- D - On-the-job training is usually provided for occupations.

In order to produce an alternative and more continuous measure of the skill content of occupations, I follow the procedure of Goos and Manning (2007) described in the previous section and construct a ranking of occupations by their average wage in a base year. Since our LFS wage data begins in 1997, I rank within that year. I use the LFS variable `hrlyearn`, which records the hourly wage in the week previous to survey. Table 1 presents a sample of occupations and their ranking across the occupational wage distribution.

Even from the small selection presented in Table 1, one can see how the occupational earnings distribution roughly captures some measure of skill. Consistent with the empirical literature on employment polarization described in the previous section, our occupational skill measure contains non-routine manual task intensive services in the lower tail (cashiers and taxi drivers), routine manual (mine labourers) and routine cognitive (machine operators) in the middle, and non-routine cognitive task intensive occupations (engineers, managers, professors) in the upper tail.[7]

[7] It is also worth noting that the ranking is imperfect: chiropractors, who according to the HRSDC require "[a] minimum of two years of university undergraduate studies in sciences and completion of a four- or five-year program at an institution accredited

Two important differences between the American CPS used by BGS and the Canadian LFS deserve to be highlighted. First, as already mentioned, the LFS does not contain data on earnings before 1997. This will severely limit our ability to test for a reversal in task prices. Second, BGS make use of the task indexes created by Autor, Levy and Murname (2003) using the Dictionary of Occupational Titles (DOT) the U.S. equivalent of the NOC. The DOT sampled workers from each occupation and included quantitative measures of various task intensities, which Autor, Levy and Murname (2003) turned into task indexes for cognitive, routine and manual tasks.

4 Empirical Results

4.1 Employment Growth across Skill Levels

I begin by documenting changes in employment shares by HRSDC skill level. Figures 1 through 5 show employment shares in each HRSDC skill level as a ratio of their 1990 level. For example, a value of 1.5 in skill level A in 2010 indicates that the share of the labour force in skill level A occupations in 2010 is 50% larger than the share in 1990. See Section 3 for definitions

by the Accreditation Commission of the Council on Chiropractic Education," are ranked very low in the skill distribution. Since it is highly unlikely that chiropractors as a whole earn less than hairstylists, this figure is likely the result of noisy data due to the small number of chiropractors surveyed by the LFS in 1997. Whenever this skill measure will be used, however, occupations will be weighted by the precision of the base year mean wage estimate. So chiropractors, who accounted for few observations in 1997, will be downweighted relative to other occupations.

of each skill level. The sample includes all individuals age 18 - 64 who were employed in the first month surveyed. The sample size for Figure 1 over the entire period is 3,585,423.

Skill level A occupations (occupations usually requiring a university education) grow by 30% between 1990 and 2012. However, all of the increase taking place in the periods 1990-1995 and 2005-2012. Between 1995 and 2004, the share of workers in skill level A occupations stays constant and the share of workers in management falls, declining by under 20% between 1995 and 2012. At the same time, the share of workers in skill level C occupations increases. However, after 2005 the share of workers in skill level A occupations begins to increase again, and the share of workers in skill level C decreases. The ratio of workers with a university degree is increasing throughout the period, so it is possible that the overall growth is driven by composition effects rather than by supply and demand forces.

One of the central predictions of the theoretical model presented by BGS is that there will be skill upgrading during the boom period and skill downgrading during the bust period. Skill upgrading means that a larger fraction of individuals are employed in cognitive occupations within each occupational class. Skill downgrading means that a lower fraction of individuals is employed in cognitive occupations within each education class. The next two figures reproduce the trends in Figure 1 for two education classes: University graduates (respondents with a bachelor's degree or more), and high school graduates, whose highest level of education completed is high school graduation.

Figure 2 shows employment shares normalized to 1990, as in Figure 1, but restricts the sample to include only respondents with at least a Bachelor degree. The sample size over the entire period is 567,378. Skill levels C and D, those with the lowest skill requirements, grow by 40% and 80% between 1990 and 2012, respectively. While there is no clear reversal at any point, the majority of the growth in the share of skill level D occupations occurs after 2000. Skill level A and management occupations decrease by about 10% over the period. If we assume that cognitive employment is mostly captured by management, skill level A and skill level B occupations, there is some evidence of skill downgrading for university-educated workers, yet scant evidence of skill upgrading in the 1990's.

Figure 3 shows employment shares normalized to 1990, as in Figure 1 and Figure 2, but restricts the sample to include only respondents with high school graduation as their highest level education achieved. The sample size over the entire period is 778,912. Skill level D occupations grow by almost 40% between 1990 and 2012, while skill level C remained relatively stable and management, skill level A and skill level B all decreased. There does not appear to be much skill upgrading for high school graduates during the 1990s. Their share of employment in management increases, but shares in skill level A and skill level B occupations decrease. There is some skill downgrading between about 1997 and 2004, with the employment shares of both management and skill level A decreasing by about 20%.

Figures 4 and 5 show the same series as Figures 2 and 3, but restrict to individuals under 35 years old. Comparing Figure 4 to Figure 2, the growth in skill level D occupations is actually lower for young bachelor's degree holders than for the population at large. This suggests that young degree-holders are not simply entering into low-skill occupations temporarily. If that were the case, we would see higher levels of low-skill employment among young graduates than among all graduates. Instead, we observe the opposite. A larger proportion of all graduates are in skill level D occupations than the proportion for all graduates. For high school graduates, on the other hand, the series for young workers closely parallels that of workers of all ages. The sample sizes for Figure 4 and Figure 5 are 203,932 and 352,132, respectively.

4.2 Skilled Employment and Wage Profiles

The next set of figures explores more explicitly the paths towards high-skilled employment taken by young graduates. Figures 6 and 7 show skilled employment and wage profiles of college graduates, respectively. I follow the procedure of Beaudry, Green and Sand (2014), which I now describe.

First, I restrict the sample to those with university degrees and positive potential experience. The LFS does not record respondents' precise years of schooling. Instead, it records their highest level of education completed (recorded in categorical variable `educlev`). Following BGS, I calculate potential experience as age minus 23 for respondents reporting a bachelor's degree as their highest level of education (`educlev = 8`) and age minus 25 for respondents with graduate degrees (`educlev = 9`). In addition, I drop any respondents who were full- or part-time students at time of survey. Respondents are then grouped into cohorts based on two-year inferred graduation year bins. For example, a 29 year-old with a graduate degree surveyed in 1999 would have four years of potential experience, and would be grouped into the cohort graduating in 1994-1995. I keep all respondents with at most 5 years of potential experience. The sample size (including all cohorts) is 56,785. The sample size for each cohort ranges between 6,773 (for the 2006-2007 cohort) and 4,749 (for the 2010-2011 cohort).

Profiles begin at the first of the two years defining the cohorts. Each profile contains two pieces of information. The point along the vertical axis at which the profile begins is the average employment share or wage among members of the cohort with potential experience equal to 1. In Figure 6, the slope of the profile is the slope coefficient from an OLS regression of a dummy equal to 1 if the respondent is employed in a skill level A or management position on potential experience and a constant term. A steeper positive slope means that an increasing proportion of college graduates within the cohort became employed in skill level A or Managment positions in the years following graduation. A flat slope means that the proportion of college graduates within the cohort employed in skill level A or Managment positions stayed constant during the first 5 years after graduation. The lengths of the profiles bear no significance.

In Figure 6, the entry-level skilled employment shares increase from around 52% for the 1990-1991 cohort to over 57% for the 1998-1999 cohort, then drops dramatically down to around 47% for the 2000-2001 cohort, then increases with every succeding cohort. In constrast, the slopes are roughly constant throughout the series. This stands in contrast to the result of Beaudry, Green and Sand (2014), who find a smaller drop in entry-level employment share, but a sharp reversal in slopes. In their U.S. data, the slopes for all post-2000 cohorts are smaller in absolute value than those before, which suggests that college-educated workers are less likely to move into skilled employment with more time in the labour force.

Figure 7 has the same structure as Figure 6, with log wages instead of skilled employment share on the vertical axis. The starting point of each employment profile represents the mean log wage among workers with one year of potential experience, and the slope of the profile is the slope from a regression of log wage on potential experience and a constant. Since LFS wage data begins in 1997, this series only includes the 1997-1998 through 2008-2009 cohorts. The drop in skilled employment share between the 2000-2001 cohort and the 2002-2004 cohort observed in Figure 6 is mirrored in wages, which fall by less than a 10th of a log point. As in Figure 6, there is little variation in the slopes.

As mentioned in the introduction, the fact that both series undergo a sharp drop around 2000 but recover in the second half of the following decade suggests that the reversal in demand—if that is indeed what caused the drop—was temporary in Canada.

4.3 Employment Growth by Skill Measure

I now turn to look at changes in employment growth using a more continuous measure of skill. Following Goos and Manning (2007), I record each occupation's mean wage in 1997. This represents a ranking of occupations by a measure of skill, the average wage. I then calculate the change in the share of total hours worked in the economy for each percentile and use the STATA command `lpoly` to fit a smoothed line, weighing each observation by the number of workers in the occupation in 1997 (a measure of the precision with which the skill measure is estimated). The horizontal axis represents the occupation's percentile in the 1997 distribution. For example, if a worker is employed in the 20th percentile occupation, then 20% of all workers in 1997 were employed in occupations with mean wages at most as large as her own. Each year of data in the figure actually represents two adjacent years pooled together to reduce noise.[8] The results are displayed in Figure 8, with occupation percentiles on the horizontal axis and change in employment share on the vertical axis, for changes between 1990-2000, 2000-2007 and 2000-2012. I report changes between 2000 and 2007 to separate the effects of the reversal in demand from the recession beginning in 2008.

It is clear from Figure 8 that occupations in the middle of the skill distribution lost the most in terms of employment share, in each period. While the trend depicted in Figure 8 is not quite polarization, with negative growth everywhere except the upper tail, it is clear that occupations between the 20th and 60th percentiles lost *relatively* more than those in the upper or lower tail. Comparing periods, it is clear that low skill occupations declined in employment share less after 2000 than before. It is difficult to make any inference on the upper tail.

While weighting by the precision of the skill measure is in many ways desirable, it can also produce results that are difficult to interpret. For example, in Figure 8, the change in employment share (expressed as a percentage) is on the vertical axis. Since the share of employment across all occupations must always sum to 100%, it must be the case that some occupations increase their employment share while others decrease. However, in Figure 8, the fitted values for changes between 2000 and 2007 lie entirely underneath zero.

[8]Years are pooled as follows: 1990 represents 1990-1991, 2000 represents 2001-2002, 2007 represents 2006-2007, and 2012 represents 2011-2012.

Due to the difficulty of interpreting such results, I have also included an unweighted version of the same graph in Figure 9. While the most high-skilled occupations experience positive change in employment share in both periods, it appears that employment growth was larger in the period 1990-2000 than in 2000-2007. However, employment growth above the 70th percentile is very similar between 1990-2000 and 2000-2012.

Green and Sand (2013) produce a similar figure to Figure 8 using Canadian Census data for changes between 2001 and 1991, and find that the largest decrease in employment in the 1990's occured between the 20th and 40th percentile, which is consistent with my finding. They also find smaller growth in the top three deciles between 2001 and 2006. This suggests that the LFS can reliably capture movements in the occupational employment distribution, despite a smaller sample size.

4.4 Panel Data Results

All of the results presented so far used the LFS as a repeated cross-section. Figures 10 through 13 were created using the panel dimension of the LFS, and allow U.S. to answer a different set of questions. In particular, a panel dimension allows U.S. to ask questions about the tightness of a labour market. A labour market can be said to be tight if firms post more vacancies than there are workers searching for jobs. In a tight labour market, a worker who is unemployed will quickly find a job, and a firm that posts a vacancy will have to wait a long time to fill it. Conversely, a labour market can be said to be slack if there are more unemployed workers than vacancies. In a slack labour market, a worker who is unemployed will search for a long time before finding a job, but a firm that posts a vacancy will fill it quickly. One can also consider whether the market for different tasks are relatively tight or slack. For example, if the market for cognitive tasks is slack due to a decrease in demand, unemployed skilled workers may also search for employment in the market for routine tasks. This would result in workers transitioning from cognitive to routine occupations.

Certain characteristics of the LFS make it possible to test such hyptheses. First consider the implications for slackness. If a respondent is not employed in the first month surveyed, `soc4` records the occupational code of their previous job, provided they last worked within a year of the survey. The LFS variable `durjless` records the number of months since a worker was last employed. There is no guarantee that the worker was searching for new work during the entire period. However, it gives an upper bound on the length of search. I construct a sample containing every respondent who is jobless during their first month surveyed and who has a non-missing value of `soc4`. The sample size for the periods 1990-1999 and 2000-2007 are 92,066 and 186,640, respectively.

The first set of figures suggests that cognitive labour markets became more slack after 2000. Figure 10 plots average months of joblessness on the vertical axis. On the horizontal axis is the skill measure (the average occupational log wage in 1997) corresponding to respondents' previous occupations. The grey vertical lines represent skill measure deciles in 1997. For example, if an occupation is at the 2nd employment decile, 20% of workers in 1997 were employed in occupations with skill measures at most as large as its own. If the demand for cognitive tasks decreases after 2000, the cognitive sector will become more slack, *ceteris paribus*. That is, a skilled worker searching for employment in the cognitive sector after 2000 will search for a longer period of time than if she were searching before 2000.

As seen in Table 1, the occupations with the highest skill measures tend to be the most intensive in cognitive tasks. In Figure 10, occupations below the 8th decile have almost identical average duration of joblessness across the two periods. However, in the 8th, 9th and 10th deciles, there is a higher average duration of joblessness during the period 2000-2007. Figure 11 shows the same result for respondents with at least a bachelor's degree, and the same trend is apparent. The sample sizes for the restricted sample are 12,458 for the period 1990-1999 and 9,303 for the period 2000-2007.

There are many reasons other than a decline in demand for cognitive tasks that could explain longer average length of joblessness. If cognitive wages are higher after 2000, it could be the case that unemployed workers can afford to hold out for longer in their search for work. Furthermore, an increase in job search time does not necessarily reflect a reversal in demand. If the occupational specificity of human capital increased among cognitive occupations between periods, it would be harder for workers to find jobs in other occupations without taking a substantial wage cut. Kambourov and Manovskii (2008) show that there are substantial returns to occupational tenure. If the degree of substitutability between tasks performed in different occupations decreased, perhaps due to higher specialization accompanying the introduction of IT and computerization, one would expect to see a similar pattern.

If a respondent is employed in the first month surveyed, the variable `soc4` records their occupation through the 4-digit NOC-S 2006 code. Each month, respondents are asked if they have switched occupations, and if their new job falls under a different occupational code it is recorded. Respondents are also asked their labour force status every month, which is recorded in the LFS variable `lfsstat`. Labour force status is broken down into employed, unemployed and not in the labour force. Respondents who are unemployed are further categorized as either temporary layoffs, job searchers or future starts. Future starts are defined as those "who did not have a job during the survey reference week and did not search for work within the previous four weeks, but were available to work and had a job to start within the next four weeks."[9]

[9]From Statistics Canada's Guide to the Labour Force 2015:

The features of the LFS described above make it possible to create a sample of occupational transitions. I first include every respondent whose occupational code in the last month surveyed is different from that in the first month surveyed. However, this does not include workers who found a new job in the same occupational category. To capture such transitions, I include every respondent whose labour force status was ever unemployed *and* job seeker (`lfsstat = 4`) and who were employed in the last month their house-hold was surveyed. Since the LFS is structured as a six-month panel and previous occupations are recorded if they occur within one year of the first survey month, this produces a large random sample of occupational transitions for people who were not working for at most 18 months. The sample size for the period 1990-1999 is 179,408. The sample size for the periods 2000-2007 and 2000-2012 are 193,781 and 366,769, respectively.

The next set of figures looks at transitions across occupations. Using the sample of occupational transitions describe above, I create a measure of skill downgrading or upgrading that I call the transitional log occupational wage ratio. Consider an individual who transitions from occupation A to occupation B. Occupation A has a skill measure (mean occupational wage in 1997) of w^A, while occupation B has a skill measure of w^B. If the worker gets a job requiring a higher degree of skill, then the ratio w^B/w^A is greater than one. If the worker gets a job requiring a lower, degree of skill, the ratio

http://www.statcan.gc.ca/pub/71-543-g/71-543-g2015001-eng.pdf is less than one. Taking logs gives the transitional log occupational ratio: $\log(w^B) - \log(w^A)$. A positive value is associated with skill upgrading, and a negative value with skill downgrading.

Figure 12 plots the average transitional log occupational wage ratio (for the periods 1990-1999 and 2000-2012) on the vertical axis and the skill measure (mean occupational wage in 1997) on the horizontal axis. The STATA command `lpoly` is used to fit smoothed lines to make the trend apparent. Similar to the results in Figures 10 and 11, we see a lower transitional log occupational wage ratio for the period 2000-2012. This means that workers who were unemployed at some point during the survey period or transitioned occupations are more likely to have transitioned to a lower skilled occupation in the later period. Figure 13 plots the same trend for the periods 1990-1999 and 2000-2007, to exclude effects of the recession beginning in 2008, and the same trend is still apparent.

Keeping the same sample of occupational transitions and returning to the discrete skill measure based on the HRSDC skill levels, Tables 2 and 3 show the probability of transitioning between any two skill levels in the periods 1990-1999 and 2000-2007, respectively. The rows correspond to the skill level of workers' previous occupation held, and the columns correspond to the skill level of their occupation held in the last month surveyed. So, for example, the cell (A,C) of Table 2 gives the probability that an unemployed worker in 1990-1999 whose previous job was in a skill level A occupation found a new job in skill level C: 1.1%.

Comparing to the equivalent matrix for the period 2000-2007, in Table 3, helps U.S. understand where the occupational transitions are coming from. The probability of finding a new job in either management or in a skill level A occupation, provided you started out in one, is lower in the period 2000-2007 than in 1990-1999. Someone coming out of a management job had a 94% probability of finding a new management job in the 1990's, but only an 89.5% probability in 2000-2007. Interestingly, the probability of transitioning from management to skill level A is higher in 2000-2007 than in 1990-1999. Someone separated from a skill level A occupation had a 96.4% chance of finding a new skill level A occupation in 1990-1999, but a 92.2% chance in 2000-2007. Furthermore, the workers were more than twice as likely to become employed in skill level B or C occupations. This shows that the trends observed in Figures 12 and 13 do not just represent workers transitioning from cognitive occupations to slightly lower ranked cognitive occupations, but rather that workers were flowing into jobs requiring a far lower degree of skill.

4.5 Task Prices

Since the LFS wage data begins only in 1997, I have mostly focused on changes in employment. However, since a decrease in demand can be identified only by a reversal in both wages and employment, I now show what I've got. Figure 14 plots task prices for routine, cognitive and manual tasks. Task prices were constructed following the method of BGS. The cognitive task price is the average log wage among University graduates between the ages of 25 and 35 between the 80th and 90th wage percentiles. The routine task price is constructed in the same way for high school graduates aged 25-35, and the manual task price is the average log wage of high school graduates between the ages of 25 and 35 between the 20th and 40th percentiles. The idea of defining task prices in this way is that young college graduates between the 80th and 90th wage percentiles are likely working in jobs requiring extensive amounts of cognitive tasks. Similarly, low-paid high school graduates are most likely performing manual service work, and high-paid ones are likely to work in routine-task intensive occupations.

In contrast to BGS, who find that all three cognitive task prices are decreasing after 1997, in Canada all three increased between 1997 and 2012. This is consistent with the general trend of wages over the period in Canada. However, all task prices decrease between 2001 and 2004, then recover. The coincides with the fall in entry-level wages observed in Figure 7. It also partially coincides with the stalling in the employment growth among skill level A occupations observed in Figure 1. The fact that both wages and employment subsequently recovered suggests a temporary demand shock.

5 Conclusion

In this paper, I used data from the Canadian Labour Force Survey covering the period 1990-2012 to investigate whether the reversal in demand for cognitive tasks and skill that Beaudry, Green and Sand (2013) show for the United States happened in Canada. In addition to reproducing several of their empirical exercises with Canadian data, I also used the panel dimension of the LFS to test implications of a reversal in demand on flows in and out of unemployment and across occupations.

I find that while there is some evidence pointing to a reversal in demand in Canada over this period, the case is much weaker than for the U.S. Almost none of the time series show a clear, striking reversal around the year 2000, as in BGS, with the one exception being the wages and entry-level employment shares into skilled occupations for young workers graduating college. However, even the sudden drop has reversed itself, with wages and skilled employment shares back at their mid-90's level. While the growth in the employment share of high-skill occupations between 2000 and 2007 was lower than between 1990 and 2000, skilled employment growth between 2000 and 2012 was comparable to that between 1990 and 2000. Despite brief periods of decline in the early 2000's and during the Great Recession, wages of well-paid young college graduates, who are most sensitive to changes in cognitive task prices, increased over the period in which wage data are available.

Curiously, I found only limited evidence of skill upgrading during the 1990's. Instead, it appears that, for most educational classes, skill downgrading began before 2000.

The LFS panel data provided some evidence that cognitive employment was harder to come by after 2000, even excluding the recession beginning in 2008. Workers who became separated from jobs in the top three wage deciles were jobless for longer on average, and those who did find new work tended to settle for occupations with lower skill requirements.

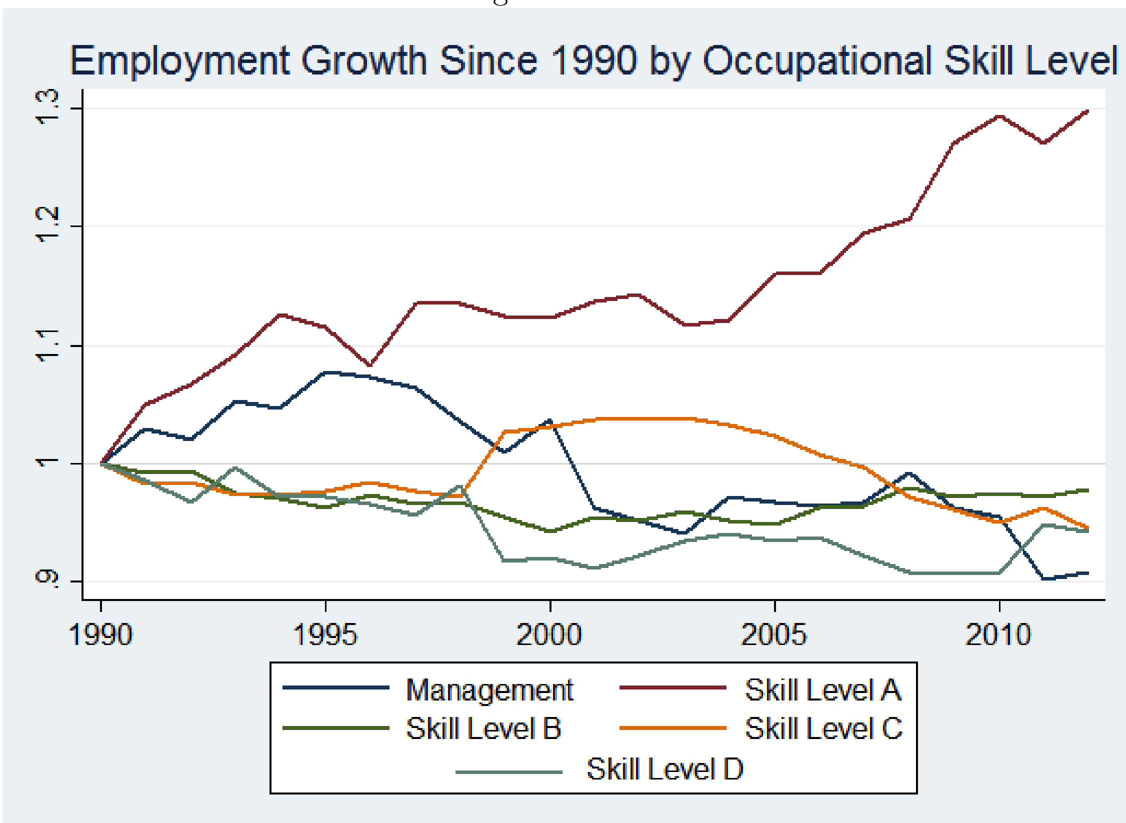
An important related question is whether or not the underlying forces causing the reversal in demand were temporary or permanent. Autor (2014), discussing the results of BGS, writes that

> Information technology investment abruptly reversed course after 2000, suggesting a rapid pullback in demand. Moreover, in the five years prior to this pullback, IT investment surged at an unprecedented rate, rising by approximately two-tenths of a percent of GDP in each year. What this pattern suggests to me is a temporary dislocation of demand for IT capital during the latter half of the 1990s followed by a sharp correction after 2000—in other words, the bursting of a bubble. The end of the tech bubble in the year 2000 is of course widely recognized, as the NASDAQ stock index erased three-quarters of its value between 2000 and

> 2003. Less appreciated, I believe, are the economic consequences beyond the technology sector: a huge falloff in IT investment, which may plausibly have dampened innovative activity and demand for high skilled workers more broadly.
>
> (p. 29)

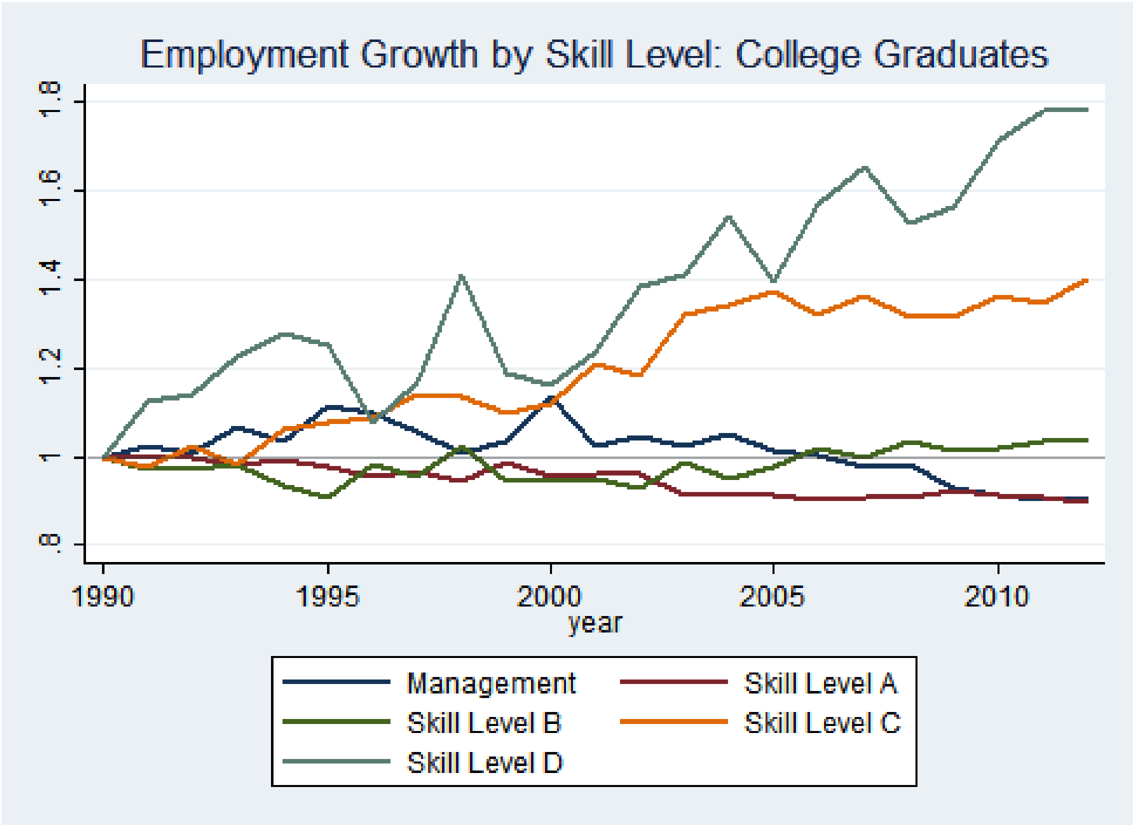
Is the reversal due to the end of an investment phase, as in the theoretical model presented by BGS? Or was it simply after-shock from the bursting of the tech bubble? The evidence presented in this paper may shed some light on these questions. If the same technological shock affected Canada and the U.S. but demand recovered in Canada, one may expect a recovery in the near future for the U.S. as well. Nothing in the data suggests a deep or permanent trend. To the extent that a great Canadian reversal in the demand for skill and cognitive tasks happened, it appears to have been temporary.

Figure 1



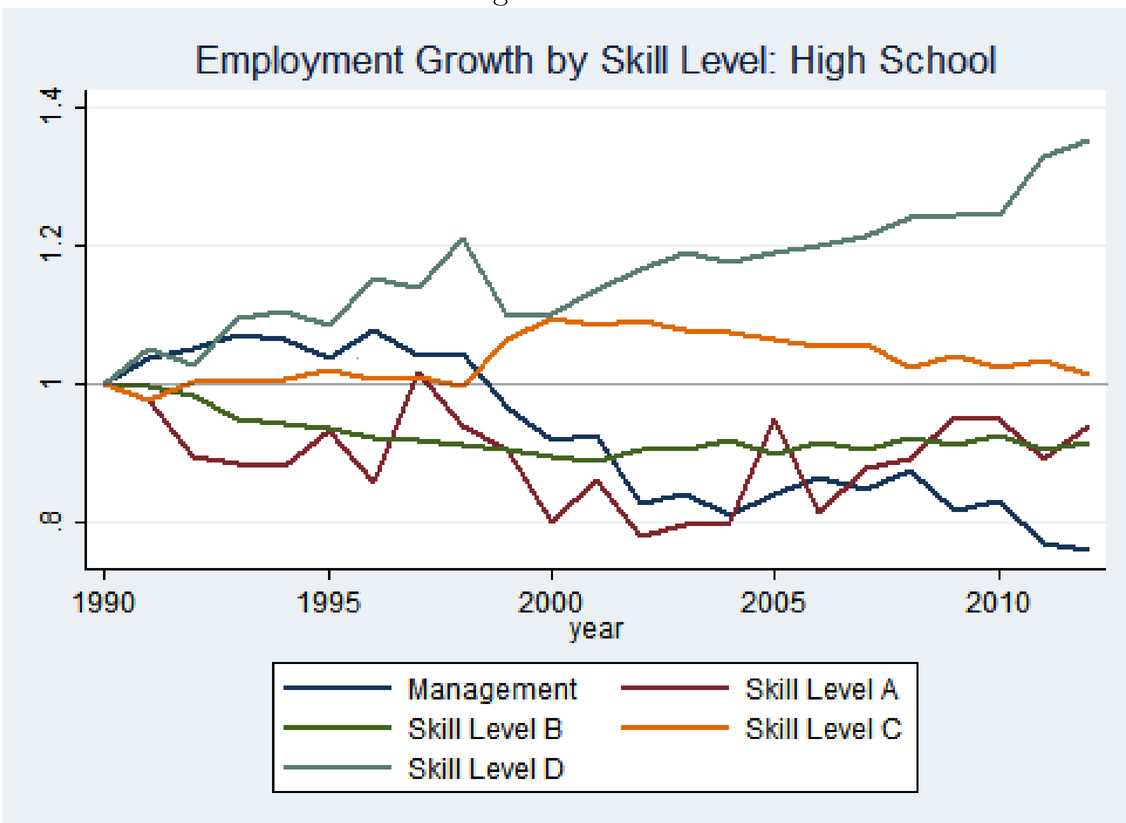
Source: author's calculations.

Figure 2



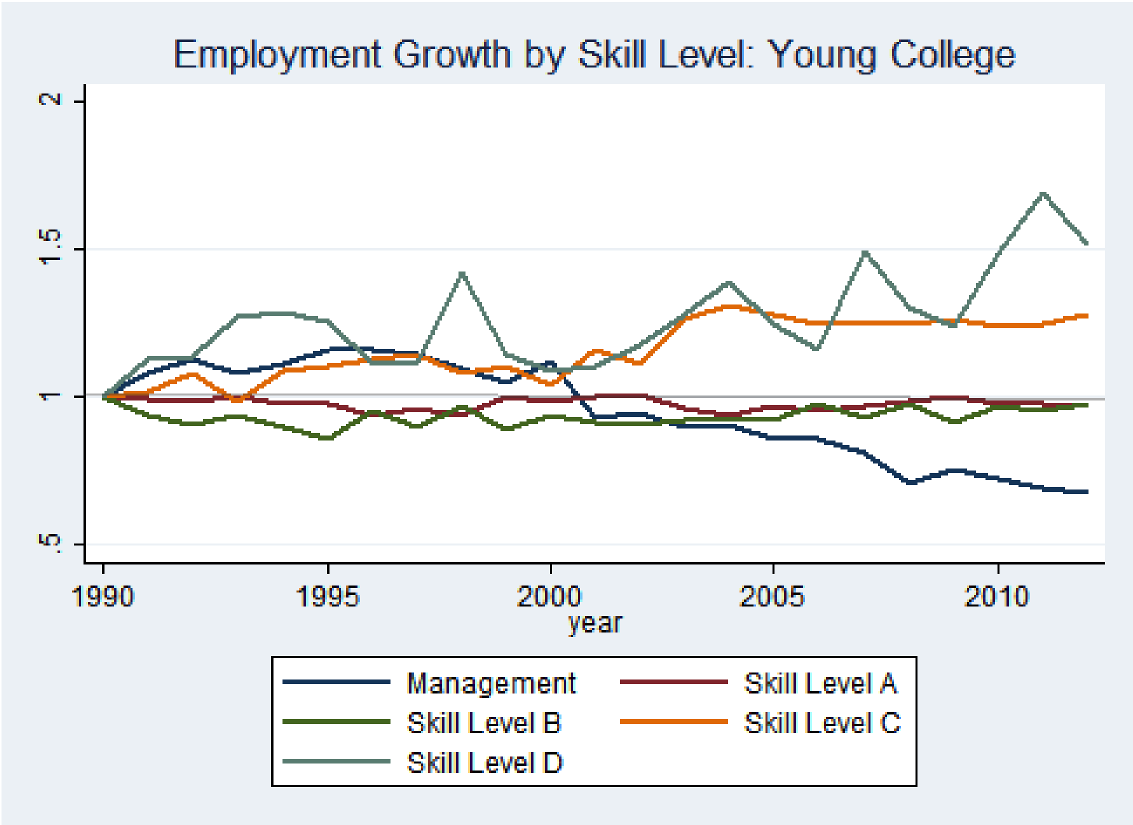
Source: author's calculations.

Figure 3



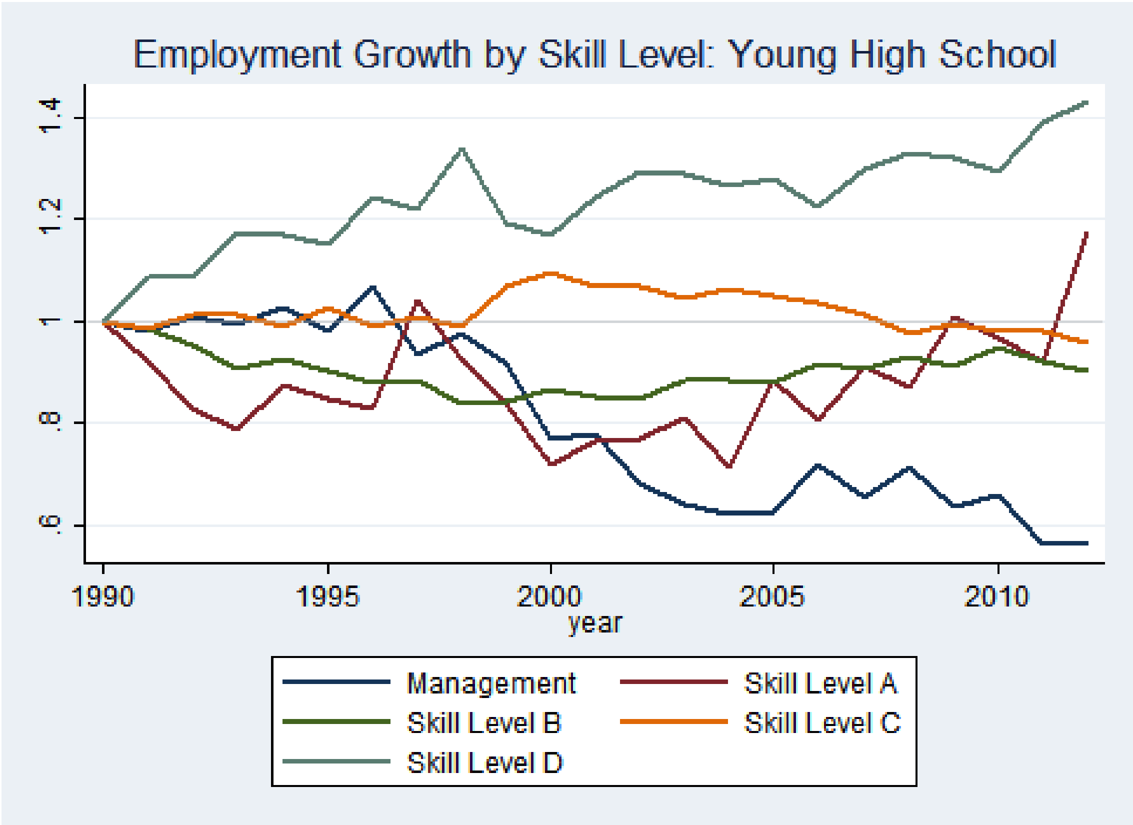
Source: author's calculations.

Figure 4



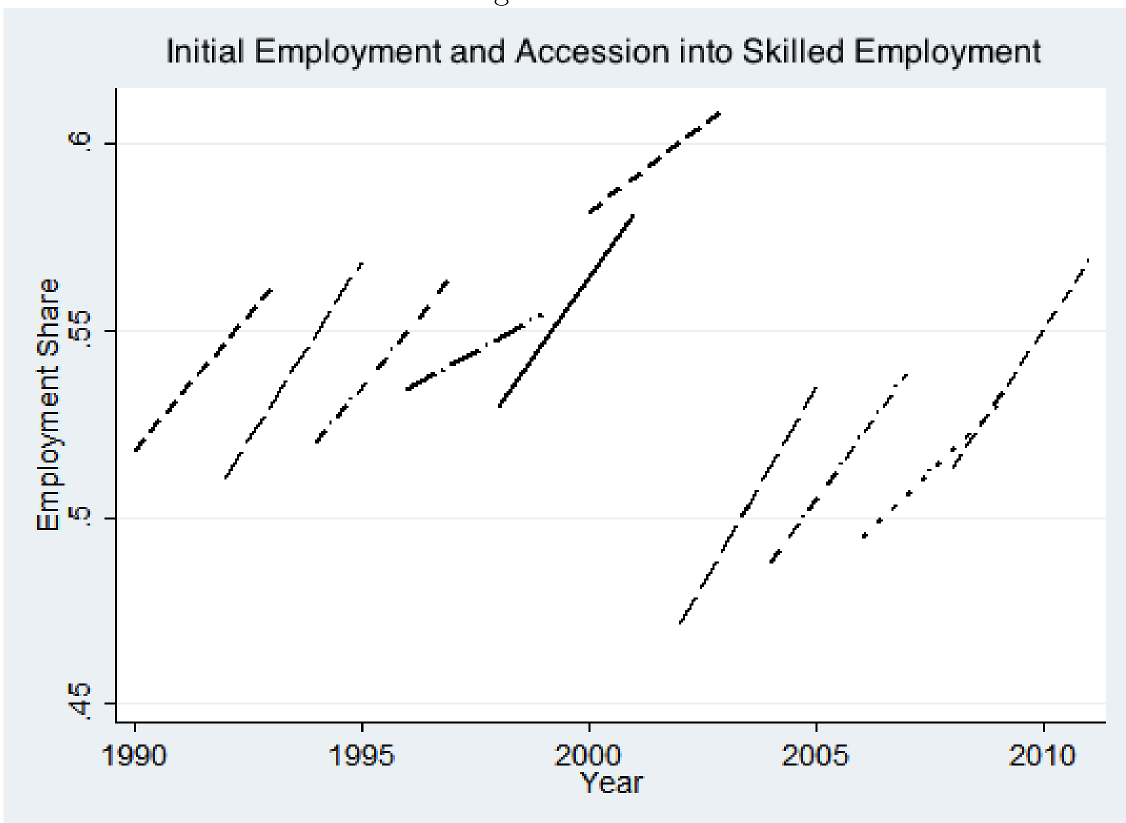
Source: author's calculations.

Figure 5



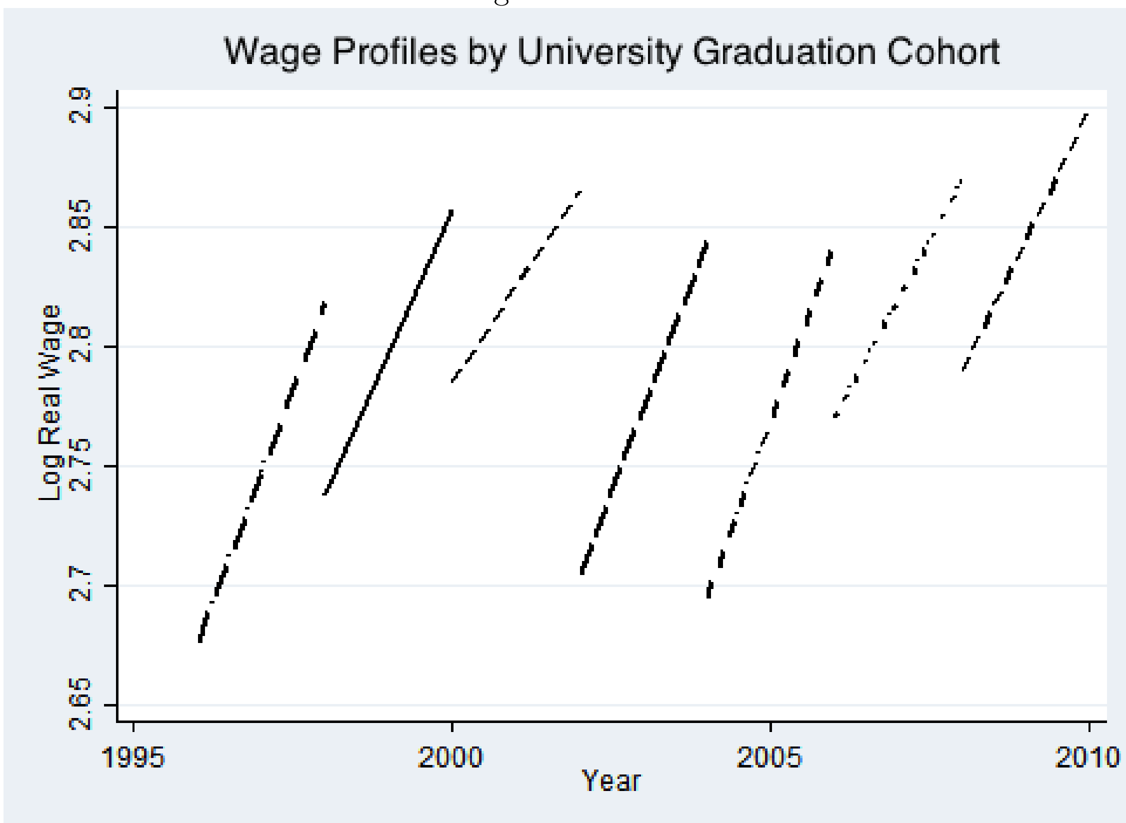
Source: author's calculations.

Figure 6



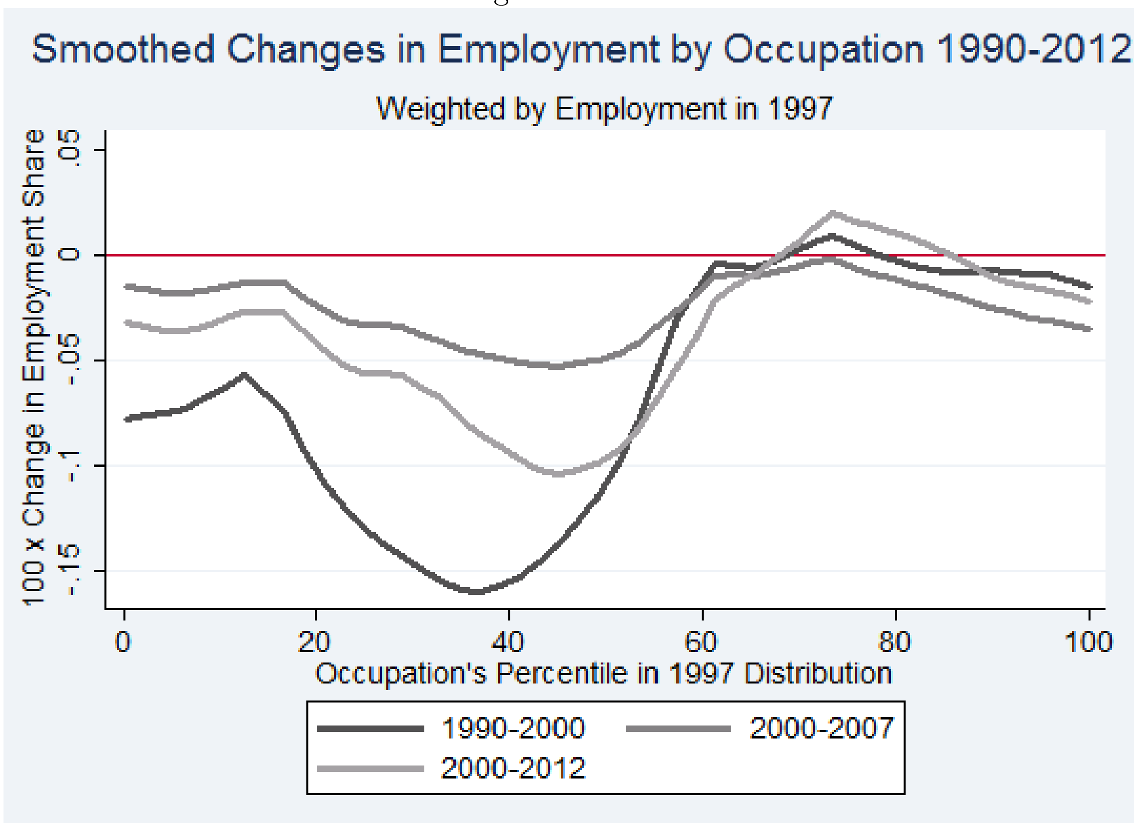
Source: author's calculations.

Figure 7



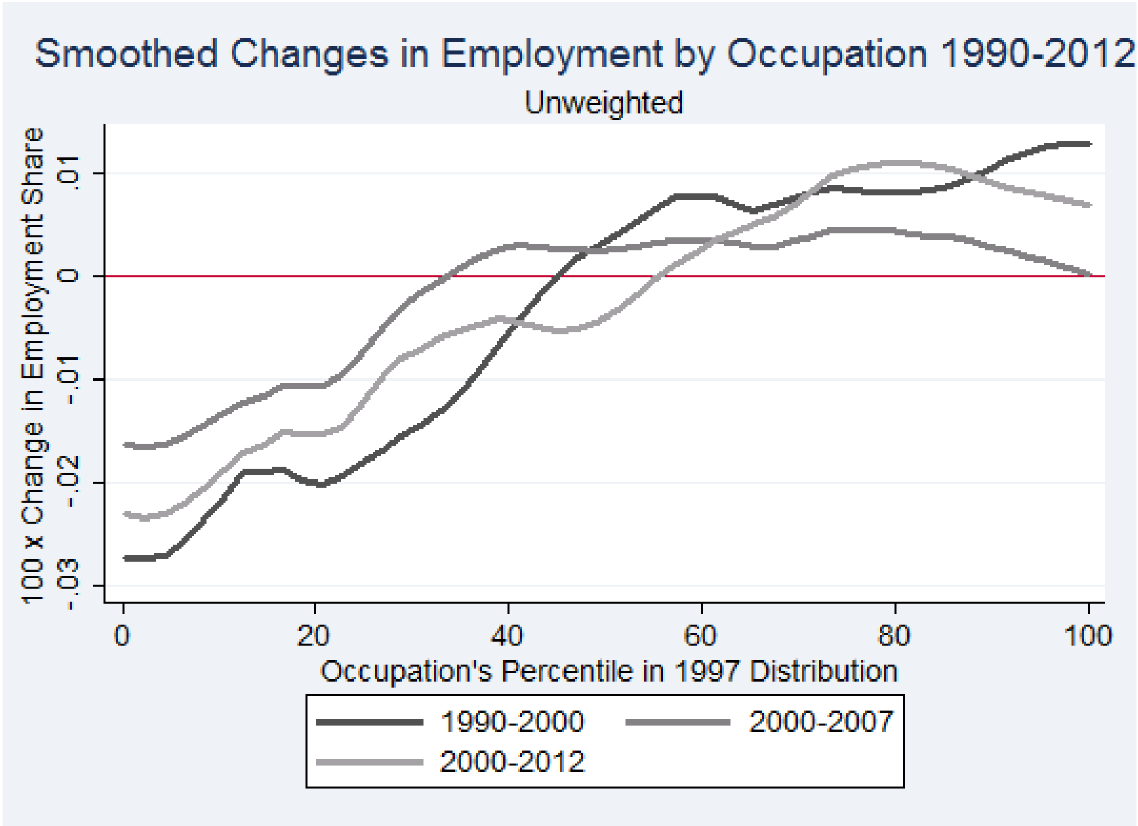
Source: author's calculations.

Figure 8



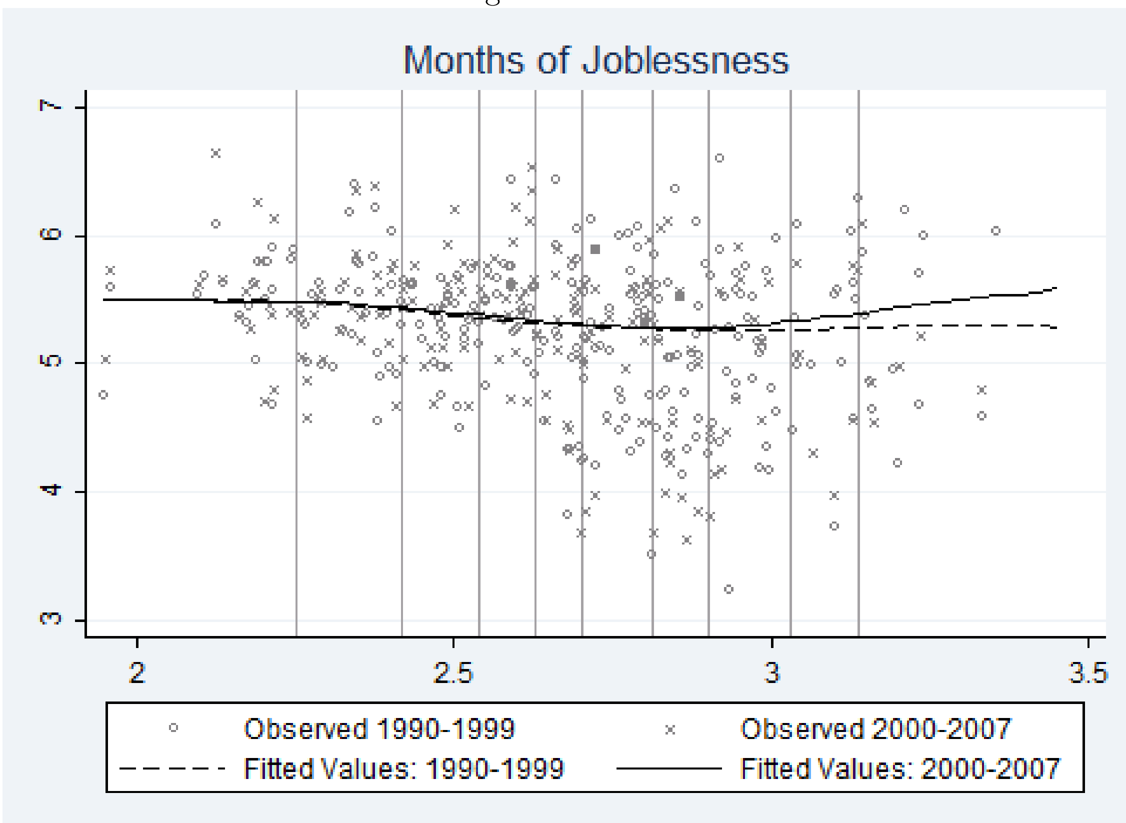
Source: author's calculations.

Figure 9



Source: author's calculations.

Figure 10



Source: author's calculations.

Figure 11

Source: author's calculations.

Figure 12

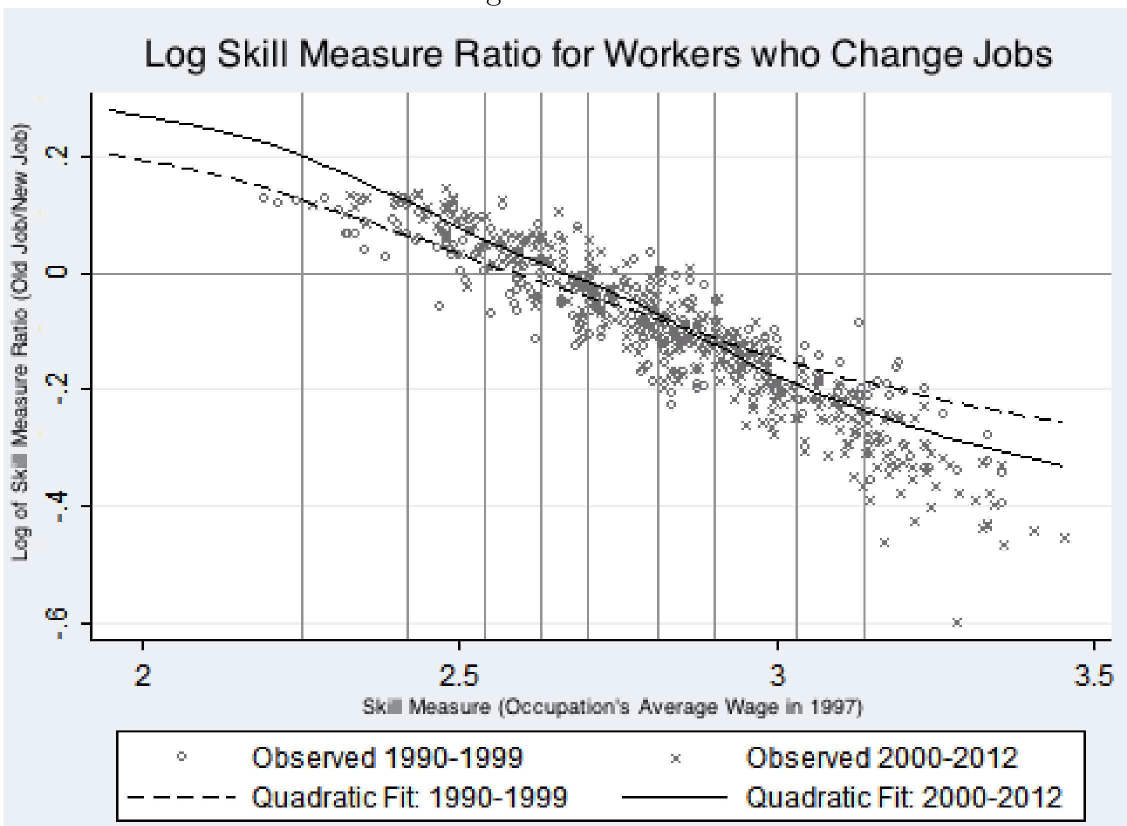


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Figure 13

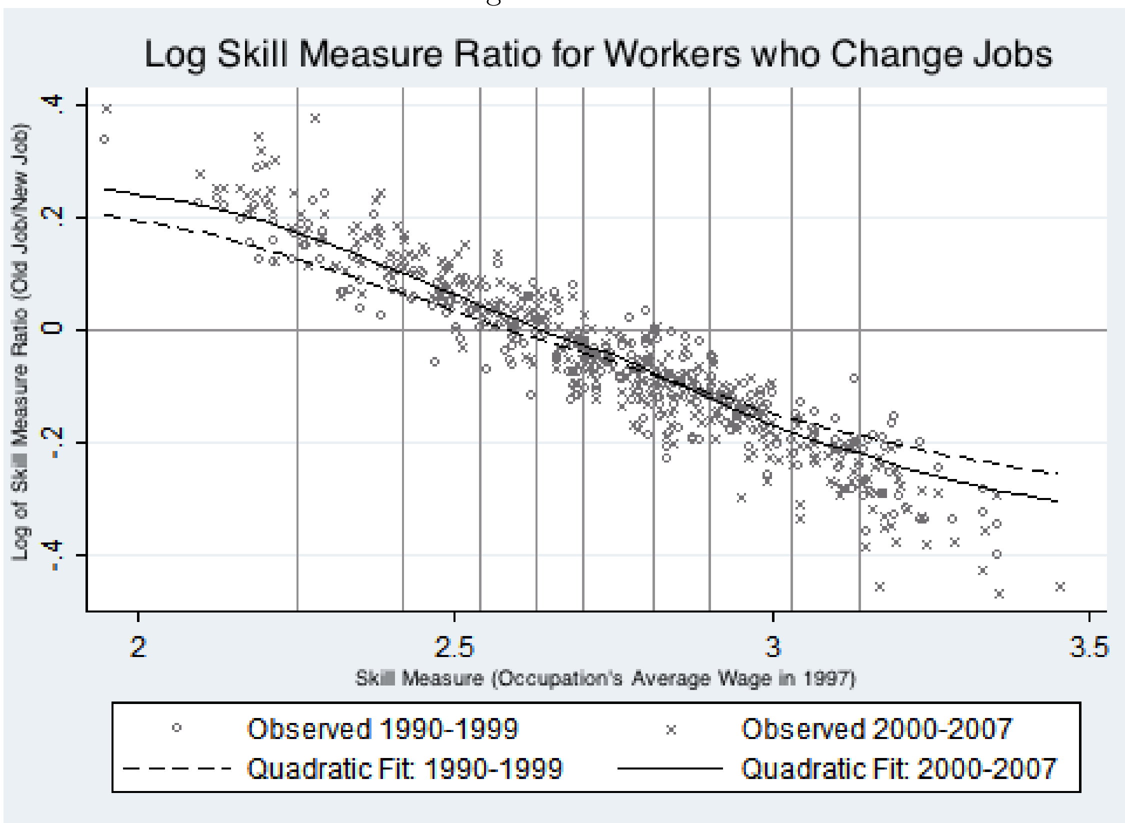

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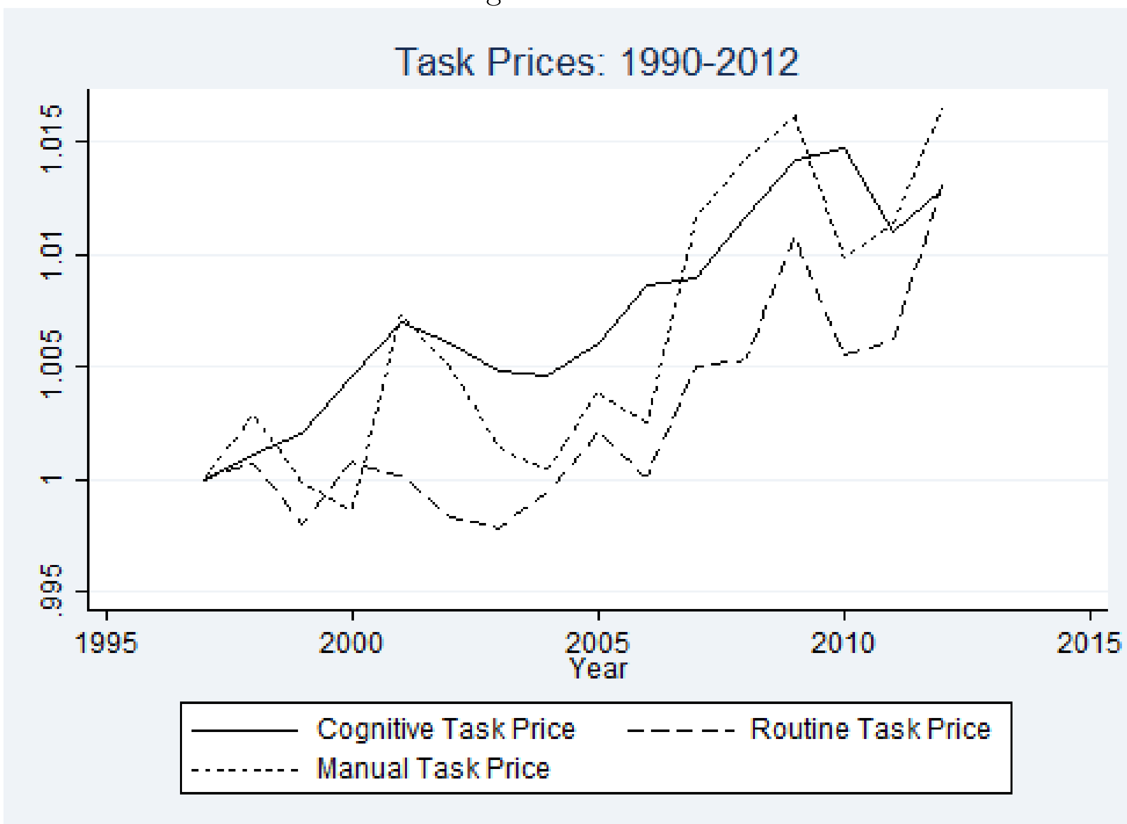
Figure 14



Source: author's calculations.

Table 1: Occupational Mean Wage in 1997 as a Skill Measure

NOC-S 2006	Ranking	Summary
G814	1	Babysitters, Nannies and Parents Helpers.
G311	5	Cashiers
D022	15	Chiropractors
G911	20	Hairstylists and Barbers
H713	50	Taxi and Limousine Drivers and Chauffeurs
I012	100	Agricultural Service Contractors
C125	150	Landscape and Horticulture Technicians and Specialists
J145	200	Paper Converting Machine Operators
I214	250	Mine Labourers
H412	300	Heavy-Duty Equipment Mechanics
C134	350	Construction Estimators
A113	400	Purchasing Managers
H721	450	Railway and Yard Locomotive Engineers
E111	500	University Professors
C011	520	Physicists and Astronomers

Source: Author's calculations.

Table 2: Probability of Transitioning between Skill Levels 1990-1999

	0	A	B	C	D
0	94.0	0.8	2.2	1.5	0.6
A	0.6	96.4	1.5	1.1	0.3
B	0.4	0.6	95.4	2.2	1.3
C	0.4	0.5	2.5	94.4	2.1
D	0.3	0.4	2.8	4.6	91.8

Source: author's calculations.

Table 3: Probability of Transitioning between Skill Levels 2000-2007

	0	A	B	C	D
0	89.5	2	4.5	3	1
A	1.1	92.2	3.4	2.6	0.7
B	1.0	1.4	91.3	4.35	2.0
C	0.7	1.1	4.6	90.2	3.2
D	0.5	0.8	5.1	7.7	85.8

Source: author's calculations.

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