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Changes in Hours Fluctuations Since the Mid-1980s: What Happened to Middle-Skilled Workers?

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Changes in Hours Fluctuations since the Mid-1980s: What Happened to Middle-Skilled Workers?[*,†]

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Abstract

We find that changes in hours volatilities since the mid-1980s have been *more* favorable for middle-skilled workers relative to high-skilled and low-skilled workers. In particular, the relative standard deviation of detrended employment of middle-skilled workers to high-skilled workers has dropped by half. This paper argues that the aggregate labor market that has become *less* favorable for middle-skilled workers at the low frequency had the opposite effects on them at the business cycle frequency. Using a firm model that matches the long-run trend of (1) the relative demand and (2) the relative wage for middle-skilled workers, we show that this simple model can explain about 40 percent of the changes in the relative employment volatility.

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1 Introduction

This paper examines the extent to which changes in hours volatilities since the mid-1980s were heterogeneous across skill groups and provide a theory to explain short-run and long-run changes in the labor market.[1] In so doing, we use the workers' (1) educational attainment and (2) occupation as proxies for their skill levels and divide them into three groups: "high-skilled," "middle-skilled," and "low-skilled" workers. Our finding indicates that the changes in employment volatilities are more *favorable* for middle-skilled workers than other skill groups. In particular, we find that between the subperiods 1979–1983 and 1984–2010, the employment volatility of middle-skilled workers compared to that of high-skilled workers decreased by about 45% when educational attainment is used for the classification of workers.[2] This finding on the short-run changes is interesting because the long-run changes of the labor market since the mid-1980s were in contrast *unfavorable* for middle-skilled workers: The relative wage and relative employment of middle-skilled to high-skilled workers have declined over time.

In this paper, we show how these two seemingly paradoxical observations can be reconciled with a simple firm model. To that end, we consider a model where middle-skilled workers perform only routine tasks while high-skilled workers perform only non-routine tasks, which is an assumption consistent with the job polarization literature (Autor and Dorn (2013) for instance). In addition, there is an information, communication, and technology (hereafter ICT) capital that is a relative substitute for middle-skilled workers and a relative complement to high-skilled workers. We first show that the secular decline of the price of ICT capital can generate an increasing trend for the relative wage and relative employment of high-skilled workers over middle-skilled workers, which are unfavorable labor market changes for the middle-skilled workers at the low-frequency. Interestingly, this model, which is widely used in the job polarization literature, can also generate the favorable labor market changes for the middle-skilled workers at the business cycle frequency: under our benchmark calibration strategy, about 40% of the

[1] In what follows, we use (total) hours and employment interchangeably since hours fluctuations at the business cycle frequency mostly come from employment fluctuations.

[2] The result is qualitatively and quantitatively the same when the latter period is extended to 2017. Results are available upon request.

observed changes in the relative employment volatility of middle-skilled to high-skilled workers can be explained by our model.

The intuition underlying our result is that the replacement of middle-skilled workers with ICT capital lowers the relative employment volatility of them, conditional on that the capital and hours comove at the business cycle frequency. Suppose that middle-skilled workers and ICT capital are perfect substitutes while high-skilled workers are perfect complements to the total routine inputs and ICT capital was not used at the beginning of the period due to its high cost. Thus, employment volatility was the same between the two groups at the initial period. More usage of ICT capital due to lower capital price will not affect employment of high-skilled workers so that employment volatility will not change that much for high-skilled workers. The overall volatility of the total routine inputs can be decomposed into volatility of the two inputs, and hence, more usage of ICT capital will decrease the volatility of middle-skilled workers than before. As a result, the lower demand for middle-skilled workers due to the routine-replacing technology changes (hereafter RRTC) seems to be beneficial for them at the business cycle frequency.

Our findings are important for two reasons. First, they enhance our understanding of the changes in employment volatilities that have occurred since the mid-1980s. For instance, Castro and Coen-Pirani (2008) find that the increase in the relative employment volatility of "skilled" workers to "unskilled" (middle-skilled and low-skilled in our classification) workers can be explained by the decline in "capital–skill complementarity" in production. Their argument is that as the degree of complementarity of skilled labor with capital declines, their employment becomes more volatile. However, our findings can be explained by RRTC: the changes in volatilities occur because the price of capital that replaces middle-skilled workers becomes cheaper, and not because of a decline in the importance of high-skilled workers in production.

Second, our study extends the insight of the "job polarization" literature from the long-run changes to short-run fluctuations by showing that the distinct behavior of the middle-skilled group has important implications for the cyclical properties of employment. In this sense, our paper is in line with the recent papers that connect job polarization and labor market fluctuations at the business cycle frequency (Jaimovich and Siu (2018); Foote and Ryan (2014); and Eden and Gaggl (2018) for instance). However, our paper has the unique contribution to show that the unfavorable long-run changes for the middle group can simultaneously have seemingly favorable effects on their employment fluctuations.

The remainder of this paper is organized as follows. In Section 2, we introduce the data and describe how we classify workers into three groups. We then present our main empirical findings in Section 3. In Section 4, we present the theory behind the findings reported in Section 3. In Section 5, we conclude the paper.

2 Data Description

2.1 Data We use two micro data sets, the March Current Population Survey (henceforth, CPS), an annual survey for the period 1975–2010 (for employment, it covers the period 1968–2010)[3], and the National Bureau of Economic Research (NBER) extracts of the CPS Merged Outgoing Rotation Groups (henceforth, MORG) for the period from January 1979 to December 2010.[4] The CPS is a monthly household survey conducted by the Bureau of Labor Statistics (BLS) to measure labor force participation and employment. The extracts contain a wealth of information about hours worked, earnings, occupation, and education for about 30,000 individuals each month and allow for nationally representative estimates when using sampling weights. In our analysis, we restrict the sample to individuals aged 16 to 64.[5] We exclude farmers and members of the armed forces. We also eliminate individuals from the sample if their earnings or hours worked are coded as zero or have a missing value.[6]

Following the method introduced in A.1, we construct monthly series for total hours worked and employment. We then seasonally adjust the aggregate monthly series by X-12 ARIMA. We also detrend each series by the Baxter–King filter, following Baxter and King (1999). We set

[3]Data were extracted from the IPUMS website: http://cps.ipums.org/cps (see King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, and Vick (2010)).

[4]Data were extracted from the NBER website: http://www.nber.org/data/morg.html.

[5]The results reported in Section 3 are robust when we restrict our sample to prime-age workers (aged 24 to 54).

[6]We assign actual hours worked in the previous week (*hourslw*) to usual hours (*uhours*) if data on usual hours are missing, following Castro and Coen-Pirani (2008), to avoid discontinuity in the series of hours worked between 1993 and 1994.

$\kappa = 12$ for the MORG data and $\kappa = 3$ for the March CPS data, where κ is the number of leads/lags used in the approximation. We set the lowest frequency at 6 quarters (2 years) and the highest at 32 quarters (8 years) for monthly data (yearly data). In this study, we mainly use the MORG data rather than the March CPS data because the frequency of the former is higher and the qualitative implications from the latter are almost identical to those from the former, as is reported in Section 3.

2.2 Classification of Groups We first use educational attainment as a proxy for skill, as usually used in the literature. Following Michaels, Natraj, and Reenen (2014), we classify workers as follows: 1. high-skilled workers are those with at least a college degree; 2. middle-skilled workers are those with a high school degree or some level of college study (short of obtaining a college degree); and 3. low-skilled workers are those with an educational qualification lower than a high school degree.[7]

We also use occupation as a proxy for skill. First, note that skill requirements vary across occupations. Consider a skill set $[\underline{s}, \bar{s}]$ of a worker where $\underline{s}$ denotes the lowest skill and $\bar{s}$ the highest skill. The usual interpretation is that the lowest skill is required to perform the least complex tasks, or manual tasks, the middle skill is required for routine tasks, and the highest skill is necessary for performing the most complex tasks, or cognitive tasks, corresponding to the classification of occupation groups usually employed in the job polarization literature (see Acemoglu and Autor (2011); Autor, Katz, and Krueger (1998); and Jaimovich and Siu (2018)). This categorization is introduced to supplement the possible misclassification problem from using only educational attainment. For instance, it is possible that a middle-educated worker is actually employed in a cognitive occupation and so she mainly utilizes her high (cognitive) skills, and not her middle skills. Hence, the actual skill level of a worker might deviate from his or her education level, and using information on occupation can supplement this classification.[8] A

[7]For a detailed classification by educational attainment, see A.1. Furthermore, in the Supplementary Online Appendix, we discuss why high school graduates are included in the middle-skilled group and not in the low-skilled group by applying two criteria for classification: (1) wage rate and (2) occupation.

[8]One can easily observe that education and occupation are highly correlated: about 70% of high-educated workers are employed in cognitive occupations, and about 65% of middle-educated workers are employed in routine occupations. Among low-educated workers, more than 30%, which is the greatest number across different

possible concern is that a worker's occupation changes over time but educational attainment mostly remains fixed and that hence occupation might not be a good measure for skill. Given that our focus is on the "aggregate" cyclical behavior of different skill groups, however, this is not problematic: we are interested in total hours or employment of different occupation groups at each point, which effectively summarizes the skills used by workers included in a specific group, and not how a specific worker changes his or her occupation over time.

3 Changes in Relative Hours Fluctuations since the Mid-1980s: Empirical Findings

In this section, we present key empirical findings. While we mainly use education as a proxy for skill, the subsequent analysis using occupation confirms the robustness of our findings. When dividing the sample period (1979–2010 in the MORG data, for instance) into two, we follow Castro and Coen-Pirani (2008), Galí and Gambetti (2009), Champagne and Kurmann (2013), and Galí and van Rens (2014) in having subperiods before and after 1984. In particular, we focus on the business cycle properties of the hours variables, including total hours worked and employment.

3.1 Education as Proxy for Skill Table 3.1 presents our main empirical findings on the relative standard deviations of the detrended total hours and employment series. Since the MORG data cover the period from 1979, the first subperiod is too short. Hence, as a robustness check, we perform the same exercise with the March CPS, whose first subperiod is longer than that of the MORG data: it covers the period from 1968 to 1983 for employment and from 1975 to 1983 for total hours. Results from the March CPS are reported in Table 3.2. Qualitatively, the observations are almost identical between the two data sets, and hence, the following discussions are based on the statistics reported in Table 3.1. We do not discuss the average hours worked here since their variation is not important at the business cycle frequency.

The key observation from the two Tables is summarized in Stylized Fact 1.

education groups, are employed in manual occupations.

Table 3.1: Relative Standard Deviations of Total Hours and Employment: MORG Data

		Middle/High	Middle/Low
	Total Hours	2.27	0.57
1979–1983	Employment	1.96	0.53
	Total Hours	1.25	0.45
1984–2010	Employment	1.03	0.41
	Total Hours	0.55	0.78
Ratio	Employment	0.53	0.76

Note: The last row shows the ratio of relative volatilities of each variable in the second period (1984–2010) to those in the first period (1979–1983).

Table 3.2: Relative Standard Deviations of Total Hours and Employment: March CPS

		Middle/High	Middle/Low
1975–1983	Total Hours	2.70	0.63
1968–1983	Employment	2.27	0.64
	Total Hours	0.78	0.31
1984–2010	Employment	0.86	0.33
	Total Hours	0.29	0.49
Ratio	Employment	0.38	0.51

Note: The last row shows the ratio of relative volatilities of each variable in the second period (1984–2010) to those in the first period (1979–1983).

Stylized Fact 1 (Relative Changes in Volatility since the Mid-1980s: Short-Run Fluctuations)**.** *Changes in hours volatility since the mid-1980s were more favorable for middle-skilled workers than for the high-skilled and low-skilled workers.*

From now on, we focus on the relationship between high-skilled and middle-skilled workers since they take more than 85% of the total employment. The above finding is interesting since it is well-known that the labor market changes at the low frequency have been less favorable for middle-skilled workers compared to high-skilled workers. Using the MORG data of the period between 1984 and 2010, we show this phenomenon graphically in Figure 3.1. Figure 3.1a (resp. Figure 3.1b) shows the trend of relative employment (resp. wage) of middle-skilled workers over high-skilled workers. Both measures imply that the relative demand for middle-skilled workers has declined over time. In other words, the aggregate labor market for the middle-skilled workers has become disadvantageous. Stylized Fact 2 summarizes the findings from Figure 3.1.

Stylized Fact 2 (Relative Labor Market Changes since the mid-1980s: Long-Run Trend)**.** *The labor market has changed unfavorably for the middle-skilled workers since the mid-1980s at the low frequency. In particular,*

- *The relative employment of middle-skilled to high-skilled workers has decreased.*
- *The relative wage of middle-skilled to high-skilled workers has decreased.*

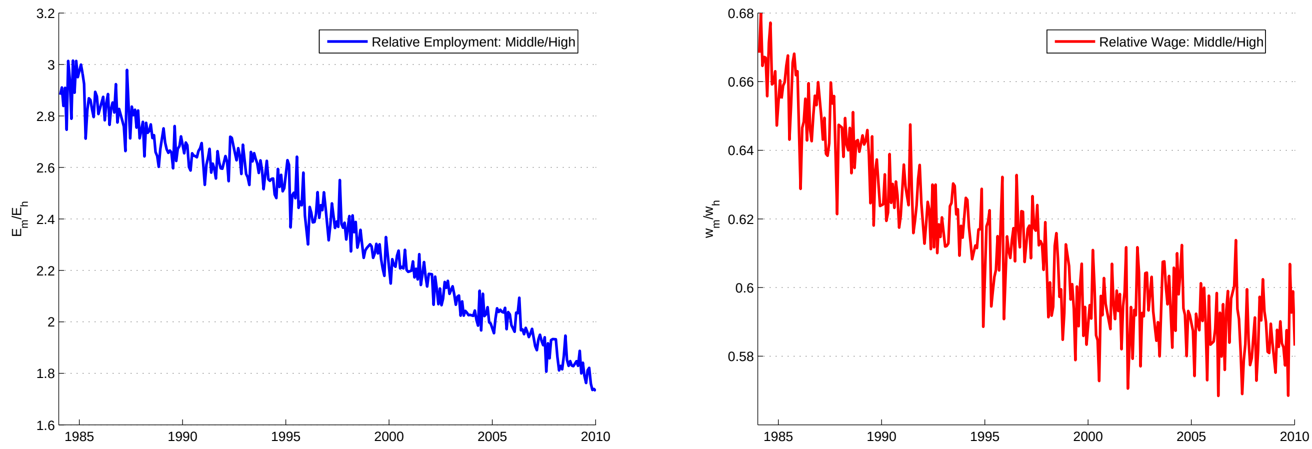

Figure 3.1a: Relative Employment

Figure 3.1b: Relative Wage

Figure 3.1: Unfavorable Long-Run Labor Market Changes for Middle-Skilled Workers
Data: CPS MORG

However, Stylized Fact 1 implies that while the long-run trend has become less favorable for middle-skilled workers than for other skill groups, the labor market changes have become more favorable for them in terms of hours volatility (i.e., at the business cycle frequency).

3.1.1 Robustness Check

In this section, we consider two sub-groups for the robustness check: (1) full-time workers;[9] and (2) male workers. First, we consider only full-time workers because part-time workers face relatively higher fluctuations than do full-time workers and because the fractions of part-time workers vary across categories of workers with different levels of educational attainment. Second, we consider only male workers because it might be expected

[9] They are defined as workers who work more than 35 hours per week.

that the hours fluctuations of female workers would exhibit more cyclicality than do the hours fluctuations of male workers, as female workers have higher elasticities of labor supply. Tables 3.3 and 3.4 show the results from the MORG data, which confirms the robustness of our main empirical findings in Table 3.1.

Table 3.3: Relative Standard Deviations of Total Hours and Employment: Full-Time Workers

		Middle/High	Middle/Low
1979–1983	Total Hours	2.41	0.60
	Employment	2.34	0.57
1984–2010	Total Hours	1.38	0.50
	Employment	1.33	0.48
Ratio	Total Hours	0.57	0.84
	Employment	0.57	0.84

Note: The last row shows the ratio of relative volatilities of each variable in the second period (1984–2010) to those in the first period (1979–1983).

Table 3.4: Relative Standard Deviations of Total Hours and Employment: Male Workers

		Middle/High	Middle/Low
1979–1983	Total Hours	2.49	0.68
	Employment	2.52	0.66
1984–2010	Total Hours	1.27	0.49
	Employment	1.09	0.46
Ratio	Total Hours	0.51	0.71
	Employment	0.43	0.70

Note: The last row shows the ratio of relative volatilities of each variable in the second period (1984–2010) to those in the first period (1979–1983).

3.2 Occupation as Proxy for Skill When categorizing workers into three groups by occupation, we follow Acemoglu and Autor (2011). Cognitive occupations include those in which cognitive tasks are performed; routine occupations, those in which routine tasks are performed; and manual occupations, those in which manual tasks are required.[10] To construct a consistent

[10] Non-routine cognitive occupations include managers; professionals; and technicians. Routine occupations include sales; office and administration; production, crafts, and repair; and operators, fabricators, and laborers. Non-routine manual occupations include protective services; cooking, building and grounds cleaning; and personal care and personal services. See Acemoglu and Autor (2011) or Autor (2010) for details.

occupation series, we use the method of "conversion factors," originally suggested by the Census Bureau but extended by authors.[11]

Table 3.5 reports the relative standard deviations of employment for each occupation group, which confirms the robustness of our earlier findings when educational attainment is used as a proxy for skill level.[12]

Table 3.5: Relative Standard Deviations of Employment by Occupation: MORG data

	Routine/Cognitive	Routine/Manual
1979–1983	2.15	1.65
1984–2010	1.52	0.96
Ratio	0.70	0.59

Note: The last row shows the ratio of relative volatilities of each variable in the second period (1984–2010) to those in the first period (1979–1983).

4 Understanding Labor Market Changes: Theoretical Consideration

Then what is the underlying mechanism behind our findings on the labor market changes for the middle-skilled group? In this section, we present a simple model that can explain both (1) unfavorable long-run changes and (2) favorable short-run changes of the aggregate labor market for middle-skilled workers. In principle, our model is the variant of the model suggested by Autor and Dorn (2013). Thus, our model is initially developed to explain long-run changes whereas we further show that the model can take the short-run changes into account by adding a stochastic shock (a productivity shock in particular).

4.1 Model In our model, we mainly focus on the problem of a representative firm producing final goods. This is because the long-run labor market changes are mostly driven by the demand side. Further, as discussed earlier, we consider only high-skilled and middle-skilled workers,

[11] See Shim and Yang (2016) for detailed discussions on the consistency of aggregate employment series for occupation groups.

[12] The March CPS with the extended first period shows similar results.

whose employment share in total is about 90% these days. We assume that all markets are perfectly competitive. The firm uses two types of tasks: routine tasks can be performed by either middle-skilled workers or ICT capital, while non-routine tasks can be performed only by high-skilled workers.[13] Moreover, there exists a capital-producing firm that supplies capital to the final goods-producing firm.

4.1.1 Capital-Producing Firm Capital is produced by a competitive firm that solves the following profit maximization problem:

$$\max p_{kt} k_t - y_t^I \tag{4.1}$$

subject to the linear technology

$$k_t = g(y_t^I) = \lambda_t y_t^I$$

where y_t^I denotes the final goods employed to produce capital and λ_t the productivity of producing capital from the final goods. We assume that λ_t increases exogenously over time and thus refers to RRTC in our model. The solution of the capital-producing firm can be given by

$$p_{kt} = \frac{1}{\lambda_t} \tag{4.2}$$

Hence, the price of capital is exogenously decreasing over time.

4.1.2 Final Goods-Producing Firm The final goods-producing firm solves the following profit maximization problem:

$$\max_{\{k_t, h_t, \tilde{h}_t\}} A_t h_t^{\alpha} \left(\tilde{h}_t^{\mu} + k_t^{\mu}\right)^{\frac{1-\alpha}{\mu}} - w_t h_t - \tilde{w}_t \tilde{h}_t - \underbrace{y_t^I}_{=p_{kt} k_t} \tag{4.3}$$

where $\mu \in (0, 1]$ and $\alpha \in (0, 1)$. h_t (resp. $\tilde{h}_t$) denotes the hours of high-skilled (resp. middle-skilled) workers and w_t (resp. $\tilde{w}_t$) is the corresponding wage rate. y_t^I is the amount of output

[13] Further inclusion of low-skilled workers in our model does not change the implications of our model.

devoted to obtain capital and A_t the total factor productivity (TFP), which is time-varying and the source of fluctuations in this economy. From the optimality condition of the capital-producing firm, $y_t^I = p_{kt}k_t$. We assume that capital fully depreciates in each period ($\delta = 1$).

The form of the production function used in this section follows that of the job polarization literature (see Autor, Levy, and Murnane (2003); Autor, Katz, and Kearney (2006); and Autor and Dorn (2013)). Here, the elasticity of substitution between high-skilled workers and total routine inputs is 1, while the elasticity of substitution between middle-skilled workers and capital is $\sigma \equiv \frac{1}{1-\mu} > 1$, since $\mu > 0$. Therefore, capital is a *relative substitute* for middle-skilled workers and a *relative complement* to high-skilled workers, and hence, capital in our model is ICT-type capital.

Equilibrium conditions of the firm are given as follows.

$$w_t = \alpha \frac{y_t}{h_t} \tag{4.4}$$

$$\tilde{w}_t = (1-\alpha)\frac{y_t}{\tilde{h}_t}\frac{\tilde{h}_t^{\mu}}{\tilde{h}_t^{\mu} + k_t^{\mu}} \tag{4.5}$$

$$p_{kt} = (1-\alpha)\frac{y_t}{k_t}\frac{k_t^{\mu}}{\tilde{h}_t^{\mu} + k_t^{\mu}} \tag{4.6}$$

To get an intuition about how the exogenous decline in the price of capital, p_{kt}, influences the relative demand for middle-skilled workers, we divide the equation (4.5) by (4.6):

$$\frac{\tilde{w}_t}{p_{kt}} = \frac{k_t}{\tilde{h}_t} \tag{4.7}$$

Fixing the wage rate of the middle-skilled workers, the capital–middle-skilled workers ratio would increase as the price of capital declines. This is the condition that is used to explain how the aggregate labor market has changed unfavorably for the middle-skilled workers in the long-run: the relative demand for middle-skilled workers decreased because the price of other production factors that can substitute for them has declined over time.

4.1.3 Supply of Labor To close the model, we assume that the labor supply of each type of worker is given as follows:

$$w_t = B_h h_t^{\psi} \tag{4.8}$$

$$\tilde{w}_t = B_m \tilde{h}_t^{\psi} \tag{4.9}$$

where $B_h > 0$ and $B_m > 0$ are constants and $1/\psi > 0$ represents the Frisch elasticity. Hence, the labor supply curves are upward-sloping in wage rates. The derivation of the labor supply curve is shown in A.2.

4.2 Intuition from Model In this section, we provide the main intuition in how our model can explain both long-run and short-run changes in the labor market observed from the data. In so doing, we assume the following production function for analytical tractability:

$$y_t = \min\{h_t, \tilde{h}_t + k_t\} \tag{4.10}$$

Hence, high-skilled workers are perfect complement to the total routine inputs while middle-skilled workers are perfect substitutes for capital, which is the limit case of the production function described in equation (4.3). Perfect substitutability between capital and middle-skilled workers indicates a tight restriction on the wage rate for middle-skilled workers (i.e., $p_{kt} = \tilde{w}_t$), whose implications on the long-run trend of the aggregate labor market are summarized in the following Proposition:

Proposition 1 (Long-run Changes in Labor Market)**.** *Suppose that p_{kt} declines and the demand for the final goods is the same over time (i.e., $y_t = \bar{y} > 0$). Then,*

1. *the relative wage of middle-skilled workers over high-skilled workers declines;*
2. *the relative demand for middle-skilled workers over high-skilled workers declines.*

In other words, the labor market changes unfavorably for the middle-skilled workers compared to high-skilled workers.

Proof. The proof directly follows from the fact that $p_{kt} = \tilde{w}_t$, equations (4.8) and (4.9). $\square$

As the price of capital declines, the wage rate for the middle-skilled workers should also decrease. Since we assume an upward-sloping labor supply curve (equation (4.9)), the lower wage implies that the supply of middle-skilled workers will decline. That is, the share of middle-skilled workers in the total routine input decreases as the usage of capital increases.

Now we can state the main finding of this paper in the next proposition.

Proposition 2 (Short-Run Changes in Labor Market)**.** *Suppose that p_{kt} declines from p_{k1} to $p_{k2} < p_{k1}$, where no capital is used under p_{k1} while capital is used p_{k2}. Let $vol(x)$ be the volatility of the variable x. Then,*

1. *Regardless of the price of capital, $\frac{vol(h_t)}{vol(y_t)} = 1$ for $t = 1, 2$.*
2. $\frac{vol(\tilde{h}_1)}{vol(y_1)} = 1 > \frac{vol(\tilde{h}_2)}{vol(y_2)}$ *as long as $cov(k, \tilde{h}) > 0$.*

As a result, the relative volatility of middle-skilled workers over high-skilled workers, $vol(\tilde{h}_t)/vol(h_t)$ becomes lower in period 2. In other words, the labor market changes favorably for the middle-skilled workers at the business cycle frequency.

Proof. The proof directly comes from $var(y_t) = var(\tilde{h}_t + k_t) = var(\tilde{h}_t) + var(k_t) + 2cov(k, \tilde{h})$. $\square$

Interestingly, and ironically, Proposition 2 comes from Proposition 1: before the decline in capital price, the fluctuations from output affected both high-skilled workers and middle-skilled workers equally. The relationship between employment volatility of high-skilled workers and volatility of output is not affected by the change in the price of capital since $y_t = h_t$ in the equilibrium. However, the level of employment for middle-skilled workers declines since capital has substituted these workers. As a result, some fraction of output fluctuations translates into the fluctuations of capital, which results in relatively low employment volatilites of middle-skilled workers in the second period. That is, the relative employment volatility of middle-skilled to high-skilled workers decreases as the demand for the middle group diminishes over time.

4.3 Main Results This section describes the main quantitative results from our model. We assume that fluctuations in this economy arise from the technology shock to the TFP, A_t, which follows the AR (1) process as follows:

$$\ln A_{t+1} = \rho \ln A_t + \varepsilon_{t+1} \quad \text{where} \quad \varepsilon_{t+1} \sim \mathbb{N}\left(0, \sigma^2\right) \tag{4.11}$$

We have 5 unknowns and 2 exogenous variable, p_{kt} and A_t, with 7 equations; hence, the model is fully specified. We first note that there is no balanced growth path in the current model since the model does not satisfy the condition for obtaining the properties of balanced growth path: either (1) the production technology takes the Cobb-Douglass form or (2) technology changes are labor-augmenting (see He and Liu (2008) for related issues). Therefore, our quantitative exercise in what follows will consider two economies with different steady-states: the first economy is with $p_{kt} = 7$ for all t and the economy fluctuates around the steady-state associated with $p_k = 7$. The second economy is with $p_{kt} = 1.5$ for all t and the economy fluctuates around the steady-state associated with $p_k = 1.5$. We choose the relative value of p_k to match the change in the skill premium $(w/\tilde{w})$ in the benchmark calibration: around 1.44 in the early 1980s and around 1.7 in 2000s. The chosen values for the price of capital are also consistent with data: Figure 4.1 plots the relative price of ICT capital to price index for personal consumption expenditures between 1979 and 2010 and it has dropped sharply over time.[14]

Table 4.1 summarizes the parameter values for the quantitative exercises. In particular, the parameter values are chosen to match (1) the relative employment of high-skilled over middle-skilled workers (about 0.32) and (2) the relative wage rate of high-skilled over middle-skilled workers (about 1.44) in the early 1980s (the average between 1979 and 1983) or chosen to be in line with the existing literature.

First of all, α is chosen to be consistent with Eden and Gaggl (2018) and Morin (2014) by taking into account that we do not consider low-skilled workers in the model: on average between 1979 and 2010, the labor income share of high-skilled workers in non-routine (high-skilled and

[14] The data are from the Bureau of Economic Analysis.

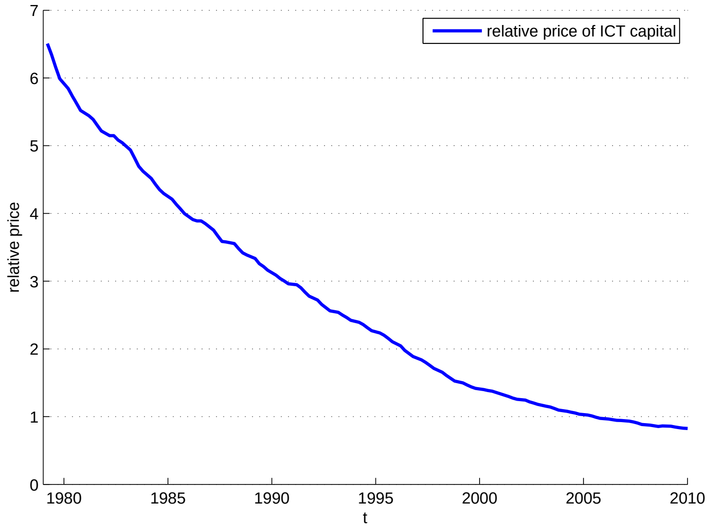

Figure 4.1: Relative Price of ICT capital

Table 4.1: Calibration

Parameter	Value	Description
α	0.30	High-skilled income share
ψ	2	Inverse Frisch elasticity
B_m	1	Utility parameter for middle-skilled workers
B_h	14	Utility parameter for high-skilled workers
μ	0.5	Elasticity between middle-skilled workers and capital is 2
ρ	0.97	AR (1) coefficient of TFP shock
σ_a	0.01	s.d. of TFP shock (normalization)

low-skilled) workers is 0.8 and the total non-routine share is about 0.38 so that $0.3 = 0.38 \times 0.8$. The Frisch elasticity is set to be 0.5 so that it is small enough to be comparable to the estimates in micro studies. The key parameter in the production function, μ, is set to be 0.5 so that $\sigma = 2$ in the benchmark experiment: this is also consistent with the estimate in Eden and Gaggl (2018). To our best knowledge, Eden and Gaggl (2018) is the only study that directly estimates the value of μ with the generalized method of moment (GMM) using the U.S. data: their estimated μ is about 0.47 and we use this value for the benchmark simulation. Since there is lack of consensus for μ, we change the value of μ from 0.4 to 0.55 so that the corresponding σ varies from 1.67 to

2.22 in the experiment.[15]

We note that while the model can match the change in the relative wage ratio between high-skilled and middle-skilled workers (an increase by about 20%), which is a target in calibration, the change in the relative employment in our model is much lower: it only increases to 0.35 in the second period while in the data it is about 0.5 during the 2000s. This mainly comes from our choice of low Frisch elasticity: even though the demand for middle-skilled workers decreases due to RRTC, the labor supply does not respond to changes in the wage rate much so that the relative employment of middle-skilled workers does not decline much. For instance, if ψ is assumed to be 1.5 so that the labor elasticity is about 0.7, there are very small changes in the labor supply elasticity, and thus, the relative employment becomes 0.37 in the second period, which is greater than the obtained value in the benchmark case.[16][17] We further discuss the implication of the change in ψ on the relative employment volatility below.

Table 4.2 presents the main results from our quantitative exercises.[18] We first focus on the results under the benchmark calibration with $\mu = 0.5$. In the data, the relative employment volatility of middle-skilled to high skilled workers dropped by about 45% when the MORG data are used (last row of the above table). When $\mu = 0.5$, our model implies that the relative employment volatility drops by about 20% from the first to the second period. Therefore, about 40% of the change in the relative employment volatility is explained by the change in the price of capital.

If ψ is set to be 1.5 and hence the Frisch labor elasticity is about 0.7 (0.2 higher than the benchmark case), the drop in the relative volatility is about 23%. That is, about 50% of the observed change is explained by the simple model. Hence, higher Frisch elasticity supports our results as one might expect since variability in hours is positively related to the labor supply elasticity. In this sense, the results in Table 4.2 can be interpreted as the lower bound.

[15]The lower bound of μ in our experiment corresponds to the value used in Morin (2014).

[16]Some parameter values are changed accordingly; $B_r = 1$, $B_c = 7.5$, and $p_k = 1.3$ in the second period to match the changes in the wage premium.

[17]If $\psi = 1$ so that the Frisch elasticity is one ($B_c = 4.4$ and $p_k = 5$ for the first period and $p_k = 1.15$ for the second period), the relative employment becomes 0.388 in the second period.

[18]We change parameters in each experiment: $B_r = 1.65$, $B_c = 19$, and $p_k = 1.9$ in the second period when $\mu = 0.4$, and $B_r = 1$, $B_c = 13.5$, and $p_k = 1.2$ when $\mu = 0.55$.

Table 4.2: Relative Employment Volatility ($\sigma_{\tilde{h}}/\sigma_h$) from Model

	$\mu = 0.4$	$\mu = 0.5$	$\mu = 0.55$
(1) Early 1980s ($p_k = 7$)	2.63	3.03	3.03
(2) 2000s ($p_k = 1.5$)	2.27	2.44	2.27
Ratio ((2)/(1)): Model	0.86	0.80	0.75
MORG data (Ratio)		0.55	

Results obtained by varying μ from 0.4 to 0.55 in the first and last columns of the table confirm that on average the relative employment volatility of middle-skilled to high-skill workers changes by about 20%. Therefore, our model, while it is very simple, can account for about 40% of the changes in the relative volatility observed from the data regardless of the chosen value for μ, which is the key parameter in the production function to differentiate the role of middle-skilled and high-skilled workers.

We now discuss the relationship between Castro and Coen-Pirani (2008)'s findings and ours. Castro and Coen-Pirani (2008) argue that the relative employment volatility of skilled (high-skill group in our paper) to unskilled workers (middle-skill and low-skill groups in our paper) has decreased since the mid-1980s because the "capital-skill" complementarity has declined. In our framework, the lower capital-skill complementarity can be interpreted as the situation where μ becomes low. As a result, the relative substitutability between (ICT) capital and middle-skilled workers (σ) decreases, which implies that the relative complementarity between capital and high-skilled declines.[19] Table 4.3 shows the results to evaluate their argument from our model.

In Table 4.3, we fix all the values of parameters with $p_k = 7$ but change values of μ in order to obtain the relative hours volatility of middle-skilled to high-skilled workers as a function of μ (first row). Then we reduce the value of p_k to 1.5 with different values of μ but other parameters are still fixed (second row). Hence, in these experiments the relative wage ratio between middle-skilled and high-skill groups is not intended to be matched to the data like the experiment in

[19] Their findings are not directly comparable to ours because treating mid-skilled and low-skilled workers as one group also provides incorrect information on the relative employment volatility (see Shim and Yang (2015)).

Table 4.2. The value in each parenthesis shows the ratio of the relative volatilities of each variable compared to the benchmark case with $\mu = 0.5$ and $p_k = 7$.

Table 4.3: Relative Employment Volatility ($\sigma_{\tilde{h}}/\sigma_h$): Interaction between μ and p_k

	$\mu = 0.3$	$\mu = 0.4$	$\mu = 0.5$
$\sigma_{\tilde{h}}/\sigma_h$ when $p_k = 7$ is fixed	2.63 (0.87)	2.86 (0.94)	3.03
$\sigma_{\tilde{h}}/\sigma_h$ when $p_k = 1.5$ is fixed	2.27 (0.75)	2.33 (0.78)	2.44 (0.80)

Suppose that the change in the price of capital is not considered in the model while the change in μ is taken into account. If μ becomes low from 0.5 to 0.3, the relative wage ratio between high-skilled and middle-skilled workers becomes about 1.7, and hence, it can explain the long-run changes in the wage premium.[20] Then, the change in the employment volatility from the benchmark case ($\mu = 0.5$ and $p_k = 7$) is about 13%, and hence, about 30% of the observed change can be accounted by the change in μ only. Therefore, Castro and Coen-Pirani (2008)'s argument is also valid in our framework while the degree of explanatory power of the model is lower than the benchmark case where p_k declines while μ is fixed.

In the second row, we further change the price of capital to 1.5, which is observed in the data as in Figure 4.1. In the extreme case where both μ and p_k decline, about 57% of the observed change in the relative employment ratio is explained by the model. However, in this case the wage ratio between high-skilled and middle-skill groups is about 2.12 so that it is too high compared to the data (about 1.70 during 2000s).

In summary, taking the possible change in μ into account together with the change in the price of capital can potentially improve the performance of the model to show that the unfavorable changes in the labor market for the middle-skilled workers at the low frequency can have opposite effects on them at the relatively short frequency.

[20] The relative employment ratio increases to about 0.35 hence consistent with our benchmark case.

5 Conclusion

This study shows that the decline in employment volatility is large for middle-skilled workers, while the changes in employment volatility for other workers are relatively small. Thus, the relative volatility of middle-skilled group to high-skilled workers has dropped by half since the mid-1980s, even though the relative demand for middle-skilled workers has declined over time. The findings of this study imply that unfavorable changes for some type of workers may seem to be beneficial for them if we take different views of data. In particular, the systematic labor market changes that have been disadvantageous for some workers, especially the middle-skilled group, can have seemingly favorable effects on them. One possible application of our findings is to study the implication of such changes on welfare costs of business cycles: Shim and Yang (2015) consider the "short-run" changes in hours fluctuations to study the heterogeneity in the welfare costs of business cycles across different skill groups. If a model that can simultaneously account for both long-run and short-run changes in the labor market is further used for such an analysis, it might provide better understanding of the relationship between the labor market changes and the welfare cost of business cycles.

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A Appendix

A.1 Aggregate Data Construction For classification by educational attainment, workers are divided into the following three groups. First, low-skilled workers are those who have not completed high school (less than 12 years of completed schooling before 1992; no high school diploma after 1992). Second, middle-skilled workers are those with a high school diploma or with some college education (12 years of completed schooling or between 13 and 15 years of completed schooling before 1992; a high school degree or a higher degree that is lower than a college degree after 1992). Last, high-skilled workers are those with at least a college degree (at least 16 years of completed schooling before 1992; a college or higher degree after 1992).[21]

The main variables of interest are constructed as follows:

1. *Employment*: In the CPS, individuals' employment status is determined on the basis of answers to a series of questions relating to their activities during the preceding week. Those who reported doing any work at all for pay or profit are classified as "employed." We aggregate employment by their education and occupation in a given month with their sampling weight:

$$Employment_{D,t} = \sum_{i \in D} \mathbf{1}_{i,t}^{employed} u_{i,t} \tag{A.1}$$

where $\mathbf{1}_{i,t}^{employed}$ indicates an individual's employment status, which equals 1 when individual i is employed at time t and 0 when she is unemployed. D is the individual's group category by education level or occupation. $u_{i,t}$ is the individual sample weight.[22]

[21] In 1992, the U.S. Census Bureau modified the CPS educational attainment code (*educ*). For years prior to 1992, *educ* reports the highest grade of completed schooling, whereas after 1992, it reports the highest degree or diploma attained.

[22] When aggregating individual data, we use the earnings weight (*earnwt*) that should be used in analyses of employment and hours/weeks worked as well as the earner study (covering weekly earnings and hourly wage).

2. *Total hours worked*: Total hours worked are calculated by aggregating the individual hours worked as follows.

$$TotalHours_{D,t} = \sum_{i \in D} h_{i,t} u_{i,t} \tag{A.2}$$

where $h_{i,t}$ is the weekly hours worked for individual i at time t.

3. *Total weekly income* and *average hourly wage*: Income wage indicates each respondent's total pre-tax wage and salary income.[23] We adjust for inflation using the Consumer Price Index prepared by the BLS, whose base year is 1982–1984. The hourly wage is calculated as total income divided by our measure of total hours.

A.2 Derivation of Labor Supply Curve

Suppose that each worker (middle-skilled and non-middle-skilled) i solves the following utility maximization problem.

$$\max_{\{c_{it}, b_{it+1}, h_{it}\}_{t=0}^{\infty}} \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \frac{\left(c_{it} - B_i \frac{h_{it}^{1+\psi}}{1+\psi} \right)^{1-\gamma} - 1}{1-\gamma} \right] \tag{A.3}$$

subject to

$$c_{it} + b_{it+1} = w_{it} h_{it} + (1 + r_{bt}) b_{it} + \pi_t$$

where the utility function is assumed to take the Greenwood–Hercowitz–Huffman (GHH) preferences form as in Greenwood, Hercowitz, and Krusell (1988), b_{it+1} is the bond that workers trade with other workers, r_{bt} is the interest rate of the bond, and π_t is the profit from the firm, which is 0 in the equilibrium. Then, it is easy to derive the labor supply function of worker i, which is $w_{it} = B_i h_{it}^{\psi}$ (no wealth effect).

[23] We use *earnwke* for weekly earnings, and this measure is top-coded in the CPS. We impute top-coded earnings by multiplying the top-coded values in the sample by 1.3, following Castro and Coen-Pirani (2008).

B Supplementary Online Appendix: Who Are Middle-Skilled Workers?

In this section, we provide two reasons that high school graduates are middle-skilled workers when educational attainment is used for the classification of workers. First, the average hourly wage rate of high school graduates is more like that of workers with some college education. Another way to make the point is to use the information on workers' occupation. Following Acemoglu and Autor (2011), we consider three groups of occupations (jobs) and provide evidence that the patterns of jobs held by high school graduates are more like those held by workers with some level of college education than those held by high school dropouts.[24]

B.1 Hourly wage rate One way to divide workers into three groups is to use information on hourly wage rates. Suppose that a worker's productivity increases in her intrinsic skill level. Then, a high (low) wage rate reflects the high (low) skill of a worker. Figure B.1 plots the hourly wage rate of workers with some college education, high school graduates, and high school dropouts.[25]

Two features in Figure B.1 are noteworthy. First, the level of the hourly wage of workers with a high school degree is closer to that of workers with some college education than it is to the hourly wage of workers who are high school dropouts. Second, the trend of the hourly wage of workers with some college education and that of those who are high school graduates show similar patterns: they are stable over time. In contrast, the hourly wage rate of high school dropouts shows a decreasing trend over time. These two findings together indicate that it is more appropriate to combine in one classification workers with some college degree and those with a high school diploma.

[24] Though not reported here explicitly, the unemployment rates of high school graduates and workers with some college education exhibit similar patterns and this finding also supports our classification strategy.

[25] Workers with a college degree or more are not reported for the sake of simplicity of presentation of the figure. The average hourly wage rate for this group during 1979–2010 is about $12.75, which is much higher than for the other groups, so that it is natural to classify these workers as high-skilled workers. In addition, it is strictly increasing in time, which is consistent with previous findings on the rise of the college premium.

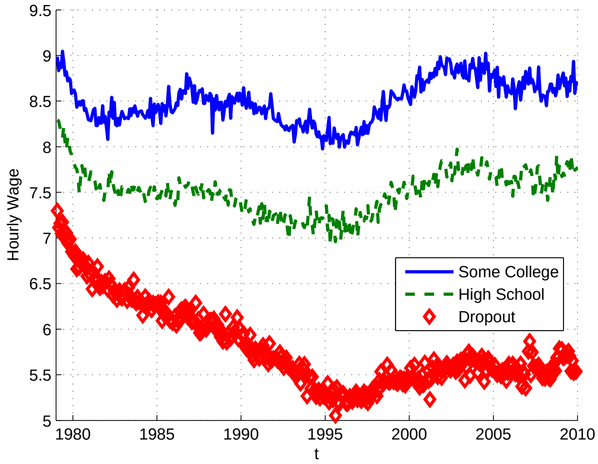

Figure B.1: Hourly Wage Rate

B.2 Occupational Status In this section, we use the workers' occupation information instead of their wage information. The idea is that workers with different levels of educational attainment are classified in the same skill group if their jobs are similar. Occupation groups are defined as discussed in Section 3 and occupation data are constructed through "the occ1990dd classification," which is suggested by Dorn (2009).[26] We compute the proportion of workers with specific levels of education who are employed in a specific occupation as depicted in Figures B.2 to B.4. In each figure, the solid blue line is the proportion of workers with a college degree or higher, the dotted green line is the proportion of workers with some college education, the red star line is the proportion of high school graduates, and the light blue circle line is the proportion of high school dropouts.

It is evident from the figures that workers with a college degree and high school dropouts are high-skilled and low-skilled workers, respectively. First, more than 70% of workers with a college degree or higher are employed in cognitive occupations, making it natural to define these workers as high-skilled workers. While we classify the dropouts as low-skilled workers, it is noticeable that about 65% of them are employed in routine occupations, as can be seen from Figure B.3.

[26]The occ1990dd classification is not a perfect way to construct consistent aggregate data as discussed in Shim and Yang (2016). For the purpose of this section, however, it does not matter whether we use the occ1990dd classification or the method of conversion factors provided by the Census Bureau.

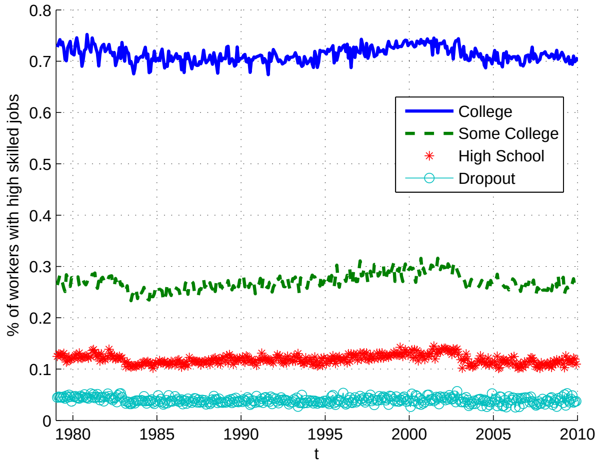

Figure B.2: Composition: Cognitive Occupations

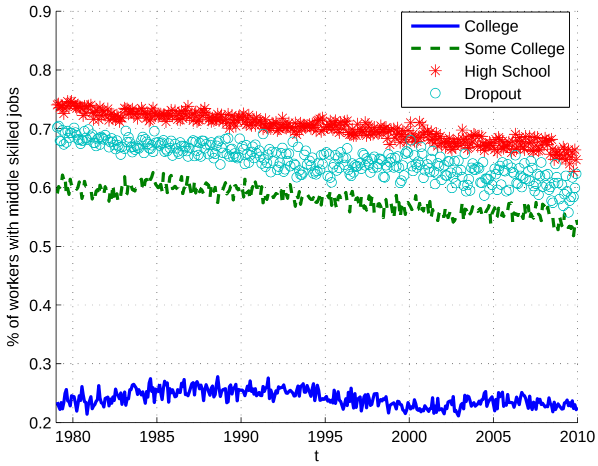

Figure B.3: Composition: Routine Occupations

These workers are low-skilled workers because relatively large fractions (about 25–40%) of them are employed in manual occupations, and this statistic is much higher than it is for the other education groups (Figure B.4).

While Figure B.3 shows a similar pattern across workers with some college education, workers with a high school diploma, and workers who dropped out of high school, it is evident from Figure B.4 that among workers employed in manual occupations, the proportion of those with some college education is similar to that of high school graduates. If high school graduates were

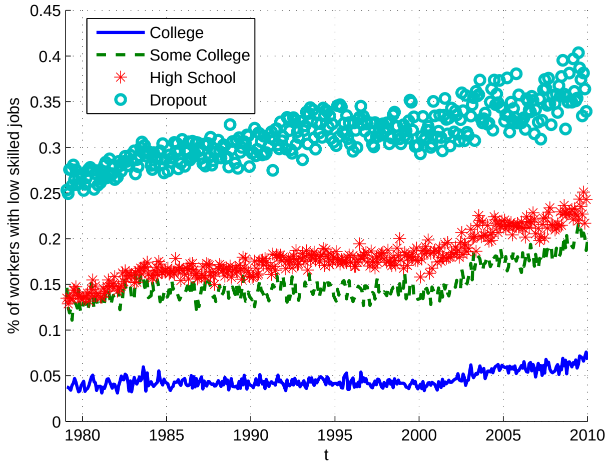

Figure B.4: Composition: Manual Occupations

included in the low-skilled group, the proportion of high school graduates with manual occupations would have to be similar to that of high school dropouts. As Figure B.4 shows, however, this is not the case. This is even more apparent if we focus on the employment level of each educational group in routine occupations as in Figure B.5. Note that the employment of workers with some college education and those with a high school diploma in routine occupations reaches similar levels over time, while the employment of high school dropouts in routine occupations shows a different pattern. Hence, whether we use wage information or occupation information, it seems natural to include high school graduates in the middle-skill group rather than in the low-skill group.

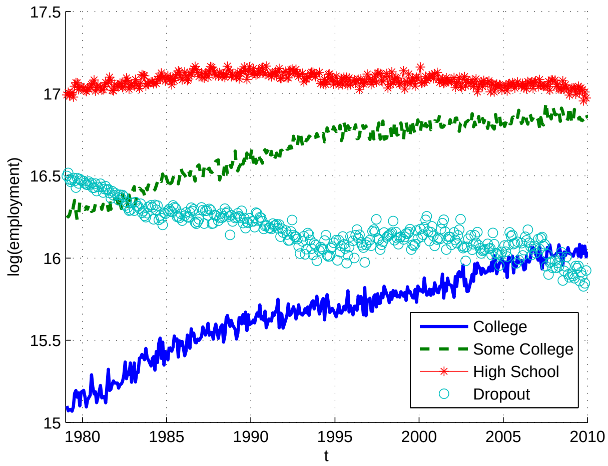

Figure B.5: Employment: Routine Occupations