Jobless Recoveries and Skill-Biased Sectoral Shift

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Abstract

This study models jobless recoveries based on two stylized facts indicating a skill-biased sectoral shift. This shift features the service sector having more college workers and becoming more productive than the goods sector. A two-sector model is built where the shift is incorporated via a sector-specific labor adjustment cost and a reallocation shock. The model successfully generates a jobless recovery.

Keywords: jobless recovery; sectoral shift; reallocation shock; labor adjustment cost

JEL: E24; E32

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I. Introduction

The recovery of employment in the U.S. has been painfully slow after each post-1990 recession; high unemployment persists long after the rebound of total output. This is the so-called "jobless recovery" phenomenon. The present study intends to explain jobless recoveries from a sectoral perspective using both empirical evidence and a structural model.

First, I establish two stylized facts using Integrated Public Use Microdata Series – Current Population Survey (IPUMS-CPS): (1) in contrast to the goods sector, college workers have predominated in service sector workforce since 1990; (2) skill premium has risen faster in the service sector than in the goods sector. Fact 1 suggests that more skilled workers have managed to join the service sector. Fact 2 suggests that the employment of skilled workers has made the service sector more productive than the goods sector. I define these two features as skill-biased sectoral shift (SBSS). I propose that SBSS prevents unskilled workers laid off in the goods sector from relocating to the service sector. Thus, it takes longer for unemployed goods sector workers to find jobs, delaying the recovery of aggregate employment.

Second, I build a two-sector model to generate a jobless recovery given the stylized facts. Particularly, the baseline model has zero labor adjustment cost and is only subject to an aggregate productivity shock. Then the SBSS is incorporated into the baseline model via two elements. Fact 1 implies that rising educational barrier has made it more costly for unemployed goods sector workers to find jobs in the service sector. Thus, the first element is a sector-specific labor adjustment cost. Fact 2 implies greater productivity gains from hiring skilled labor in the service sector than in the goods sector. Thus, the second element is a reallocation shock making productivity higher in the service sector relative to the goods sector while keeping aggregate productivity intact. The baseline model is calibrated using the post-1990 data. The SBSS-embedded model adopts the baseline calibration, making SBSS the sole differentiating factor. Simulation shows a jobless recovery only in the SBSS-embedded economy.

For a model to generate a jobless recovery, it needs a mechanism that decouples the movements of output and employment. The combination of reallocation shock and adjustment cost provides this mechanism. The reallocation shock makes labor more productive in the service sector relative to the goods sector, raising output and employment in the former while reducing both in the latter. The service sector in the calibrated model has a bigger production share of total output than the goods sector. Thus, the rise in service sector output overwhelms the fall in goods sector output, and total output increases. Meanwhile, the adjustment cost makes it harder for labor to move from the goods to the service sector. Thus, the fall in goods sector employment overwhelms the rise in service sector employment, and aggregate employment decreases. As a result, a rise in total output is accompanied by a fall in aggregate employment.

The rest of the paper is organized as follows. Section II relates this study to the existing literature. Section III provides empirical evidence on jobless recoveries and SBSS. Section IV outlines a two-sector model, Section V details my calibration, and Section VI describes the simulation results. Section VII discusses some of the model implications and presents empirical evidence supporting the sectoral explanation. Section VIII concludes.

II. Related Literature

Linking sectoral shifts to the cyclicality of the aggregate labor market is not a novel approach (Lilien 1982; Abraham and Katz 1986). Compared to service sectors, recessions tend to hit goods sectors harder and result in higher sectoral unemployment. Since it takes time for an unemployed worker in one sector to find a job in another sector, aggregate unemployment stays high for a long time. The following are some of the studies that have revisited this sectoral explanation for the recent jobless recoveries.

Groshen and Potter (2003) define structural change as the permanent job relocation from one industry to another. Using payroll data from seventy industries, they show that structural change has been intensifying in the U.S. since the early 1990s, causing jobless recoveries.[1] Andolfatto and MacDonald (2006) use a two-sector model to show that a slowly-diffusing technological shock favoring one sector can induce a jobless recovery when combined with time-consuming job search.[2] Garin et al. (2013) define reallocation shock as a shock that raises productivity of one sector relative to another but leaves aggregate productivity intact. They build a two-island model in which the reallocation shock during a recession motivates workers in the relatively less productive island to move to the relatively more productive island. However, these workers have to experience a long period of unemployment before they can join production on the other island, generating a jobless recovery.

This paper complements the above studies. First, it provides empirical evidence to support the presence of reallocation shocks. A widening skill premium gap implies greater productivity gains in the service sector than in the goods sector. Second, this paper suggests a potential cause of the reallocation shock. The service sector starts to have more college workers than the goods sector, raising productivity in the former relative to the latter. Last, this paper proposes a two-sector model that generates jobless recoveries. Admittedly, a reallocation shock is used to break the co-movement of output and employment. My model considers workers of different skills and uses micro-founded adjustment costs to delay intersectoral labor relocation. In Andolfatto and MacDonald (2006) and Garin et al. (2013), skill variation is absent and a mandatory period of unemployment is used to prevent a quick employment recovery.

In addition, this paper regards SBSS as a promising theory but does not claim that it fully explains jobless recoveries. In fact, many studies have given alternative explanations. For example, Koenders and Rogerson (2005) qualitatively generate a jobless recovery using a model in which organizations wait till recessions to eliminate the excess labor they hoard during

[1] Aaronson et al. (2004) argue against their finding.

[2] They also present a non-sectoral model with costly human capital accumulation and show that a technological shock of the same nature can induce a jobless recovery. Thus, sectoral shifts are only a necessary condition for generating a jobless recovery.

long expansions.[3] Bachmann (2012) attributes jobless recoveries to the trade-off between a firm's intensive margin (hours worked) and extensive margin (number of workers). Shimer (2012) shows how wage rigidity and weak aggregate demand can cause jobless recoveries. Though I do not compare my explanation with these others, Section VII offers some empirical evidence in favor of the sectoral explanation.

III. Empirical Evidence

A. Jobless recovery

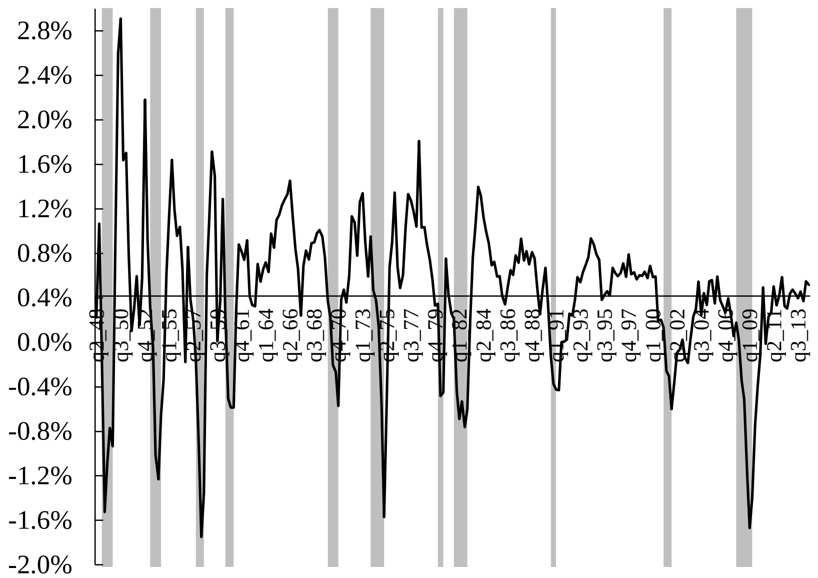
Aggregate employment in the U.S. has taken much longer to recover after each post-1990 recession. The Current Employment Statistics (CES) survey shows that total non-farm employment took at most two quarters to return to its end-of-recession level before 1990 but at least six quarters after 1990 (see Table 1). To adjust for population growth, Table 1 also reports the recovery timeline of per capita non-farm employment (i.e., total non-farm employment over all civilian non-institutionalized individuals aged 16 years and older). It took per capita non-farm employment at most six quarters to return to its end-of-recession level before 1990 but at least eleven quarters after 1990. Figure 1 plots the quarterly growth rate of total non-farm employment from 1948 to 2014. The rate came back and rose above the 0.4% mean immediately after a recession prior to 1990. Such quick recoveries were absent for the three recent recessions.

Table 1 Total Non-farm Employment Recovery Timeline

NBER recession	# of quarters to recover to end-of-recession level	
	aggregate	*per capita*
1948Q4 – 1949Q4	1	1
1953Q2 – 1954Q2	2	3
1957Q3 – 1958Q2	1	1
1960Q2 – 1961Q1	1	1
1969Q4 – 1970Q4	1	6
1973Q3 – 1975Q1	2	4
1980Q1 – 1980Q3	1	1
1981Q3 – 1982Q4	1	2
1990Q3 – 1991Q1	6	11
2001Q1 – 2001Q4	10	has not returned
2007Q4 – 2009Q2	8	20

[3] Berger (2012) develops a general equilibrium version of the model and studies its quantitative nature.

Figure 1 Total Non-farm Employment Quarterly Growth Rate, 1948–2014



B. Skill-biased sectoral shift

Fact 1: *In contrast to the goods sector, college workers have predominated in service sector workforce since 1990.*

According to the Bureau of Labor Statistics, the goods sector consists of mining, construction, and manufacturing. The service sector consists of transportation, utilities, trade, financial activities, and other services. In 1968, the IPUMS-CPS started to report the industry where the respondent worked in the previous year. Following Autor et al. (2008), I restrict my sample to full-time employees aged 18 to 64. I define a person who has completed no more than 12 years of schooling as attaining a non-college education (i.e., high school dropouts and high school graduates) and at least 13 years of schooling as attaining a college education (i.e., some college and college plus).

Figures 2 and 3 show the weighted percentage of workers by their educational attainment in the goods and the service sector, respectively.[4] Before 1990, most workers in the

[4] Frazis and Stewart (1996) report that the CPS changed its educational attainment questions in 1992. The previous questions were: "What is the highest grade or year of regular school [the respondent] has ever attended?" and "Did [the respondent] complete the grade?" In 1992, these two questions were replaced with one single question: "What is the highest level of school [the respondent] has completed or the highest degree has received?" The CPS provides a recoded variable EDUC that combines the pre- and post-1992 questions to bridge the break in the series. Figures 2 and 3 show that the break is still visible even with the use of the recoded variable. However, the change of

two sectors had non-college education. After 1990, college-educated workers started to predominate in service sector workforce and this trend has since proven resilient. Though the percentage of college workers has been rising in the goods sector, it was not until 2007 that these workers finally predominated in their sectoral workforce.

Figure 2 Goods Sector Workforce by Education, 1968–2014

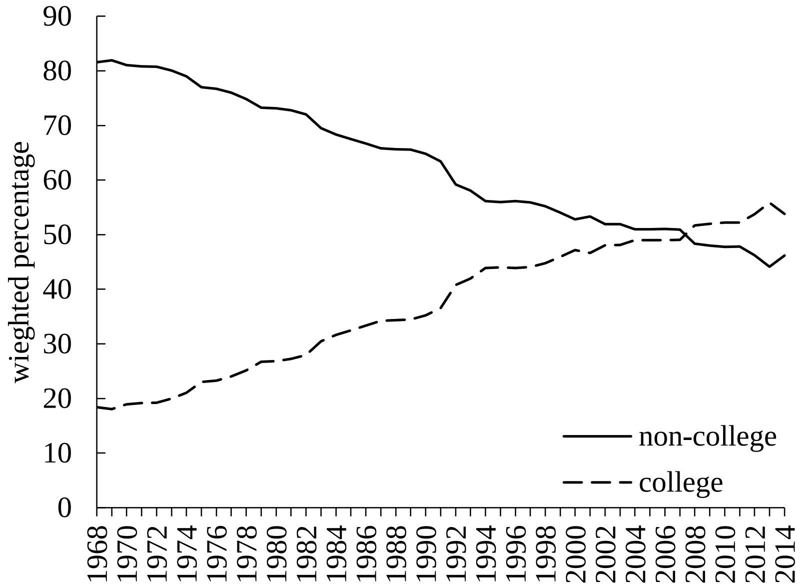
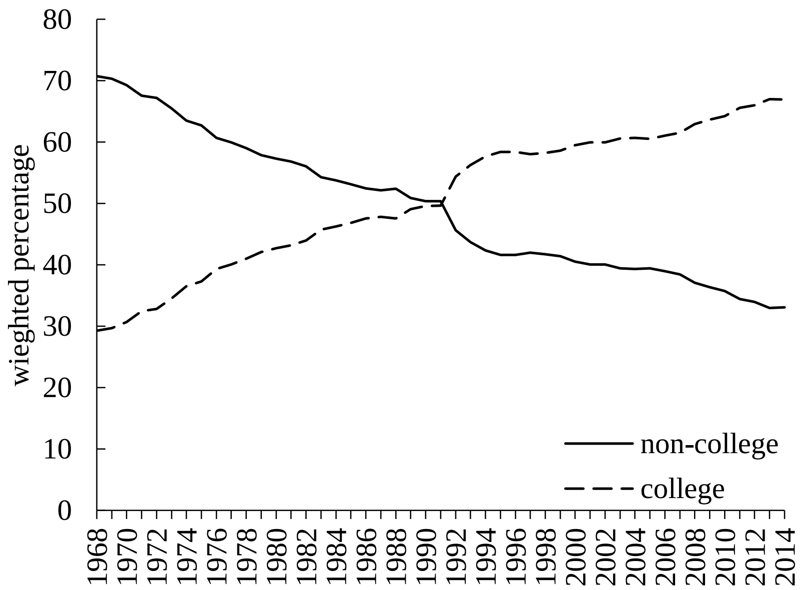


Figure 3 Service Sector Workforce by Education, 1968–2014



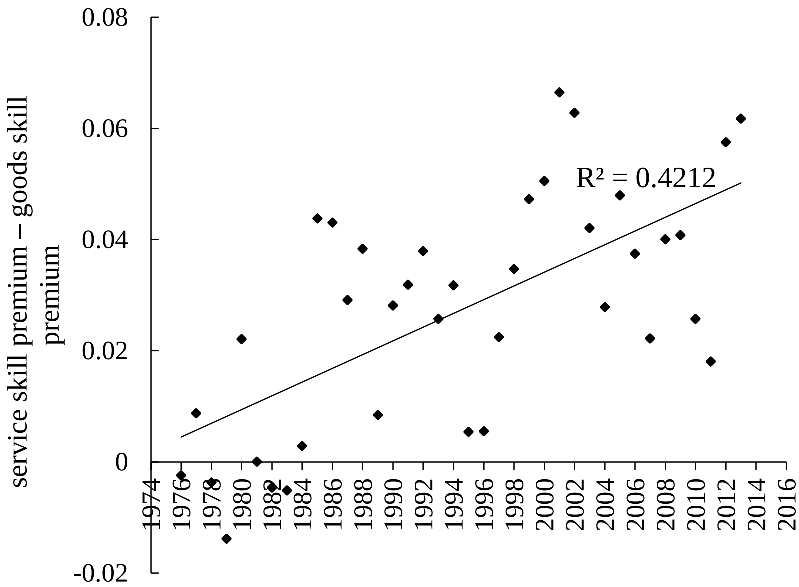
questions applies to both sectors and the long-run trend is the main focus here, so the conclusion drawn from the comparison between the two sectors should still be valid.

Fact 2: *Skill premium has risen faster in the service sector than in the goods sector.*

I use the same sample as in Fact 1 to compute the sectoral skill premium, but the number of weeks and hours per week worked last year were unavailable until 1976. I calculate hourly wage as a respondent's last year total pre-tax wage income divided by the product of weeks worked last year and usual hours worked per week. The hourly wage is then normalized to the 1999 U.S. dollar. The skill premium within a sector is computed as the log difference between the mean hourly wage of college workers and that of non-college workers.

Figure 4 shows a widening cross-sector skill premium gap, indicating higher wages for skilled workers in the service sector relative to the goods sector. Thus, college workers in the service sector are more productive than their goods sector counterparts.

Figure 4 Cross-Sector Difference in Skill Premiums, 1976–2014



Taken together, Fact 1 implies that more skilled (college) workers than unskilled (non-college) workers have managed to join the service sector, and Fact 2 implies that the service sector has had greater productivity gains than the goods sector from hiring skilled workers. These two facts define SBSS and assert its growing presence in the post-1990 U.S. economy.

IV. Model

The economy has one representative household and two sectors. Each sector has a representative firm. The two sectors are denoted as *g* for goods and *s* for services. There are two types of labor, denoted by 0 for unskilled and 1 for skilled. No labor can change its type, and only unemployed labor can switch sectors. A quadratic cost has to be paid to move labor across sectors. All newly-moved labor joins production in the following period.

A. Law of motion for labor

Let $i \in \{0,1\}$ denote labor type and $j \in \{g,s\}$ denote sector. Since labor participation decision is not a main focus, the total amount of labor type *i* in the economy, L_i, is set as a parameter.[5] Let n_{ji} be the amount of labor type *i* employed in sector j. Let u_i be the sum of labor type *i* unemployed in both sectors. Let m_{ji} be the fraction of unemployed labor type *i* that is moved to sector *j* and becomes employed there in the following period. The representative household chooses m_{ji} by solving an optimization problem detailed in Subsection E. Lastly, each labor type is subject to an exogenous sector-specific separation rate, χ_{ji}. The law of motion for labor, where an apostrophe denotes the next period, is:

$$n_{ji}^{'} = \underbrace{(1-\chi_{ji})n_{ji}}_{\text{still employed in sector } j} + \underbrace{m_{ji}u_i}_{\text{amount of unemployed who got moved to sector } j} \tag{1}$$

$$u_i^{'} = \underbrace{\sum_j \chi_{ji} n_{ji}}_{\text{seperated in sector } j} + \underbrace{(1-\sum_j m_{ji})u_i}_{\text{amount of unemployed who did not get moved}} \tag{2}$$

$$L_i = \sum_j n_{ji} + u_i \tag{3}$$

$$1 = L_0 + L_1 \tag{4}$$

B. Timing

[5] It is worth noting that sectoral shifts can affect labor participation decisions. For example, Lee (2004) finds that the decline of agriculture is linked to the fall of older males' labor participation rate in Korea.

There are two shocks: an aggregate total factor productivity (TFP) shock and a reallocation shock. At the beginning of each period, the two shocks hit the economy. After seeing both shocks, firms make their production decisions and pay wages to the employed labor. The household then chooses how much of unemployed labor to move to each sector for next period's production. At the end of the period, all exogenous labor separations are realized.

C. Final good production

Let y_j denote the intermediate good produced by sector *j* and p_j denote the price of the good. The final good, *Y*, is produced for the household to consume by a representative final good firm using the two intermediate goods. The production technology is

$$Y = (\alpha^{\frac{1}{\rho}}(y_g)^{\frac{\rho-1}{\rho}} + (1-\alpha)^{\frac{1}{\rho}}(y_s)^{\frac{\rho-1}{\rho}})^{\frac{\rho}{\rho-1}}, \tag{5}$$

where α is the production share of sector-g's good and ρ is the elasticity of substitution between the two intermediate goods.

The final good firm makes zero profit and its optimal demand for each intermediate good, given that the final good price is normalized to one, can be expressed as follows.

$$y_g = \frac{\alpha Y}{(p_g)^{\rho}} \tag{6}$$

$$y_s = \frac{(1-\alpha)Y}{(p_s)^{\rho}} \tag{7}$$

D. The intermediate good firm's problem

The representative firm in sector *j* hires both labor types 0 and 1. Since employment is the main focus, the model abstracts capital from production and assumes labor as the only input. Specifically, a standard Cobb-Douglas production technology is assumed for both sectors:

$$y_j = z\epsilon_j (n_{j0})^{\nu_j} (n_{j1})^{1-\nu_j}, \tag{8}$$

where z is the aggregate TFP, ϵ_j is the sector-specific productivity, and ν_j is the production share of labor type 0 in sector j.

Let Z denote the set including all aggregate states, namely $Z = \{z, N_{g0}, N_{s0}, N_{g1}, N_{s1}\}$, where N_{ji} is the aggregate labor type i employed in sector j. The state variables for the firm are ϵ_j and Z. Let w_{ji} denote the sector-specific wage for labor type i. The firm's problem can then be formulated in a recursive manner:

$$J(\epsilon_j, Z) = max_{\{n_{j0}, n_{j1}\}} \quad p_j y_j - w_{j0} n_{j0} - w_{j1} n_{j1} + \mathbb{E}_{z'} d(Z, Z') \cdot \mathbb{E}_{\epsilon'_j} J(\epsilon'_j, Z') \tag{9}$$

subject to:

$$0 \le n_{ji} \le L_i, \qquad i \in \{0,1\}.$$

Here, $d(Z, Z')$ is the firm's discount factor consistent with the household's problem below.[6]

E. The household's problem

The representative household values consumption and leisure. In each period, it chooses its current consumption and next period's labor supply, taking the prevailing wages as given. The household also pays quadratic labor adjustment costs and collects the profits from the intermediate good firms. The household's problem is formulated in a recursive manner.

$$V(n_{g0}, n_{s0}, n_{g1}, n_{s1}, Z) = \max_{\{c, m_{ji}, n'_{ji}\}} \log(c) - \psi(n_{g0} + n_{s0} + n_{g1} + n_{s1}) + \beta \mathbb{E}_{Z'} V(n'_{g0}, n'_{g1}, n'_{s0}, n'_{s1}, Z') \tag{10}$$

subject to:

$$0 < c \le \sum_{j,i} w_{ji} n_{ji} - \underbrace{\sum_{j,i} (\frac{\phi_{ji}}{2} m_{ji}^2) n_{ji}}_{\text{quadratic cost}} + \sum_j \Pi_j$$

$$0 \le m_{ji} \le 1, \text{ and } (1) - (4).$$

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[6] $d(Z, Z') = \frac{\beta U'(c(Z'))}{U'(c(Z))}$, where β is the household's discount factor and $U'(c)$ is the marginal utility of consumption.

Here, Π_j denotes intermediate good firm j's profit. Also, n_{ji} represents the extensive margin (employment), so this model has no intensive margin (hours of work).

As mentioned earlier, the labor adjustment cost is motivated by Fact 1. Goldin and Katz (2007) identify changes in the educational attainment of the workforce, comparable to Fact 1, as affecting the supply of skills. Therefore, it is more appropriate to have the household face the adjustment cost. Also, given the model's general equilibrium setting, variations in wage and productivity still affect labor demand despite zero adjustment cost for the firms.

F. Equilibrium prices

To close the model, equilibrium prices of intermediate goods, p_j, clear the goods market. Specifically, for the final good:

$$Y = c + \sum_{i,j} (\frac{\phi_{ji}}{2} m_{ji}^2) n_{ji} \tag{11}$$

where Y satisfies (5), $j \in \{g, s\}$, and $i \in \{0,1\}$. For intermediate goods, y_g and y_s are produced using technology (8), and satisfy (6) and (7) respectively.

Equilibrium wages, w_{ji}, clear the labor market. Specifically,

$$n_{ji}^h = n_{ji}^f \tag{12}$$

where n_{ji}^h is the amount of labor the household supplies and n_{ji}^f is the amount of labor the intermediate good firms demand.

V. Calibration

The model has a quarterly frequency. The household's discount rate is set $\beta = 0.99$, corresponding to a 4% annual real interest rate. The labor disutility, ψ, is set to 0.33.

A. Labor market

Labor market parameters are calibrated using the available 1990–2010 IMPUS-CPS monthly data. As in Section III, all industries are divided into two groups: goods and services. Non-college workers are labor type 0 and college workers are labor type 1.

Following Shimer (2005), the monthly labor separation rate is calculated as:

$$\chi_{ji,t} = \frac{u_{ji,(t+1)}}{e_{ji,t}(1-\frac{1}{2}\sum_j f_{ji,t})}$$

where $e_{ji,t}$ is the number of type *i* workers employed in sector *j* at month *t*, $u_{ji,t}$ is the number of type *i* unemployed workers at month *t* whose last job was in sector *j*, and $f_{ji,t}$ is the fraction of type *i* unemployed workers who found a job in sector *j* at month *t*. I compute $f_{ji,t} = \left(e_{ji,(t+1)} - e_{ji,t}\right) / \left(\sum_j u_{ji,t}\right)$. After obtaining the monthly separation rates, I calculate their quarterly averages and set χ_{ji} to the mean of these quarterly averages. Specifically, $\chi_{g0} = 0.09$, $\chi_{g1} = 0.08$, $\chi_{s0} = 0.06$, and $\chi_{s1} = 0.04$.

To calculate type *i* labor force, I first compute $\tilde{L}_{i,t} = \sum_j e_{ji,t} + \sum_j u_{ji,t}$, so $\tilde{L}_{i,t}$ is the actual number of workers. Assuming a constant population of one, I then calculate $L_{i,t} = \tilde{L}_{i,t} / \left(\sum_i \tilde{L}_{i,t}\right)$. Finally, after obtaining the monthly labor force data, I compute their quarterly averages and set L_i to the mean of these quarterly averages. Specifically, $L_0 = 0.44$ and $L_1 = 0.56$.

Based on Fact 1, I assume zero cost for unemployed labor to move across sectors in the baseline model (i.e., $\phi_{ji} = 0$). For the SBSS-embedded model, I choose the value of ϕ_{ji} based on the mean job finding rate for labor type *i* in sector *j* (i.e., the mean of quarterly averages of monthly $f_{ji,t}$). Specifically, I set $\phi_{g0} = 1.0$, $\phi_{g1} = 2.0$, $\phi_{s0} = 3.0$, and $\phi_{s1} = 12.0$ given that $f_{g0} = 0.01$, $f_{g1} = 0.02$, $f_{s0} = 0.03$, and $f_{s1} = 0.12$.

B. Production

To calibrate production parameters, I use the 1990–2013 industry value added data in current dollars from the Bureau of Economic Analysis (BEA), together with the IMPUS-CPS. The industry value added data are only available annually.

The labor type 0 income share of sector j 's total output determines ν_j. Thus, I first obtain sector j 's nominal output at year t, $y_{j,t}$, from the industry value added data. Following the procedure outlined in Fact 2, I use the IMPUS-CPS to compute the mean nominal hourly wage for labor type i in sector j at year t, $w_{ji,t}$. Assuming 40 work hours per week (1,920 hours per year), I calculate $\tilde{\nu}_{ji,t} = (1920 \cdot w_{ji,t} e_{ji,t}) / y_{j,t}$. Further assuming that production only involves these two labor types, I let $\nu_{j0,t} = \tilde{\nu}_{j0,t} / (\tilde{\nu}_{j0,t} + \tilde{\nu}_{j1,t})$. Finally, I set ν_j to the mean of $\nu_{j0,t}$. Specifically, $\nu_g = 0.49$ and $\nu_s = 0.36$.

For final good production, I set $\rho = 2.0$ based on Broda and Weinstein's (2006) estimate of 2.2 for the median elasticity at the three-digit sector level. Assuming that the economy only has two sectors, I set $\alpha = 0.23$ to the goods sector's share of aggregate value added.

C. Shocks

The same IPUMS-CPS and value added data are used to calibrate shock processes. I first retrieve non-detrended sectoral Solow residuals:

$$y_{j,t} = \underbrace{z_t \epsilon_{j,t}}_{A_{j,t}} (e_{j0,t})^{\nu_j} (e_{j1,t})^{1-\nu_j}, \qquad \text{and}$$

$$\underbrace{\log Z_t + \log \epsilon_{j,t}}_{\log A_{j,t}} = \log y_{j,t} - \nu_j \log\left(e_{j0,t}\right) - (1-\nu_j) \log\left(e_{j1,t}\right).$$

As illustrated above, the time trend of TFP (i.e., Z_t) and the time trends of two sector-specific productivities (i.e., $\epsilon_{j,t}$) are not separately identifiable. Hence, a normalization is needed.

Specifically, I assume that the sector-*g* productivity $\epsilon_{g,t}$ equals one. The aggregate TFP shock Z_t and the reallocation shock ϵ_t can then be computed as:

$$\log Z_t = \log y_{g,t} - \nu_g \log(e_{g0,t}) - (1-\nu_g)\log(e_{g1,t})$$

$$\log \epsilon_t = \log A_{s,t} - \log A_{g,t} = \log \epsilon_{s,t} - \log \epsilon_{g,t} = \log \epsilon_{s,t}.$$

Given the normalization, the reallocation shock is equivalent to sector-*s* productivity.

The next step is to detrend $\log Z_t$ and $\log \epsilon_t$ using a time trend and run a separate AR(1) regression on each:

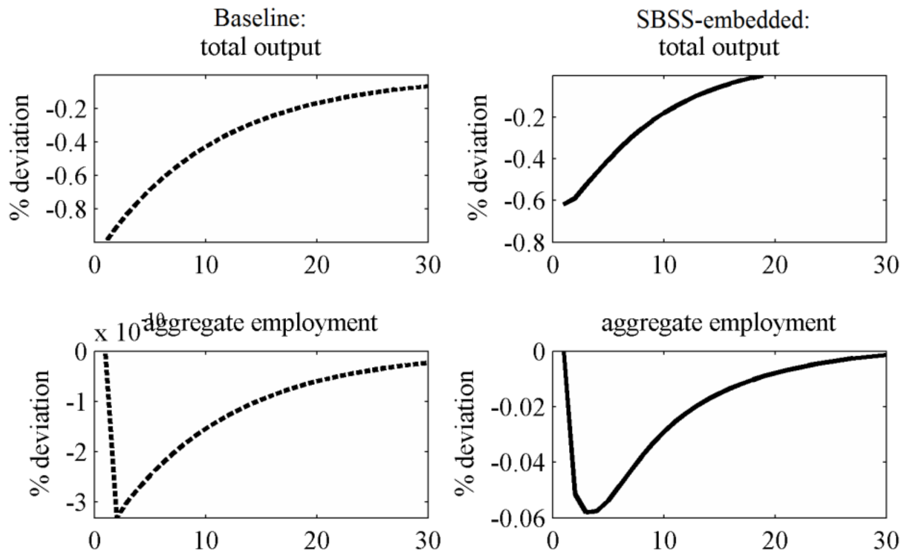
$$\log Z_t = 0.69 \log Z_{t-1} + u_{z,t}$$
$$\log \epsilon_t = 0.86 \log \epsilon_{t-1} + u_{\epsilon,t}$$

where $\sigma_z^2 = 0.003$ and $\sigma_\epsilon^2 = 0.001$ are the variances of innovations. Since the value added data have an annual frequency, the quarterly persistence is computed as $\rho_z = 0.69^{0.25} = 0.91$ and $\rho_\epsilon = 0.86^{0.25} = 0.96$. The quarterly variances of innovations are $\sigma_z^2 = 0.0082^2$ and $\sigma_\epsilon^2 = 0.0043^2$. Appendix A details the adjustment procedure for the variance. Also, $u_{z,t}$ and $u_{\epsilon,t}$ are assumed to be independent and move in opposite directions, making sector-*s* productivity higher relative to that of sector-*g* during a recession. Motivated by Fact 2, I assume no reallocation shock and keep the same aggregate TFP shock process for the baseline model.

VI. Simulation Results

Figure 5 shows the impulse responses of total output (i.e., *Y*) and aggregate employment (i.e., $N = \sum_{ji} n_{ji}$) to a negative aggregate TFP shock for both baseline and SBSS-embedded cases. The left panel indicates the baseline economy where total output and aggregate employment recover simultaneously. The right panel indicates the SBSS-embedded economy where aggregate employment recovers more slowly than total output. Thus, only the SBSS-embedded model generates a jobless recovery.

Figure 5 Impulse Responses: Baseline vs. SBSS-embedded

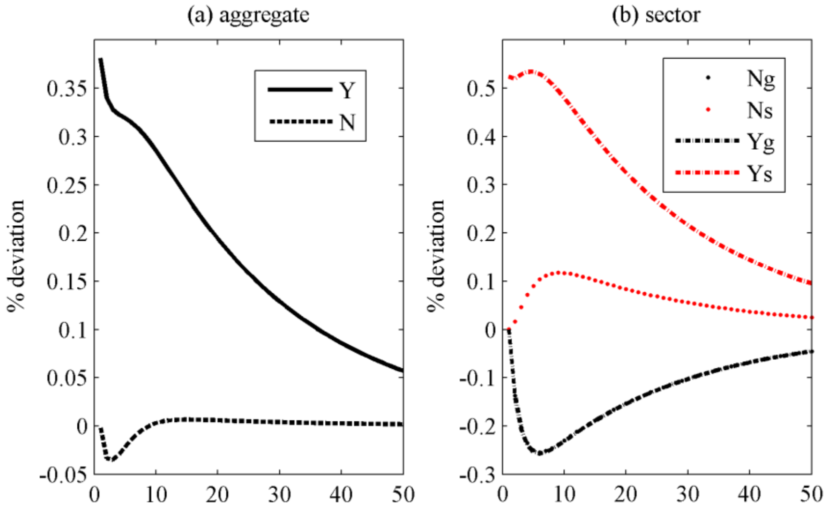


The SBSS is the only difference between the baseline and the SBSC-embedded economy. Specifically, the SBSS-embedded economy is subject to: (1) sector-specific labor adjustment costs and (2) a reallocation shock in addition to the negative TFP shock. These two elements provide a mechanism that decouples the movement of total output from that of aggregate employment.

On one hand, the reallocation shock raises the marginal product of labor (MPL) in the service sector relative to the goods sector. The higher MPL in the service sector motivates the household to move labor from the goods to the service sector. As a result, employment increases in the service sector but decreases in the goods sector, causing output to rise in the service sector but fall in the goods sector. Since the service sector has a bigger production share of total output, the rise in service sector output overwhelms the fall in goods sector output. Thus, total output increases and the reallocation shock has a positive effect on total output.

On the other hand, the labor adjustment cost makes it more costly to move labor from the goods to the service sector, slowing down the intersectoral labor relocation. Hence, the fall in goods sector employment overwhelms the rise in service sector employment, and aggregate employment decreases. The combination of reallocation shock and adjustment cost leads to a rise in total output but a fall in aggregate employment. Figure 6 shows the described effects.

Figure 6 Impulse Responses: SBSS only



The reallocation shock changes the relative productivity between the two sectors but has no impact on aggregate productivity. When a negative aggregate TFP shock hits the SBSS-embedded economy, it lowers productivity in both sectors and drives down their sectoral output. As a result, total output falls on impact; however, it recovers quickly given the positive effect of reallocation shock on total output. Meanwhile, the labor adjustment cost prevents aggregate employment from rising immediately, generating a jobless recovery.

VII. Discussion

A. Model implications

Adjustment Cost. Figure 7 shows the impulse responses of employment and consumption under three sizes of adjustment cost to the service sector (i.e., baseline, half baseline, double baseline). The baseline costs sum to about 4% of total output. Regarding welfare, cutting the cost noticeably improves aggregate employment but hardly affects consumption. Halving the cost raises employment by 13% and shortens its transition by 4 quarters. However, it only raises consumption by 1% and shortens its transition by 1 quarter.[7] This is because lower adjustment costs increase both employment and reallocation. While the

[7] The model is intrinsically symmetric, so doubling the cost has the opposite effects of same magnitudes.

former boosts income, the latter drives up the total adjustment cost paid. As a result, consumption barely changes.

Figure 7 Impulse Responses by Adjustment Costs

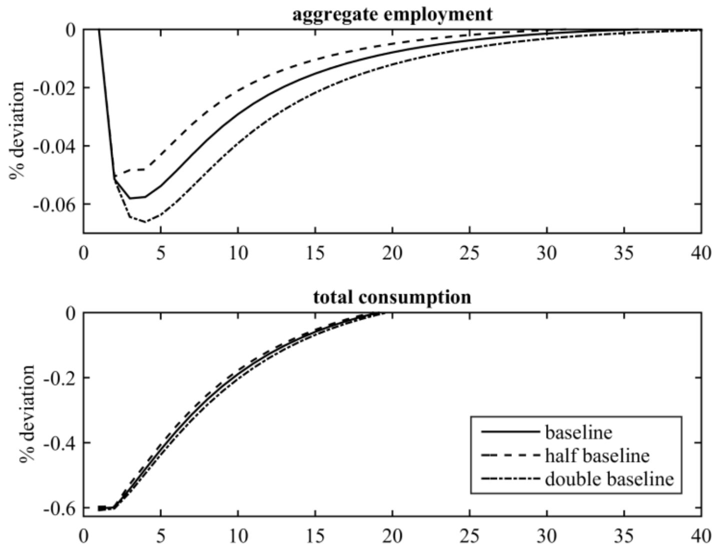


Figure 8 Detrended Quarterly Sectoral Unemployment Rates by Skills, 1989–2010

Sectoral Joblessness. My model attributes most of joblessness to unskilled workers in the goods sector. Based on the IPUMS-CPS, this implication is at least consistent with the data for two of the three recent recessions (see Figure 8).[8] The unemployment rate of unskilled goods sector workers remains the highest during the recovery phase of the 1990 and the Great

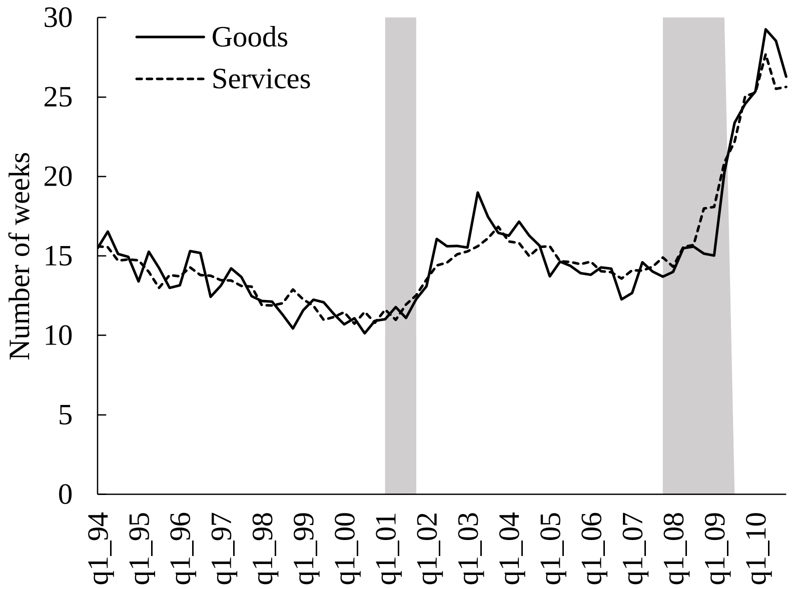
[8] Appendix B details the sample selection and statistical procedures for Figures 8–10.

Recession. The pattern is much less discernable for the 2001 recession where all unemployment rates appear to cluster together.

Unemployment Duration. My model has two implications for unemployment duration. First, unemployment duration is longer for unskilled workers in the goods sector than those in the service sector. Second, unemployment duration in the goods sector is longer for unskilled workers than skilled workers.

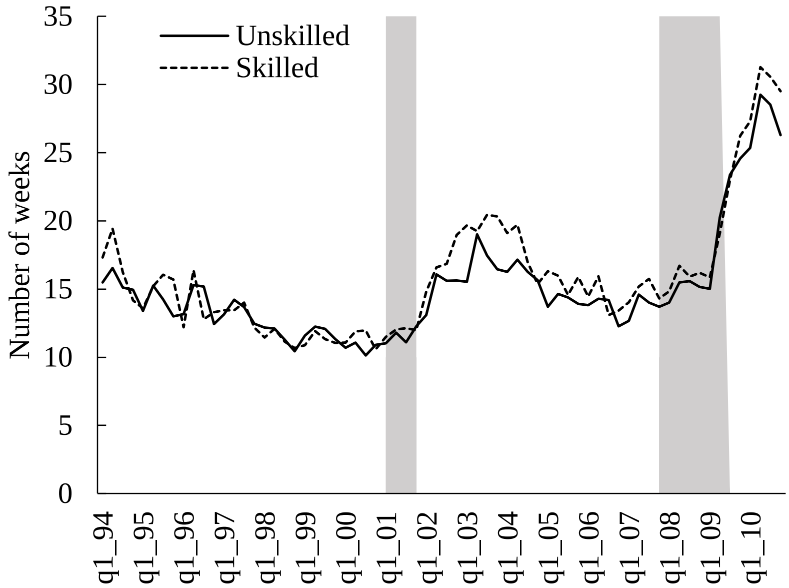
Based on the IPUMS-CPS, the first implication is consistent with the data (see Figure 9). Unskilled goods sector labor on average has longer unemployment duration than their service sector counterpart for at least six quarters after each recession trough date.

Figure 9 Average Number of Continuous Weeks Unemployed for Unskilled Workers by Sectors, 1994–2010



The second implication is at odds with the data (see Figure 10). Average unemployment duration within the goods sector is higher for the skilled than the unskilled. This could be due to the different nature of skilled and unskilled jobs, a missing dimension in my model. Unskilled jobs are more likely to be temporary and part-time, while skilled workers tend to look for permanent full-time jobs that typically have a lengthier recruiting process. This logic also reconciles with Figure 8. Despite longer unemployment spells, more skilled workers are able to find jobs and stay employed than unskilled workers within the goods sector. My model captures the cross-skill extensive margin (unemployment rate) of the goods sector but not its cross-skill intensive margin (unemployment duration).

Figure 10 Average Number of Continuous Weeks Unemployed for Goods Sector Workers by Skills, 1994–2010



B. Sectoral explanation

Figure 11 replicates Figures 1 and 14 in Berger (2012).[9] Berger points out that removing manufacturing and construction weakens but fails to eliminate jobless recoveries. Hence, jobless recoveries are not "an artifact of the secular decline in manufacturing employment." This viewpoint conflicts with my sectoral explanation and merits some scrutiny.

I by no means claim that sectoral shift is "the" cause of jobless recoveries which could be driven by multiple rather than single factors. Thus, it is not surprising that jobless recoveries do not simply vanish after excluding certain sectors. However, I argue that sectoral shift is as promising as other alternative theories, such as Berger's countercyclical reconstructing.

In contrary to Berger, I consider Figure 11 in favor of the sectoral explanation. Jobless recovery almost disappears after excluding manufacturing and construction for the 1990 and the 2001 recession. The employment growth rate stays barely negative for only three quarters.

9 The employment series in Figure 11 are in log-deviations normalized to zero at each recession trough date.

For the Great Recession, the exclusion more than halves the fall in employment growth and shortens the interval to five quarters.[10] The drastic reduction in the duration and magnitude clearly indicates a promising role of sectoral shift.

Figure 11 Employment Behavior during Business Cycle Recoveries

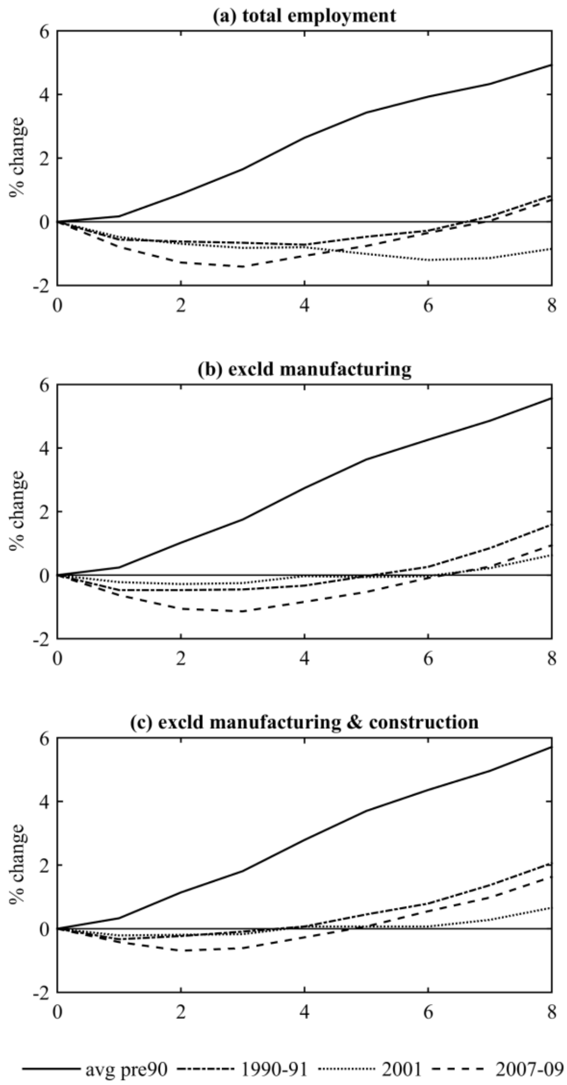
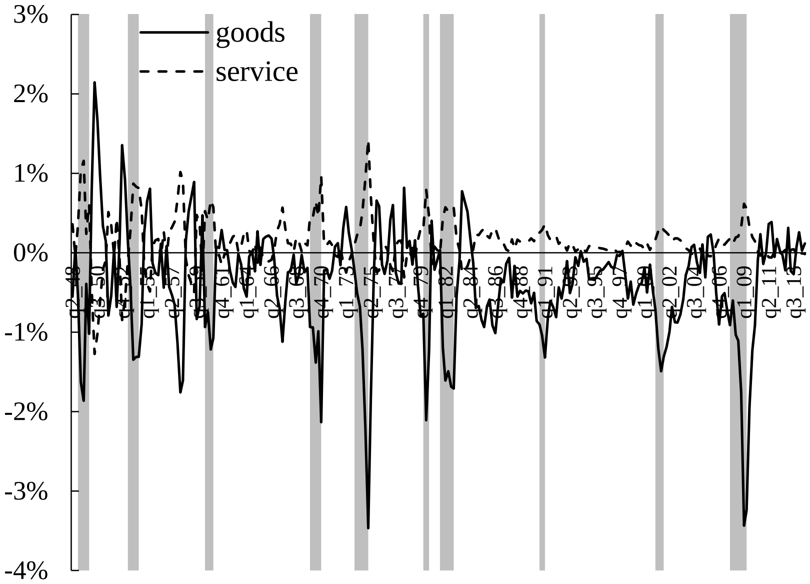


Figure 12, another piece of supporting evidence, plots the spread between sectoral and aggregate employment growth rates.[11] First, the goods (service) sector growth rate is on average 0.4% lower (0.2% higher) than the aggregate growth rate; jobs are permanently moving

[10] As expected, the employment growth path after recovery remains much weaker for the three recent recessions, reflecting the Great Moderation (Stock and Watson 2002).
[11] The employment data are seasonally adjusted and drawn from the CES survey. Aaronson et al. (2004) conduct a similar analysis on manufacturing durables employment.

out of the goods into the service sector. Second, the goods sector started to see jobless recovery after 1990. Some of the goods sector unemployment dissipated into the service sector prior to 1990. The relative growth rate jumped up in the service sector while falling in the goods sector. This dissipation has notably weakened since 1990. The relative growth rate stabilizes around its mean in the service sector but continues to fall in the goods sector during each recession. In line with my model's implication, as fewer unemployed goods sector workers relocate to the service sector, we observe jobless recoveries in the goods sector and at the aggregate level.

Figure 12 Relative Sectoral Employment Quarterly Growth Grates, 1948–2013



VIII. Conclusion

This paper establishes two stylized facts that define SBSS. Specifically, service sector have had more college workers and become more productive than the goods sector. A two-sector model is developed where the SBSS is incorporated via a sector-specific labor adjustment cost and a reallocation shock. The model successfully generates a jobless recovery. Simulation also shows that reducing adjustment costs noticeably boosts employment and shortens the duration of joblessness. Thus, training unemployed goods sector workers to gain skills needed for working in the service sector could help overcome future jobless recoveries.

Appendix

A. Frequency adjustment for shock process

Let $\{S_t\}$ be a stationary series of quarterly frequency following the AR(1) process:

$S_{t+1} = \rho S_t + \sigma e_{t+1}$, where e_{t+1} is white noise with a zero mean and a variance of one.

Then the quarterly unconditional variance is:

$$\mathbb{E}\left(S_{+1}\right)^2 = \mathbb{E}(\rho S + \sigma e_{t+1})^2 = \rho^2 \mathbb{E}(S)^2 + \sigma^2 \Rightarrow \mathbb{E}(S)^2 = \frac{\sigma^2}{1-\rho^2}.$$

Thus, the annual unconditional variance can be computed as

$$\mathbb{E}(\sum_{t=0}^{3} S_{+t})^2 = \mathbb{E}\left(\sum_{t=0}^{3}\left(\rho^t S + \sigma \sum_{t'=1}^{t} \rho^{t-t'} e_{+t'}\right)\right)^2 = \left(4 + \sum_{t=1}^{3} 2(4-t)\rho^t\right)\frac{\sigma^2}{1-\rho^2}.$$

The annual unconditional variance also equals $\frac{\sigma_a{}^2}{1-\rho_a{}^2}$, where a denotes annual frequency.

Given the values of ρ_a and σ_a, we can obtain the value of σ by solving the following equation:

$$\frac{\sigma_a{}^2}{1-\rho_a{}^2} = \left(4 + \sum_{t=1}^{3} 2(4-t)\rho^t\right)\frac{\sigma^2}{1-\rho^2}, \text{ where } \rho = \rho_a{}^{1/4}.$$

B. IPUMS-CPS sample selection and statistical procedures

I use the monthly IPUMS-CPS and restrict the sample to those aged 18 to 64. For an employed respondent, the industry in which he worked during the week prior to the survey is reported. For an unemployed respondent, the industry of his most recent job is reported. I use this information to assign a respondent's sector. I adjust monthly data to quarterly frequency by taking quarterly averages. All reported statistics are weighted.

Respondents' employment status is available monthly starting in 1989. The unemployment rate of skilled workers in a sector is computed as the number of skilled workers unemployed in the sector over the sectoral labor force. The same calculation applies to the unemployment rate of unskilled workers. I detrend each unemployment rate series using its mean over the sample period. Since sectoral output is only available annually, I choose not to normalize the unemployment rates using their corresponding sectoral output.

For unemployment duration, the IMPUS-CPS reports the number of continuous weeks a currently unemployed respondent has been without a job and looking for work. This is only available monthly starting in 1994.

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