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The aggregate effects of long run sectoral reallocation

by Claire Reicher

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Keywords: Sectoral shifts, reallocation, Beveridge Curve, employment, unemployment, vacancies, dispersion.

JEL classification: C32, E24, E32.

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The aggregate effects of long run sectoral reallocation

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Abstract

The construction bust which accompanied the Great Recession, and the accompanying need to shift workers across sectors, have provoked a discussion about mismatch and the Beveridge Curve, alongside a discussion about firm-level dispersion. These discussions echo an ongoing discussion about the effects of long run sectoral reallocation. Based on estimates from a large state space model over a long sample for the United States, long run sectoral reallocation does not appear to be systematically related to movements in the Beveridge Curve, although reallocation does appear to be countercyclical and related to falls in the trend employment-population ratio. The recent shift in the Beveridge Curve during the Great Recession is unusual in this respect. An analysis of historical patterns reveals a handful of additional reallocative episodes, with large episodes occurring during the mid-1970s and early 2000s recessions, in addition to during the Great Recession. In addition, these episodes appear to be related to other dispersion shocks which have been increasingly discussed in the literature.

*Email: claire.reicher at ifw hyphen kiel dot de. I wish to thank Susanto Basu, Mikhail Dmitriev, Henning Weber, Sebastian Braun, Chris Nekarda, Garey Ramey, Ellen Rissman, Chris Foote, seminar participants at IfW-Kiel, Boston College, the Deutsche Bundesbank, the Federal Reserve Board, and the BEA, and conference participants at the 2013 Midwest Macro meeting and the 2013 Econometric Society Australasian Meeting for their helpful comments. All errors, omissions, and opinions are mine.
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1 Introduction

The Great Recession accompanied a large construction bust in the United States. The need to move workers as a result of this construction bust, on net, from construction to other sectors has motivated a discussion regarding the extent and consequences of "mismatch" unemployment, a loss in matching efficiency, and an outward shift in the Beveridge Curve. In parallel with this discussion, another discussion has focused upon the countercyclicality of dispersion in firm-level outcomes as a result of "risk shocks" or "uncertainty shocks". Both of these discussions echo an older discussion on "sectoral shifts" or "sectoral reallocation". In fact, an analysis based on a large state space model can help to disentangle the ways in which shocks which cause sectoral reallocation ("reallocative shocks") are related to either shifts in the Beveridge Curve or to firm-level dispersion.[1] Based on an estimated large-scale state space model estimated using Bayesian methods on U.S. data from 1960 through 2013, reallocative shocks are robustly countercyclical and are related to falls in the trend employment-population ratio, while reallocative shocks are not related to shifts in the Beveridge Curve in a robust way. The events surrounding the Great Recession are unusual in that a reallocative episode and a shift in the Beveridge Curve occurred at the same time; during other reallocative episodes (most notably the mid-1970s and the early 2000s) this was not the case. Furthermore, reallocative shocks appear to be strongly related to the types of firm-level dispersion shocks currently discussed in the literature, which suggests that a better understanding of the sources of sectoral reallocation might also help to uncover the sources of these dispersion shocks.[2]

The estimation results cast light on the recent debate about mismatch and the Beveridge Curve. The estimates indicate that reallocative shocks most probably account for only a small portion of a probable recent outward shift in the Beveridge Curve, defined here as a shift in the trend unemployment rate or the trend vacancy rate. This debate has followed a nonlinear path. Kocherlakota (2010), for instance, originally claimed that mismatch in the supply and demand for different types of workers can account for an important share of the rise in unemployment during and following the Great Recession, although more recent statements point toward a belief that mismatch can account for a smaller share of this rise than previously indicated. Others have offered differing estimates, with Tasci and Lindner (2010) arguing for a small role for mismatch and with Schmitt and Warner (2011) for

[1] It is important to keep in mind that this analysis, like others in the reallocation literature, uncovers a set of reduced-form statistical effects rather than a set of structural relationships.

[2] There is also a small theoretical literature on the effects of sectoral reallocation, for instance, the work of Phelan and Trejos (2000). The results presented here are purely empirical in nature.

no role. Barnichon and Figura (2013) estimate that dispersion in labor market tightness across labor market segments (which results in decreased matching efficiency) can account for approximately a 1.5% increase in the unemployment rate during the Great Recession, and Şahin, Song, Topa, and Violante (2012) arrive at a similar set of conclusions with regard to industrial and occupational mismatch, allowing additionally for endogenous movements of workers into and out of the labor force. This particular point is interesting given that the estimates presented here also indicate that net movements out of the labor force seem to occur following reallocative shocks. Herz and van Rens (2012), argue that the period following the Great Recession did not feature an extraordinary amount of mismatch unemployment relative to the size of the recession, and that recent fluctuations in mismatch unemployment therefore seem to be primarily cyclical in character. To the extent that sectoral reallocation and mistmatch are linked, the conclusion of Herz et al. (2012) is in line with the results presented here, which show no robust relationship between reallocation and shifts in the Beveridge Curve.

The results presented here also have important implications with respect to the large and growing literature on the time-series behavior of cross-sectional dispersion from the perspectives of firms, workers, geographic units, etc. To cite a few examples from this literature, Davis and Haltiwanger (1992, 1999) find that a measure of job reallocation in the manufacturing sector is strongly countercyclical. Bloom (2009) and Bloom, Floetetto, Jamovich, Saporta-Eksten, and Terry (2012) discuss countercyclical "uncertainty shocks" which increase the dispersion of firm outcomes. Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011) discuss countercyclical "volatility shocks", while Christiano, Motto, and Rostagno (2014) discuss countercyclical "risk shocks". Cesa-Bianchi and Fernandez-Corugedo (2014) find that these types of shocks can have an important effect on aggregate activity. Altogether, these types of shocks appear to be related in a systematic way to sectoral reallocation, with the correlation between certain measures of firm-level dispersion and reallocative shocks on the order of +0.6. Reallocative shocks and risk shocks appear to be similar things, and it might pay to look at the sources of reallocative shocks in order to understand the sources of dispersion shocks.

Methodologically, the state space approach used to estimate the effects of reallocative shocks sits firmly within the empirical literature on sectoral shifts or sectoral reallocation.[3] This literature starts with Lilien (1982), who finds that shocks which induce dispersion in sectoral employment growth are countercyclical. Abraham and Katz (1986) point out that some

[3] Gallipoli and Pelloni (2013) provide a comprehensive survey of the literature on reallocation and sectoral shifts, which includes a discussion of "purging".

sectors (e.g. construction and manufacturing) are much more procyclical than others, and that after taking this issue into account, sectoral shifts are not an important driving force behind aggregate fluctuations. To deal with this issue, subsequent authors have developed ways to "purge" normal cyclical movements in sectoral employment shares from the data. Loungani, Rush, and Tave (1990) and Brainard and Cutler (1993) identify sectoral shifts using dispersion in stock market returns, and Rissman (1993) identifies sectoral shifts using the Phillips curve. Mills, Pelloni, and Zervoyianni (1995) and Campbell and Kuttner (1996) apply VAR techniques on a wider range of industries, and they find support for the sectoral shifts hypothesis. Pelloni and Polasek (2003) directly model sectoral shifts as relating to time-varying volatility; they implement a VAR with GARCH errors and find a strong countercyclical relationship between reallocation and the business cycle. Rissman (1997, 2009) and Aaronson, Rissman, and Sullivan (2004) directly purge growth in sectoral employment shares of the effects of a common cycle, finding that sectoral reallocation appears to be more or less acyclical. In comparison with these earlier models, the state space model presented here applies this purging concept to a larger set of observables in a model which distinguishes idiosyncratic trends from a common cycle (allowing for differing factor loadings across observables) and which treats the reallocative process as an unobservable time-varying process to be estimated. Additionally, the estimates are based on a dataset cleansed of large, temporary movements such as strikes. In contrast with the results of Rissman et al., sectoral reallocation again appears to be somewhat countercyclical, although it contributes a far smaller share to business cycle fluctuations than earlier estimates would suggest. An approach which treats the issues of purging and time-varying volatility in this particular manner, though computationally intensive, seems to give fairly sharp results with regard to the statistical effects of long-run sectoral reallocation.

2 A model of reallocation and its effects

2.1 The reallocation process

The analysis of sectoral reallocation is based on a large state space model which is estimated through Bayesian methods. The main objects of interest in this model are a time-varying reallocative process S_t and the coefficients governing the effects of S_t on the real economy. When S_t is high, the economy experiences a wave of reallocation. When S_t is low, the economy experiences less reallocation. S_t feeds into the economy in several ways. Most importantly, when S_t is high, the cross-sectional variance of long run employment growth at the sectoral level is high; this means that workers subsequently find themselves moving across sectors at a faster rate. In addition, S_t can directly affect the aggregate economy—it can have an effect on trend employment, trend unemployment, trend productivity, trend vacancies, and the business cycle. S_t is unobserved by the econometrician and must be estimated along with its effects. An exploratory analysis does not reveal any posterior autocorrelation in S_t, so it is reasonable to assume that the reallocative process is independent and identically distributed over time according to a lognormal distribution with a logarithm of mean zero and a constant variance, such that:

$$E[\log(S_t)^2] = \sigma_S^2. \tag{1}$$

2.2 Observation equations

The unobserved states can be divided into trends (which are always denoted by z) and cyclical components (which are always denoted by w). White noise observation errors (in the case of output) are denoted by x. Normal error terms which are i.i.d across time are always denoted by ε. The observables are the unemployment rate u_t, the log employment-population ratio e_t, log output per person y_t, the vacancy rate v_t, and the log sectoral employment shares $n_{i,t}$ for each sector i.

The model is linked to the data through a set of observation equations. The observation equations for the unemployment rate, the log employment-population ratio, the vacancy rate, log sectoral employment shares, and log output are given by:

$$u_t = z_t^u + w_t^u; \tag{2}$$

$$e_t = z_t^e + w_t^e; \tag{3}$$

$$v_t = z_t^v + w_t^v; \tag{4}$$

$$n_{i,t} = z_{i,t}^n + w_{i,t}^n; \tag{5}$$

and

$$y_t = z_t^e + z_t^y + w_t^y + x_t^y, \tag{6}$$

respectively. The unemployment rate, the log employment-population ratio, the vacancy rate, and log sectoral employment shares are simply the sum of their trends and cycles. Log output per person is the sum of four components—the trend log employment-population ratio z_t^e, trend productivity z_t^y, cyclical output w_t^y, and a white noise measurement error component x_t^y.

2.3 Laws of motion for the driving processes

The trends for unemployment, employment, productivity, and vacancies all follow a unit root process, and cyclical output follows a stationary autoregressive process of order P. These driving processes may exhibit correlation in their contemporaneous error structure, and these errors can also be correlated with the reallocation process S_t. The trend unemployment rate z_t^u, the trend log employment rate z_t^e, the trend log productivity level z_t^y, the trend vacancy rate z_t^v, and the level of cyclical output w_t^y together follow a law of motion given by:

$$\begin{bmatrix} \Delta z_t^u \\ \Delta z_t^e \\ \Delta z_t^y \\ \Delta z_t^v \\ w_t^y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \mu^{zy} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \delta_{S,zu} \\ \delta_{S,ze} \\ \delta_{S,zy} \\ \delta_{S,zv} \\ \delta_{S,wy} \end{bmatrix} \log(S_t) + \sum_{p=1}^{P} \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \rho_p^{zy} \end{bmatrix} w_{t-p}^y + \begin{bmatrix} \varepsilon_t^{zu} \\ \varepsilon_t^{ze} \\ \varepsilon_t^{zy} \\ \varepsilon_t^{zv} \\ \varepsilon_t^{wy} \end{bmatrix}, \tag{7}$$

where ε_t^z is multivariate normal with a mean zero and a covariance matrix given by $E[\varepsilon_t^z\,(\varepsilon_t^z)'] = \Sigma_z$, and where ε_t^z denotes the stacked residuals $\begin{bmatrix} \varepsilon_t^{zu} & \varepsilon_t^{ze} & \varepsilon_t^{zy} & \varepsilon_t^{zv} & \varepsilon_t^{wy} \end{bmatrix}'$. There are no restrictions on Σ_z except that it be of full rank. This law of motion allows for S_t to feed into aggregate economic dynamics in levels. If the δ_S coefficients which multiply $\log(S_t)$ are positive, then a high rate of reallocation today results in a permanently higher rate of trend unemployment, trend employment, trend productivity, or trend vacancies, or a transitory increase in cyclical output. These coefficients are the major objects of investigation, alongside S_t itself.

Trend employment shares also follow a unit root process which is independent from that given in (7). Changes in trend employment shares $z_{i,t}^n$ follow a set of mutually correlated AR(1) processes with intercepts and persistence coefficients, such that for each i:

$$\Delta z_{it}^n = \mu_i^{zn} + \rho_i^{zn} \Delta z_{it-1}^n + \varepsilon_{it}^{zn}, \tag{8}$$

where for a set of stacked errors $\varepsilon_{i,t}^{zn}$ denoted by ε_t^{zn}, ε_t^{zn} is multivariate normal with a mean zero and a covariance matrix given by $E[\varepsilon_t^{zn}(\varepsilon_t^{zn})'] = S_t\Sigma_{zn}$. The intercepts μ_i^{zn} in equation (8) reflect systematic movements in employment shares over time, in particular the decline in manufacturing employment and the rise in service-sector employment. The persistence coefficients ρ_i^{zn} reflect the sluggish movement of workers between sectors, perhaps due to retraining costs, hiring costs, or other labor market frictions. One should expect a number of negative off-diagonal elements in the "usual" covariance matrix of errors given by Σ_{zn} since as a matter of accounting, a fall in the share of construction workers implies a rise in the share of other sectors. The covariance matrix is multiplied by the reallocation process S_t. The presence of S_t in this covariance matrix of shocks formalizes the notion that sectoral reallocation occurs when the shocks to sectoral trends are large in magnitude.

2.4 Laws of motion for cyclical components

To round out the model, it is necessary to specify the behavior of the short-run components, which are assumed to follow a common cycle. The short-run components of the unemployment rate, the log employment-population ratio, the vacancy rate, and log sectoral employment shares are allowed to comove with cyclical output but with a possible lag. These relationships are given by:

$$w_t^u = \sum_{p=0}^{P} \alpha_p^{wu} w_{t-p}^y + \varepsilon_t^{wu}, \text{ where } E[(\varepsilon_t^{wu})^2] = \sigma_{wu}^2; \tag{9}$$

$$w_t^e = \sum_{p=0}^{P} \alpha_p^{we} w_{t-p}^y + \varepsilon_t^{we}, \text{ where } E[(\varepsilon_t^{we})^2] = \sigma_{we}^2; \tag{10}$$

$$w_t^v = \sum_{p=0}^{P} \alpha_p^{wv} w_{t-p}^y + \varepsilon_t^{wv}, \text{ where } E[(\varepsilon_t^{wv})^2] = \sigma_{wv}^2; \tag{11}$$

and

$$w_{i,t}^n = \sum_{p=0}^{P} \alpha_{i,p}^{wn} w_{t-p}^y + \varepsilon_t^{wu}, \text{ where } E[(\varepsilon_{i,t}^{wn})^2] = \sigma_{wn,i}^2, \tag{12}$$

for each i, respectively. The idiosyncratic output factor x_t^y is given by a white noise term:

$$x_{i,t}^y = \varepsilon_t^{xy}, \text{ where } E[(\varepsilon_t^{xy})^2] = \sigma_{xy}^2. \tag{13}$$

The errors to these equations are all univariate normal and are iid across time and across equations. The α coefficients give the factor loadings which relate the short-run components of the observables to the business cycle. For instance, it is well-known that unemployment covaries negatively with the cycle with a slight lag, while the manufacturing share in employment tends to covary positively with the cycle. Including these equations in the estimation procedure addresses the Abraham-Katz (1986) critique in a statistically coherent way. If one knows the output gap and one knows the coefficients $\alpha_{i,p}^{wn}$, then one could "purge" sectoral shares of their cyclical components, leaving only their idiosyncratic trends.

2.5 Data and priors

2.5.1 Data

The analysis begins in the first quarter of 1960 in order to avoid the large strikes of the 1950s, and the analysis ends in the second quarter of 2013. Data for the unemployment rate and the log employment-population ratio come from the CPS. Data on GDP come from the NIPA. These are economywide measures based on quarterly averages. GDP is divided by the civilian noninstitutional population 16 and over, smoothed for breaks, and then taken in logs. The vacancy rate is a composite of the JOLTS series (from January 2001 onward) joined with the composite vacancy series produced by Barnichon (2010) using print and online help wanted indices. Monthly JOLTS vacancy rates are expressed as an average of the previous month's end-of-month value and the current month's end-of-month value, then taken as a quarterly average.

Sectoral establishment employment data come from the BLS's Current Employment Statistics program, broken out by the NAICS. There are three sectoral breakdowns: a thirteen-sector model, a fourteen-sector model, and a five-sector model. The thirteen-sector model covers the following sectors: Construction, durable goods manufacturing, nondurable goods manufacturing, wholesale trade, retail trade, transportation and utilities, leisure and hospitality, information, financial activities, professional and business services, education and health services, other services, and government. Mining and logging are omitted from the thirteen-sector model because that sector is small, volatile, and strike-prone. Results are also presented for a fourteen-sector model which includes mining. The monthly employment series are manually corrected for large strikes, statistical breaks, weather events, and census workers. The corrected data are taken as quarterly averages and then expressed as log employment shares. The share of government workers is omitted from the estimation algorithm in order to avoid singularity in Σ_{zn}.

The five-sector model collapses the fourteen sectors into a pseudo-SIC industry structure. The production sector consists of mining and logging, durable goods manufacturing, and nondurable goods manufacturing. Construction stands on its own. The trade, leisure, and transportation sector consists of wholesale trade, retail trade, leisure and hospitality, and transportation and utilities. The financial and business services sector consists of information, financial activities, and professional and business services. The public and private services sector consists of education and health services, other services, and government. Again, to avoid singularity in Σ_{zn}, the latter sector is omitted from the analysis. This sectoral classification approximates the industrial classification system used by several foreign countries, and it also closely approximates the SIC. Information goes into the financial and business services sector because the more volatile components of the information sector belong to that supersector on an SIC basis.

The state space model can also be used to discuss geographic reallocation. To address this issue, results are presented for nine census divisions using data from the Current Employment Statistics program. The data cover the New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific census divisions. To avoid singularity in Σ_{zn}, the Pacific census division is omitted from the analysis. Results for the statistical effects of geographic reallocation are presented on the same basis as those for sectoral reallocation.

2.5.2 Priors

Table 1 shows the prior distributions used in the estimation. The priors on all regression coefficients are uninformative normal—i.e. normal with a mean of zero and a variance of infinity. The variance terms for the shocks all have a weakly informative inverse gamma or inverse Wishart prior distribution, with the number of prior observations set to 0.5. This set of priors helps to ensure computational stability. These priors are rather loose, and they represent rough guesses as to the order of magnitude of these objects, with the prior mean of the variance of $\log(S_t)$ set large enough (to 9) so that observed sectoral dispersion lines up reasonably well with estimated dispersion. The results of this exercise are robust to different priors on the variances so long as those priors are not too informative.

Each of the equations governing the cyclical components of output, employment, unemployment, and vacancies features a lag length P of two. The data clearly indicate that the one lag is insufficient at describing cyclical dynamics; the estimated coefficients using two lags consistently give a hump-shaped response of the cycle to a cyclical shock. Moving beyond two lags does not yield a substantially different picture of business cycle dynamics than staying with two lags. The system is estimated using the Markov Chain Monte Carlo (MCMC) algorithm discussed in Appendix A. Posterior statistics are calculated after running 500,001 draws from the MCMC and discarding the first 10,000. The remaining draws approximate the posterior distributions of the parameters and unobserved variables of interest.

3 Estimation results

3.1 Main results on sectoral and geographic reallocation

Altogether, the coefficient estimates suggest that sectoral reallocation appears to be countercyclical and is related to falls in the trend employment-population ratio. However, sectoral reallocation does not show a robust relationship with shifts in the Beveridge Curve or with movements in trend productivity. Furthermore, geographic reallocation is also countercyclical, and the estimates do not indicate that there is not a strong relationship between geographic reallocation and the trend employment-population ratio or between geographic reallocation and shifts in the Beveridge Curve. Taken together, the evidence in favor of an effect of reallocation on the Beveridge Curve is weak, although reallocation does appear to be robustly countercyclical.

The 5-sector model shows a moderate effect of sectoral reallocation on the levels of all four aggregate trends as well as on the business cycle. Table 2 shows selected posterior percentiles for the δ_S coefficients for the 5-sector model, along with the probabilities that these coefficients are above zero.[4] The posterior median estimates indicate that sectoral reallocation may have a positive statistical effect on the trend unemployment rate as given by the coefficient $\delta_{S,zu}$, a negative effect on the trend log employment-population ratio as given by the coefficient $\delta_{S,ze}$, a positive effect on the trend productivity level as given by

[4] An exhaustive battery of model estimates is available from the author upon request. These estimates fit other well-known facts about the business cycle–for instance, its persistence and the cyclical behavior of various aggregates.

the coefficient $\delta_{S,zy}$, a positive effect on the trend vacancy rate as given by the coefficient $\delta_{S,zv}$, and a negative effect on cyclical output as given by the coefficient $\delta_{S,wy}$. All of these coefficients have a reasonably strong posterior probability of adhering to a given sign, and they are of moderate economic significance. The posterior median shares of the variance of innovations to these five objects which are accounted for by reallocative shocks are moderate (between 12 and 24 percent), although there also seems to be a great degree of uncertainty with respect to these shares. Put together, these estimates based on the 5-sector model imply that sectoral reallocation seems to be associated with both shorter-lived and longer-lived reductions in economic activity, although the exact degree to which sectoral reallocation is an important driver in these fluctuations remains unclear.

Different sectoral breakdowns confirm these results with respect to the effects of sectoral reallocation on the trend employment-population ratio and on the business cycle, although the results on the other trends do not appear to be robust. Table 3 shows selected posterior percentiles for the δ_S coefficients for the 13-sector model, along with the probabilities that these coefficients are above zero. Table 4 shows the same set of results for the 14-sector model. Both of these sectoral breakdowns produce results which broadly resemble each other, with the 14-sector model giving weaker results with respect to the relationship between sectoral reallocation and the trend employment-population ratio. The posterior median estimates for these breakdowns indicate that sectoral reallocation may have an approximately neutral effect on the trend unemployment rate as given by the coefficient $\delta_{S,zu}$, a moderate negative effect on the trend log employment-population ratio as given by the coefficient $\delta_{S,ze}$, a weak positive effect on the trend productivity level as given by the coefficient $\delta_{S,zy}$, an approximately neutral effect on the trend vacancy rate as given by the coefficient $\delta_{S,zv}$, and a negative effect on cyclical output as given by the coefficient $\delta_{S,wy}$. These coefficients are uniformly smaller in magnitude than for the 5-sector model, despite a similar posterior estimate for σ_S, and are more sharply estimated. Similarly, the posterior median share of the variance of innovations to these five objects accounted for by reallocative shocks now rests in the low-to-mid-single digits, with sectoral reallocation accounting for between 4 and 5 percent of fluctuations in the business cycle. Altogether, several results emerge when looking at the 5-sector, 13-sector, and 14-sector models side by side. Sectoral reallocation appears to be related to falls in cyclical output and to falls in the trend employment-population ratio, although sectoral reallocation appears to account for only a modest share of fluctuations in these objects. Furthermore, sectoral reallocation does not appear to be related in a robust way to shifts in the Beveridge Curve or to movements in trend productivity.

As with sectoral reallocation, geographic reallocation appears to be countercyclical, and there is also no clear statistical relationship between geographic reallocation and the Beveridge Curve. There is also no clear statistical relationship between geographic reallocation and the trend employment-population ratio, although geographic reallocation does appear to be related to falls in trend productivity. Table 5 shows selected posterior percentiles for the δ_S coefficients for the 9-division model, along with the probabilities that these coefficients are above zero. The posterior median coefficient $\delta_{S,wy}$ is of a similar magnitude to that estimated under the 13-sector and 14-sector models, and geographic reallocation in the median case can account for about 9% of the variance of innovations to the business cycle. Geographic reallocation also has a weak negative relationship with trend productivity as given by the coefficient $\delta_{S,zy}$, with geographic reallocation in the median case accounting for about 6% of the variance of changes in trend productivity. Altogether, both sectoral and geographic reallocation appear to show a negative relationship with the cyclical component of output, while sectoral and geographic reallocation do not appear to show a robust relationship with movements in the Beveridge Curve.

3.2 The historical behavior of reallocation measures

Figures 1 through 4 show the estimated posterior geometric mean of S_t along with a related dispersion measure based on that of Lilien (1982) as well as a simple weighted dispersion measure, for the 5-sector, 13-sector, 14-sector, and 9-division models, respectively. The "Lilien" measure is calculated as $\sum w_{it}(\varepsilon_{it}^{zn}/(1-\rho_i^{zn}))^2$ across sectors i, for sectoral employment weights w_{it} equal to an average of sector i's employment share in t and $t-1$. This dispersion measure gives the weighted variance of shocks which cause long-run movements in the allocation of labor across sectors or geographic divisions. The "weighted" measure is calculated as $(\varepsilon_t^{zn})'(\Sigma_{zn})^{-1}\varepsilon_t^{zn}$, which is the limited information maximum likelihood estimate of S_t given known values for the components of equation (8). This latter measure serves as a reality check for the estimates of S_t–if the other two measures and S_t deviate too much from each other, then such a deviation could indicate that S_t is not a good measure of sectoral reallocation. In Figures 1 through 4, all three reallocation measures are normalized to have a unit variance when taken in logs and are taken as a 4-quarter (logged) moving average.

Several patterns become apparent when plotting all three reallocation measures. First of all, the three reallocation measures line up relatively closely with each other in all cases. Since these three reallocation measures line up in such a manner, S_t appears to serve as a reasonable measure of long-run sectoral reallocation in the labor market. Secondly, for the three sectoral breakdowns, S_t exhibits notable "spikes" during the mid-1970s recession, the early-2000s recession, and the Great Recession, with S_t also rising during the early-1990s recession under the 13-sector and 14-sector breakdowns. While some recessions are associated with an increased rate of sectoral reallocation, other recessions (notably the 1969-1970 recession and the two early-1980s recessions) are not associated with an increased rate of sectoral reallocation. For the 9-division breakdown, S_t spikes during a different set of episodes–especially an episode during the early 1970s–with a smaller upward blip during the Great Recession. Measures of sectoral reallocation and geographic reallocation do not appear to capture the same episodes, although both types of reallocation do occur disproportionately during recessions.

3.3 Reallocation and other measures of dispersion

The posterior estimates of S_t also coincide with other measures of firm-level dispersion increasingly discussed in the business cycle literature, most notably the literature on "risk shocks" and "uncertainty shocks". Figure 5 plots the posterior estimates of S_t alongside measures of dispersion in firm-level stock returns and in firm-level sales growth taken from Bloom et al. (2012), taken as 4-quarter logged moving averages. Both of these measures, particularly stock return dispersion, show "spikes" during the mid-1970s recession, the early-2000s recession, and the Great Recession. These episodes are the same episodes which have featured an increased rate of sectoral reallocation as well. Indeed, sectoral reallocation and firm-level dispersion appear to be strongly related. Table 6 shows the correlation coefficients among all four measures of S_t and the two measures of firm-level dispersion. While sectoral reallocation and geographic reallocation appear to show a weak positive correlation with each other, sectoral reallocation at the 14-sector level in particular appears to show a strong correlation with dispersion in stock returns (+0.64) and also a moderately strong correlation with dispersion in sales growth (+0.48). Altogether, the relationship between "risk shocks" and sectoral reallocation appears to be a strong one which deserves further exploration.

3.4 The historical and recent behavior of economic trends

The estimation procedure produces estimates of sectoral and aggregate trends as a byproduct. Some of these trends are interesting in their own right, for instance, the trend sectoral employment shares given by $exp(z_{it}^n)$. Figure 6 plots the posterior geometric means of these trends for the 5-sector model, with the trend for public and private services calculated as a residual. Of particular note, the construction sector seems to have undergone its share of booms and busts. The mid-1960s, mid-1970s, early-1990s, and late-2000s periods saw construction busts, the last three of which coincide with reallocative episodes. Meanwhile, the financial and business services sector shows particularly large busts during the early-2000s and late-2000s reallocative episodes. While construction busts appear to have something to do with sectoral reallocation, the sectors which participate in reallocative episodes do not appear to be the same sectors in every episode. While reallocative episodes exhibit some similarities, each reallocative episode also exhibits some differences.

Figures 7 through 9 show posterior trends in aggregate labor market variables. Figure 7 shows the evolution of trend unemployment z_t^u along with posterior credible intervals. Figure 8 shows the trend employment-population ratio $exp(z_t^e)$, and Figure 9 shows the trend vacancy rate z_t^v. In line with what an ocular detrending procedure would produce, trend unemployment appears to have risen gradually during the 1970s and fallen gradually into the 2000s, to a rate of about 5.0% in the fourth quarter of 2006. Since the Great Recession, trend unemployment appears to have risen to 6.0% as of the middle of 2013. While the exact level of the trend unemployment rate is not precisely measured, this change is positive with a posterior probability of about 95%. Similarly, the trend employment-population ratio shows a gradual rise and then a temporary fall during each reallocative episode, with a large, sustained fall occurring during Great Recession. This fall occurs with a high degree of statistical certainty. The deterioration in unemployment and employment trends during the Great Recession accompanied an unusual shift in the Beveridge Curve. As noted by others, the trend vacancy rate rose sharply during the Great Recession, and this rise has occured with a posterior probability of about 99%. Judging from the rest of Figure 9, this rise is not typical of other reallocative episodes. While a reallocative shock and an outward shift in the Beveridge Curve seem to have occurred during the Great Recession, other reallocative episodes do not accompany noticeable shifts in the Beveridge Curve.

Altogether, a coherent picture with respect to economic trends emerges. The reallocative episodes identified by S_t do not seem to be driven consistently by any particular sector, although construction and increasingly financial and business services have played roles in individual reallocative episodes. Furthermore, the reallocative episodes identified by S_t do not seem to be associated with any particular pattern of behavior in trend unemployment or vacancies, while these episodes seem to be associated with unusually large falls in employment relative to what would occur during a typical recession. The Great Recession is unusual in that a large reallocative shock and a large outward shift in the Beveridge Curve seem to have occurred at the same time. Based on the historical behavior of the Beveridge Curve, a typical reallocative shock would not have coincided with such a shift in the Beveridge Curve. This time appears to be different.

4 Conclusion

Based on estimates from a large state space model, several results emerge regarding the aggregate statistical effects of shocks which cause long run sectoral and geographic reallocation. Sectoral reallocation appears to be related to falls in the trend employment-population ratio, and sectoral reallocation and geographic reallocation both appear to be countercyclical. The relationship between sectoral or geographic reallocation and the Beveridge Curve (i.e., movements in trend unemployment and vacancies) is not a robust fact, and the shift in the Beveridge Curve following the Great Recession is unusual when seen in light of previous reallocative shocks. It appears that a narrow focus on the Beveridge Curve to the exclusion of other observables seems to miss out on the main statistical effects of sectoral reallocation, which appear in the trend employment rate and in the business cycle, but not in the trend unemployment rate. These results, taken together, imply that sectoral reallocation and mismatch might have important effects on net flows of workers into or out of the labor force.

The historical behavior of the sectoral reallocation process itself is interesting. Sectoral reallocation since 1960 seems to have taken place in a number of episodes, with the most prominent episodes occurring during the mid-1970s, the early 2000s, and the Great Recession. Some, but not all, episodes of sectoral reallocation have tended to accompany construction busts, with some contribution from financial and business services during the early-2000s and late-2000s episodes. Furthermore, sectoral reallocation seems to coincide to a large degree with the types of dispersion shocks currently discussed in the macroeconomic literature. Altogether, future research might benefit from further exploring the link between reallocative shocks and these other types of dispersion shocks, given that research has uncovered plausible mechanisms through which dispersion shocks could generate meaningful economic fluctuations.

Another avenue for future research becomes apparent, which is to find ways to disentangle cause and effect when discussing reallocative shocks. The results presented here are purely observational in nature, based on a large time-series model. It may be the case that sectoral reallocation causes recessions, that recessions cause sectoral reallocation, or that some other shock or set of shocks causes both phenomena. It is still unclear at this point to what degree reallocative shocks may be driven by an aggregate shock which has sectoral consequences (for which likely candidates would be an investment wedge or a financial market shock) or by shocks which originate within specific sectors of the economy. Future work may help to uncover which sets of primitive shocks might underlie the reduced-form reallocative shocks discussed here.

A Appendix: The MCMC algorithm

The state space model is estimated using an MCMC algorithm which simulates the posterior distribution of model parameters and hyperparameters of interest. The MCMC algorithm starts with a set of initial values. For each MCMC draw (i), the algorithm goes through the following steps.

First the algorithm draws a set of unobservable trends and cycles:

$$\{\varsigma_t\}^{(i)} = \{w_t^u, w_t^e, w_t^v, w_t^y, w_t^n, x_t^y, z_t^u, z_t^e, z_t^v, z_t^y, z_{i,t}^n, \Delta z_t^u, \Delta z_t^e, \Delta z_t^v, \Delta z_t^y, \Delta z_t^n\}^{(i)},$$

from its posterior distribution, conditional on the observables:

$$Y_t = \{u_t, e_t, v_t, y_t, n_t\},$$

the parameters:

$$\Xi^{(i-1)} = \{\mu^{zy}, \delta_S, \rho^{zy}, \mu^{zn}, \rho^{zn}, \alpha^{wu}, \alpha^{we}, \alpha^{wv}, \alpha^{wn}, \sigma_S^2, \Sigma_z, \Sigma_{zn,}\sigma_{wu}^2, \sigma_{we}^2, \sigma_{wv}^2, \sigma_{wn}^2, \sigma_{xy}^2\}^{(i-1)},$$

and the unobservable reallocative process $\{S_t\}^{(i-1)}$. This can be done recursively through the Kalman Filter. The formula for the Kalman Filter is discussed by Hamilton (1994, Chapter 13), with the prior mean for the first observation of each nonstationary trend set with a mean equal to the analogous observable and with a variance of one (which is large in the current context).

Next, the algorithm draws an unobervable reallocative process $\{S_t\}^{(i)}$ from its posterior distribution, conditional on $\{\varsigma_t\}^{(i)}$, Y_t, and $\Xi^{(i-1)}$. This is done in a Metropolis-Hastings step, since the likelihood conditional on S_t is rather complicated, equal to the product of the normal likelihoods of (7), where $\log(S_t)$ appears in the intercept, and of (8), where S_t appears in the variance. To draw $\{S_t\}^{(i)}$ requires first to draw a series of draws $\{S_t'\}^{(i)}$ from a proposal distribution with a density $q(x_t|S_t^{(i-1)})$, the form of which is chosen to give a moderate acceptance rate between 20 and 40 percent. Given a pair of prior densities $p(S_t^{(i)})$ and $p(S_t^{'(i)})$ which are lognormal with a mean log of zero and with a log variance of $(\sigma_S^2)^{(i-1)}$, and given a pair of likelihoods $l(\{\varsigma_t\}^{(i)}, Y_t|\Xi^{(i-1)}, \varsigma_{t-1}, S_t^{(i)})$ and $l(\{\varsigma_t\}^{(i)}, Y_t|\Xi^{(i-1)}, \varsigma_{t-1}, S_t^{'(i)})$ which are separable across t, the algorithm either carries forward $S_t^{(i-1)}$ into $S_t^{(i)}$, or else it sets $S_t^{(i)} = S_t^{'(i)}$ with a probability given by

$$\Pr(S_t^{(i)} = S_t^{'(i)}) = \frac{q(S_t^{(i-1)}|S_t^{'(i)})p(S_t^{'(i)})l(\{\varsigma_t\}^{(i)}, Y_t|\Xi^{(i-1)}, \varsigma_{t-1}, S_t^{'(i)})}{q(S_t^{'(i)}|S_t^{(i-1)})p(S_t^{(i-1)})l(\{\varsigma_t\}^{(i)}, Y_t|\Xi^{(i-1)}, \varsigma_{t-1}, S_t^{(i)})}.$$

Next, the algorithm draws a set of parameters $\Xi^{(i-1)}$ from its posterior distribution, conditional on $\{\varsigma_t\}^{(i)}$, Y_t, and $\{S_t\}^{(i)}$. Here, it is useful to take advantage of the block structure of the model along with the presence of conjugate priors, treating the priors as dummy observations. First of all, $(\sigma_S^2)^{(i)}$ has an inverse gamma distribution conditional on $\{S_t\}^{(i)}$ and its prior. Next, $\Sigma_z^{(i)}$ has an inverse Wishart distribution given the elements of $\{\varsigma_t\}^{(i)}$, $\{\mu^{zy}, \delta_S, \rho^{zy}\}^{(i-1)}$, and its prior, based on equation (7). Next, $\{\mu^{zy}, \delta_S, \rho^{zy}\}^{(i)}$ has a joint normal distribution conditional on $\{\varsigma_t\}^{(i)}$, $\Sigma_z^{(i)}$, and its prior, also based on equation (7). This distribution, which is for the posterior distribution of a Bayesian SUR, is identical to that given by Hamilton (1994, Section 11.3) for the maximum likelihood estimate of a restricted VAR. Next, $\Sigma_{zn}^{(i)}$ has an inverse Wishart distribution conditional on $\{\varsigma_t\}^{(i)}$, $\{\mu^{zn}, \rho^{zn}\}^{(i-1)}$, and its prior, based on equation (8). Next, $\{\mu^{zn}, \rho^{zn}\}^{(i)}$ has a joint normal distribution conditional on $\{\varsigma_t\}^{(i)}$, $\Sigma_{zn}^{(i)}$, and its prior, also based on (7).

Continuing through the elements of $\Xi^{(i)}$, $(\alpha^{wu})^{(i)}$ has a multivariate normal distribution conditional on the law of motion for w_t^u, $\{\varsigma_t\}^{(i)}$, $(\sigma_{wu}^2)^{(i-1)}$, and its prior; and $(\sigma_{wu}^2)^{(i)}$ has an inverse gamma distribution conditional on the law of motion for w_t^u, $\{\varsigma_t\}^{(i)}$, $(\alpha^{wu})^{(i)}$, and its prior. An analogous set of calculations yields $(\alpha^{we})^{(i)}$, $(\sigma_{we}^2)^{(i)}$, $(\alpha^{wv})^{(i)}$, $(\sigma_{wv}^2)^{(i)}$, $(\alpha_i^{wn})^{(i)}$ for each sector i, $(\sigma_{wn,i}^2)^{(i)}$ for each sector i, and $(\sigma_{xy}^2)^{(i)}$. Variance decompositions and dispersion measures are also calculated at this time. All of these items are saved in memory, and then the counter moves from draw (i) to draw $(i+1)$ in order to repeat the whole process. The process is repeated for 500,001 draws and then the first 10,000 draws are discarded. The remaining 490,001 draws are used to calculate posterior statistics. An odd number of draws is used so that the median and other round-numbered percentiles exist, and because it is enjoyable to do so.

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Table 1: Prior distributions for coefficients of interest

Parameter	Prior distribution	Remarks
Σ_z	Inv. Wishart (Mean=$(0.005^2)\mathbf{I}$, #Obs=0.5)$^{(*)}$	Keeps cov. away from zero.
Σ_{zn}	Inv. Wishart (Mean=$(0.005^2)\mathbf{I}$, #Obs=0.5)$^{(**)}$	Keeps cov. away from zero.
σ^2_{wu}	Inv. Gamma (Mean=0.01^2, #Obs=0.5)	Keeps var. away from zero.
σ^2_{we}	Inv. Gamma (Mean=0.01^2, #Obs=0.5)	Keeps var. away from zero.
σ^2_{wv}	Inv. Gamma (Mean=0.01^2, #Obs=0.5)	Keeps var. away from zero.
σ^2_{xy}	Inv. Gamma (Mean=0.01^2, #Obs=0.5)	Keeps var. away from zero.
$\sigma^2_{wn,i}$ for all i	Inv. Gamma (Mean=0.01^2, #Obs=0.5)$^{(**)}$	Keeps var. away from zero.
σ^2_S	Inv. Gamma (Mean=3^2, #Obs=0.5)	Gives good fit to dispersion.
$\{\mu^{zn}_i, \rho^{zn}_i\}$	Multivariate Normal (Mean=$\mathbf{0}$, Std.=$\infty\mathbf{I}$)	Diffuse prior.
$\{\mu^{zy}, \rho^{wy}_p, \delta_{S,z}\}$	Multivariate Normal (Mean=$\mathbf{0}$, Std.=$\infty\mathbf{I}$)	Diffuse prior.
α^{wu}	Multivariate Normal (Mean=$\mathbf{0}$, Std.=$\infty\mathbf{I}$)	Diffuse prior.
α^{we}	Multivariate Normal (Mean=$\mathbf{0}$, Std.=$\infty\mathbf{I}$)	Diffuse prior.
α^{wv}	Multivariate Normal (Mean=$\mathbf{0}$, Std.=$\infty\mathbf{I}$)	Diffuse prior.
$\alpha^{wn}_{i,p}$ for all i	Multivariate Normal (Mean=$\mathbf{0}$, Std.=$\infty\mathbf{I}$)	Diffuse prior.
δ_S	Multivariate Normal (Mean=$\mathbf{0}$, Std.=$\infty\mathbf{I}$)	Diffuse prior.

This table gives the prior distributions used for the model parameters. Notes: $(*)$ The element corresponding to w^y (the fifth element) is set to have a prior mean of 0.01^2. $(**)$ This table reports the priors for the 5-sector model. For the 13-sector, 14-sector, and 9-division models, the prior means are multiplied by 13/5, 14/5, and 9/5, respectively, in order to reflect the higher volatility expected at the sectoral level in these breakdowns.

Table 2: Selected posterior percentiles for model parameters, 5-sector model

Posterior statistic \ Percentile	2.5	5	50	95	97.5	Pr>0
Effect of S_t on Δz^u_t given by $\delta_{S,zu}$	0.0000	0.0001	0.0006	0.0011	0.0012	97.23%
Share of variance accounted for by S_t	0.2%	0.8%	17.2%	43.6%	48.4%	
Effect of S_t on Δz^e_t given by $\delta_{S,ze}$	-0.0036	-0.0033	-0.0018	-0.0007	-0.0005	0.35%
Share of variance accounted for by S_t	2.1%	4.1%	23.6%	51.8%	57.4%	
Effect of S_t on Δz^y_t given by $\delta_{S,zy}$	-0.0002	0.0003	0.0026	0.0055	0.0062	96.73%
Share of variance accounted for by S_t	0.1%	0.5%	14.2%	45.6%	52.8%	
Effect of S_t on Δz^v_t given by $\delta_{S,zv}$	0.0000	0.0001	0.0004	0.0009	0.0010	98.54%
Share of variance accounted for by S_t	0.3%	1.1%	15.4%	39.6%	44.5%	
Effect of S_t on w^y_t given by $\delta_{S,wy}$	-0.0035	-0.0030	-0.0015	-0.0003	-0.0001	2.10%
Share of variance accounted for by S_t	0.2%	0.7%	12.7%	35.7%	40.8%	
$Std(log(S_t))$ given by σ_S	0.68	0.72	0.91	1.14	1.19	

Statistics are posterior percentiles and probabilities of being above zero for the model parameters which govern the long run and cyclical responses to reallocative shocks, after 500,001 draws with a burn-in of 10,000 draws. The data cover 5 industries.

Table 3: **Selected posterior percentiles for model parameters, 13-sector model**

Posterior statistic \ Percentile	**2.5**	**5**	**50**	**95**	**97.5**	**Pr>0**
Effect of S_t on Δz_t^u given by $\delta_{S,zu}$	-0.0005	-0.0004	0.0000	0.0004	0.0005	47.76%
Share of variance accounted for by S_t	0.0%	0.0%	1.1%	9.2%	12.0%	
Effect of S_t on Δz_t^e given by $\delta_{S,ze}$	-0.0015	-0.0014	-0.0006	0.0001	0.0003	8.96%
Share of variance accounted for by S_t	0.0%	0.0%	3.3%	14.7%	17.7%	
Effect of S_t on Δz_t^y given by $\delta_{S,zy}$	-0.0014	-0.0011	0.0006	0.0023	0.0026	72.09%
Share of variance accounted for by S_t	0.0%	0.0%	1.5%	12.0%	15.4%	
Effect of S_t on Δz_t^v given by $\delta_{S,zv}$	-0.0003	-0.0002	0.0001	0.0004	0.0004	67.64%
Share of variance accounted for by S_t	0.0%	0.0%	1.3%	10.6%	13.6%	
Effect of S_t on w_t^y given by $\delta_{S,wy}$	-0.0010	-0.0009	-0.0004	0.0000	0.0001	5.59%
Share of variance accounted for by S_t	0.0%	0.1%	4.0%	15.2%	18.0%	
$Std(log(S_t))$ given by σ_S	0.71	0.74	0.92	1.13	1.17	

Statistics are posterior percentiles and probabilities of being above zero for the model parameters which govern the long run and cyclical responses to reallocative shocks, after 500,001 draws with a burn-in of 10,000 draws. The data cover 13 industries.

Table 4: **Selected posterior percentiles for model parameters, 14-sector model**

Posterior statistic \ Percentile	**2.5**	**5**	**50**	**95**	**97.5**	**Pr>0**
Effect of S_t on Δz_t^u given by $\delta_{S,zu}$	-0.0005	-0.0004	0.0000	0.0004	0.0005	47.33%
Share of variance accounted for by S_t	0.0%	0.0%	1.1%	9.4%	12.3%	
Effect of S_t on Δz_t^e given by $\delta_{S,ze}$	-0.0012	-0.0011	-0.0004	0.0003	0.0005	18.80%
Share of variance accounted for by S_t	0.0%	0.0%	1.7%	10.7%	13.2%	
Effect of S_t on Δz_t^y given by $\delta_{S,zy}$	-0.0020	-0.0017	-0.0001	0.0015	0.0019	47.57%
Share of variance accounted for by S_t	0.0%	0.0%	0.9%	7.7%	10.0%	
Effect of S_t on Δz_t^v given by $\delta_{S,zv}$	-0.0003	-0.0002	0.0001	0.0003	0.0004	65.22%
Share of variance accounted for by S_t	0.0%	0.0%	1.2%	9.5%	12.3%	
Effect of S_t on w_t^y given by $\delta_{S,wy}$	-0.0009	-0.0008	-0.0004	0.0000	0.0000	3.98%
Share of variance accounted for by S_t	0.0%	0.1%	4.6%	15.9%	18.6%	
$Std(log(S_t))$ given by σ_S	0.71	0.74	0.90	1.10	1.15	

Statistics are posterior percentiles and probabilities of being above zero for the model parameters which govern the long run and cyclical responses to reallocative shocks, after 500,001 draws with a burn-in of 10,000 draws. The data cover 14 industries.

Table 5: Selected posterior percentiles for model parameters, 9-division model

Posterior statistic \ Percentile	**2.5**	**5**	**50**	**95**	**97.5**	**Pr>0**
Effect of S_t on Δz_t^u given by $\delta_{S,zu}$	-0.0002	-0.0001	0.0002	0.0005	0.0006	85.65%
Share of variance accounted for by S_t	0.0%	0.0%	3.3%	18.5%	22.8%	
Effect of S_t on Δz_t^e given by $\delta_{S,ze}$	-0.0007	-0.0005	0.0000	0.0005	0.0007	45.76%
Share of variance accounted for by S_t	0.0%	0.0%	1.0%	8.5%	11.3%	
Effect of S_t on Δz_t^y given by $\delta_{S,zy}$	-0.0030	-0.0026	-0.0011	0.0001	0.0003	5.90%
Share of variance accounted for by S_t	0.0%	0.1%	6.0%	23.2%	27.5%	
Effect of S_t on Δz_t^v given by $\delta_{S,zv}$	-0.0004	-0.0003	-0.0001	0.0001	0.0002	24.79%
Share of variance accounted for by S_t	0.0%	0.0%	1.5%	11.1%	14.1%	
Effect of S_t on w_t^y given by $\delta_{S,wy}$	-0.0013	-0.0012	-0.0006	-0.0001	-0.0001	1.49%
Share of variance accounted for by S_t	0.2%	0.6%	9.2%	25.8%	29.5%	
$Std(log(S_t))$ given by σ_S	0.90	0.94	1.20	1.54	1.62	

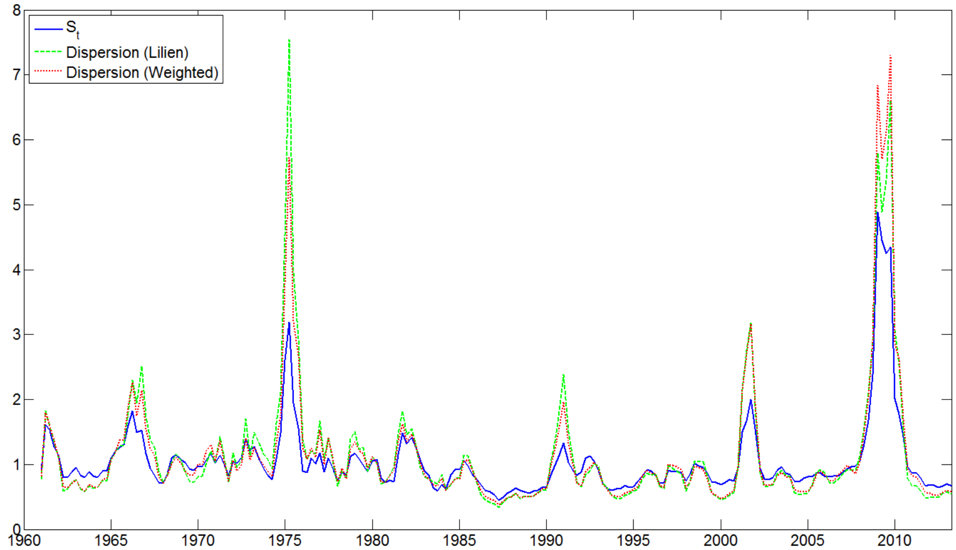
Statistics are posterior percentiles and probabilities of being above zero for the model parameters which govern the long run and cyclical responses to reallocative shocks, after 500,001 draws with a burn-in of 10,000 draws. The data cover 9 census divisions.

Table 6: Correlations among reallocation and dispersion measures, 4-quarter moving averages

	5 Sectors	13 Sectors	14 Sectors	9 Divisions	Stock returns
13 Sectors	0.58				
14 Sectors	0.54	0.94			
9 Divisions	0.30	0.26	0.36		
Stock returns	0.32	0.57	0.64	0.14	
Sales growth	0.04	0.38	0.48	-0.04	0.57

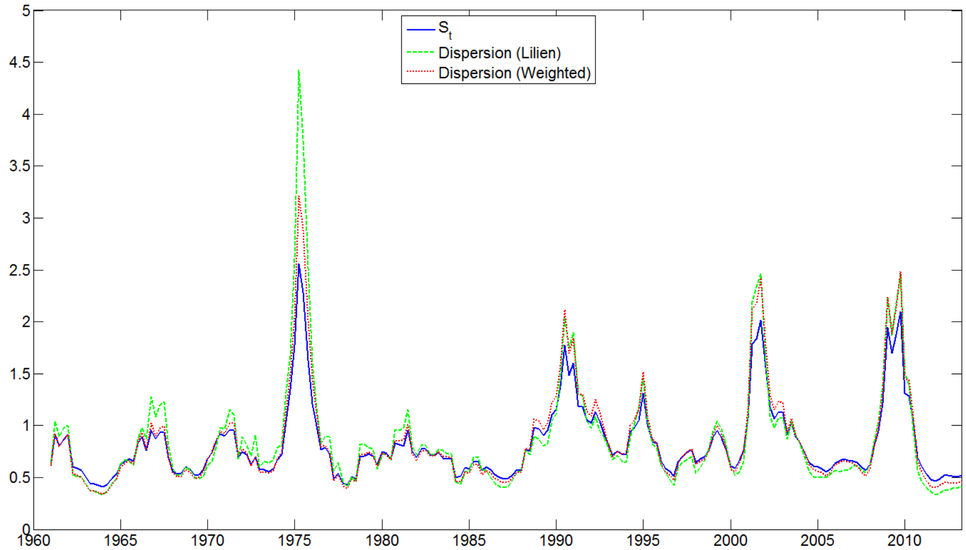
Statistics are correlation coefficients among posterior means of $log(S_t)$ and among dispersion in stock returns and sales growth, taken as a 4-quarter moving average. Source for S_t: Author's calculations using state space model. Source for stock return and sales dispersion: Bloom et al. (2012), taken as log interquartile ranges.

Figure 1: Posterior geometric mean of S_t, 5-sector model



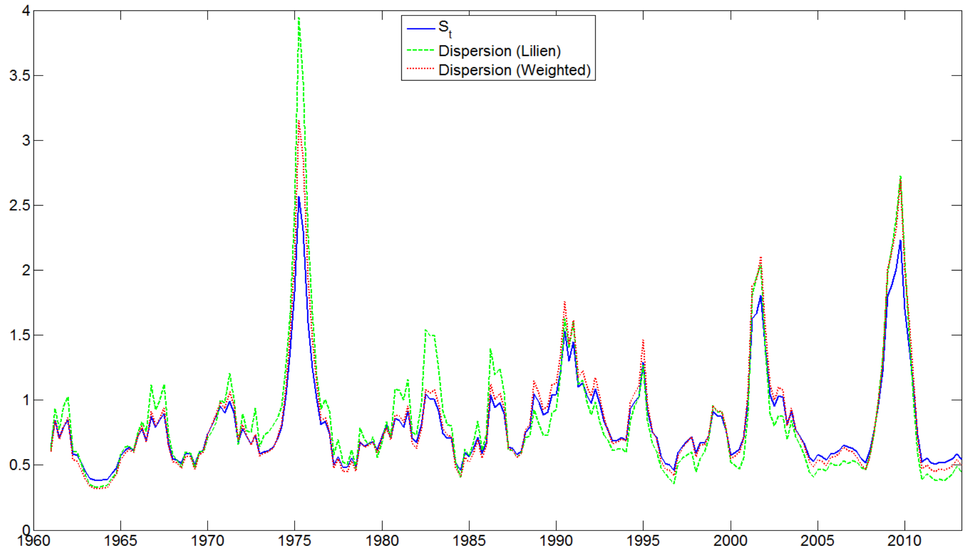
Posterior geometric mean of the reallocation process S_t. Source: Author's calculations using state space model. Results are based on a 4-quarter moving average of $log(S_t)$.

Figure 2: Posterior geometric mean of S_t, 13-sector model



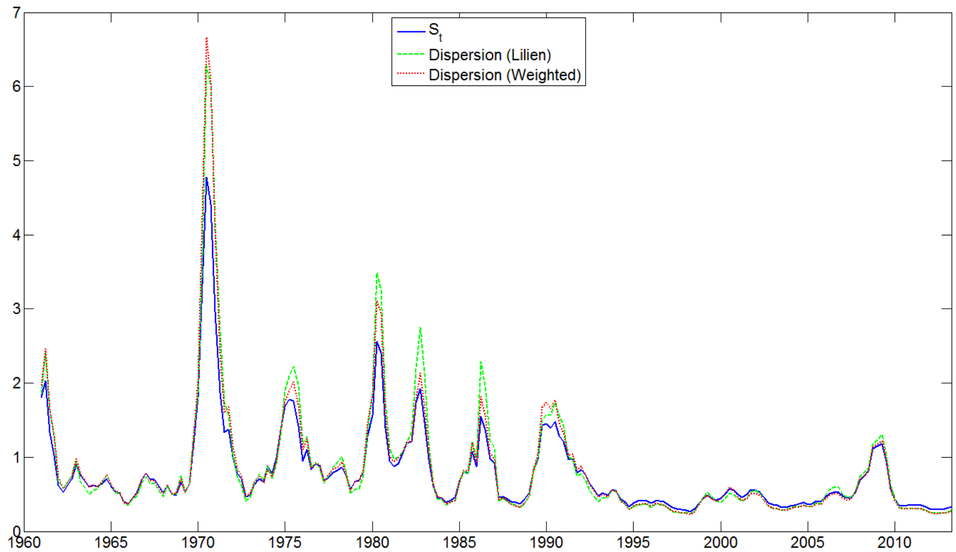
Posterior geometric mean of the reallocation process S_t for the model with 13 sectors. Source: Author's calculations using state space model. Results are based on a 4-quarter moving average of $log(S_t)$.

Figure 3: Posterior geometric mean of S_t, 14-sector model



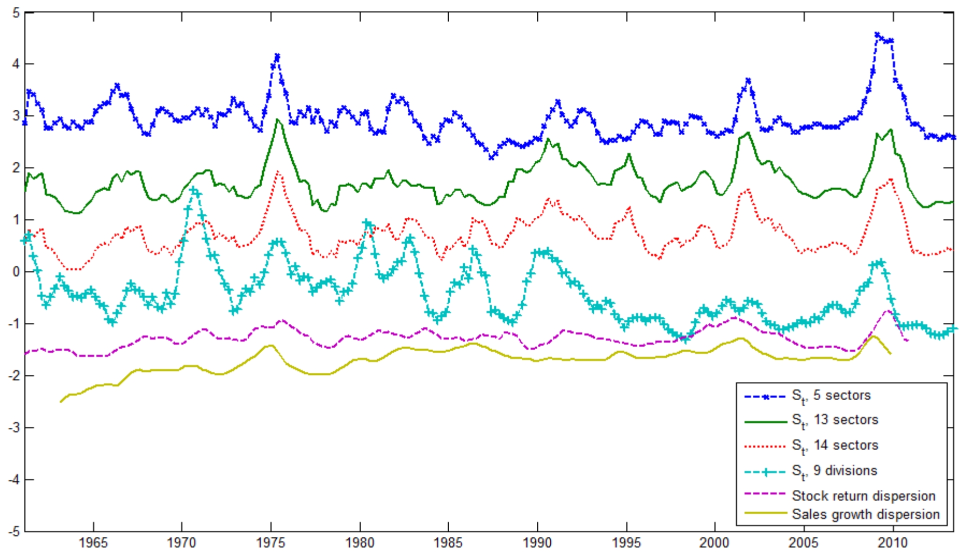
Posterior geometric mean of the reallocation process S_t for the model with 14 sectors. Source: Author's calculations using state space model. Results are based on a 4-quarter moving average of $log(S_t)$.

Figure 4: Posterior geometric mean of S_t, 9-division model



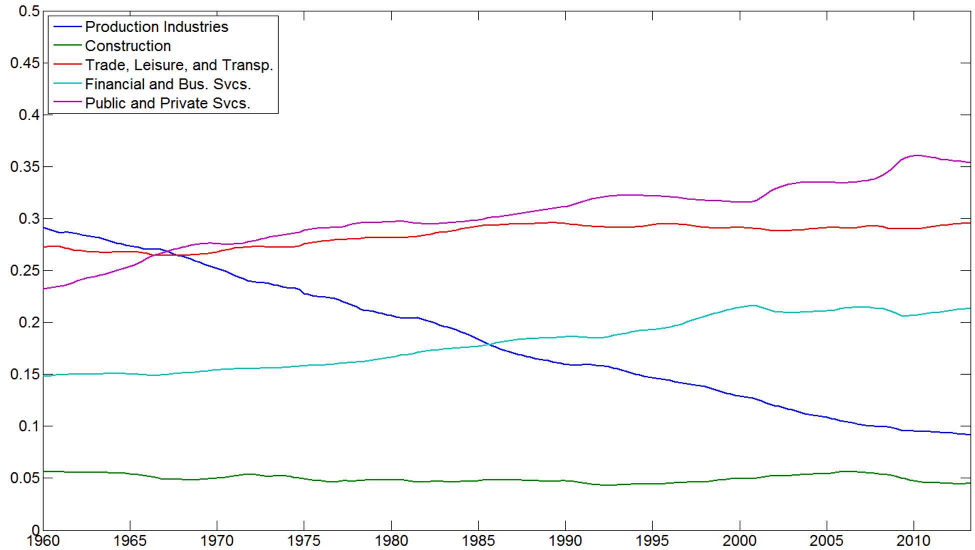
Posterior geometric mean of the reallocation process S_t for the model with 9 geographic divisions. Source: Author's calculations using state space model. Results are based on a 4-quarter moving average of $log(S_t)$.

Figure 5: A comparison of dispersion measures



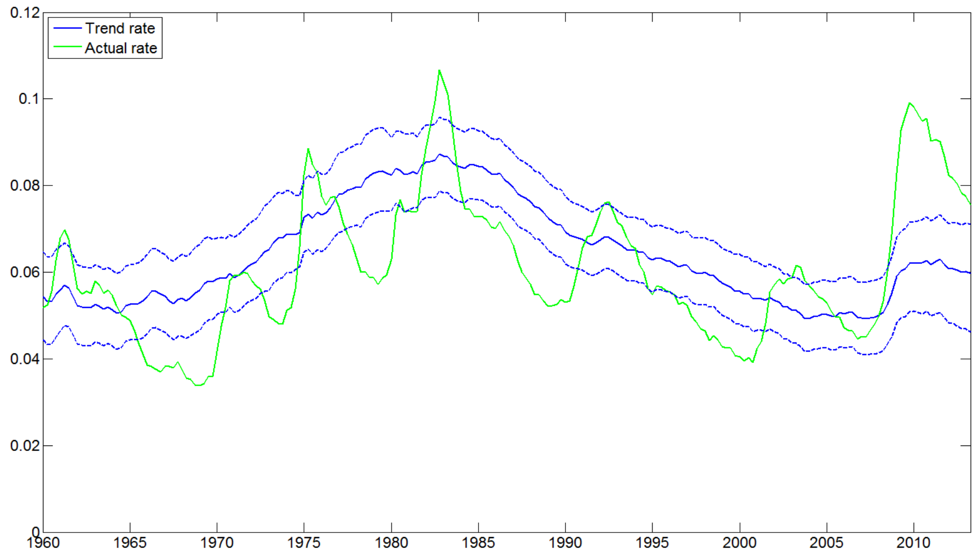
The measures marked S_t are the mean of the log reallocation process $log(S_t)$. The measures marked 'Stock return dispersion' and 'Sales growth dispersion' represent the log interquartile ranges of stock returns and sales growth. Source: Author's calculations using state space model, for S_t. Bloom et al. (2012) for log interquartile ranges of stock returns and sales growth. Results are based on a 4-quarter moving average and are translated upward or downward in order to facilitate visual comparison.

Figure 6: Posterior geometric mean of $z^n_{i,t}$, 5-sector model



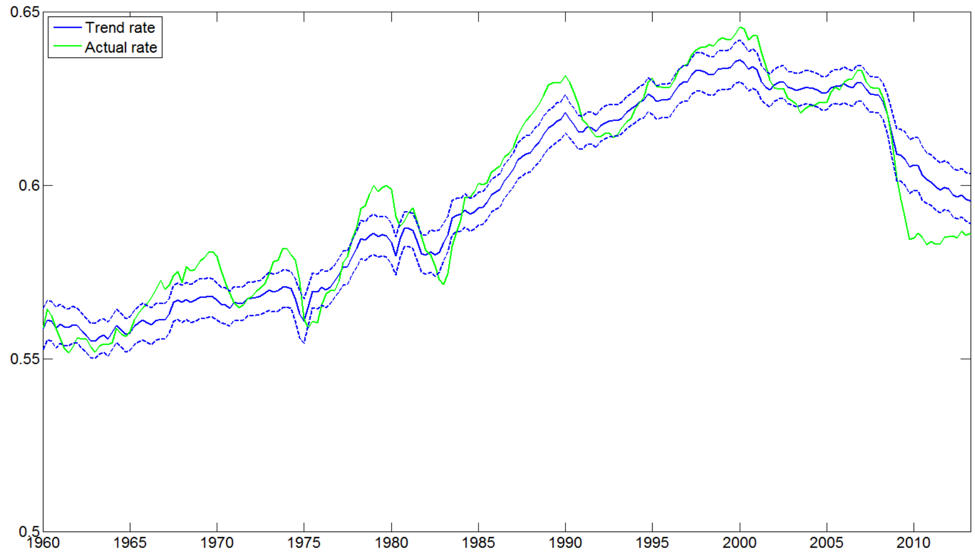
Posterior geometric mean of trend sectoral employment shares $z^n_{i,t}$. The share for public and private services is calculated as a residual. Source: Author's calculations using state space model.

Figure 7: Posterior trend unemployment rate z_t^u, 5-sector model



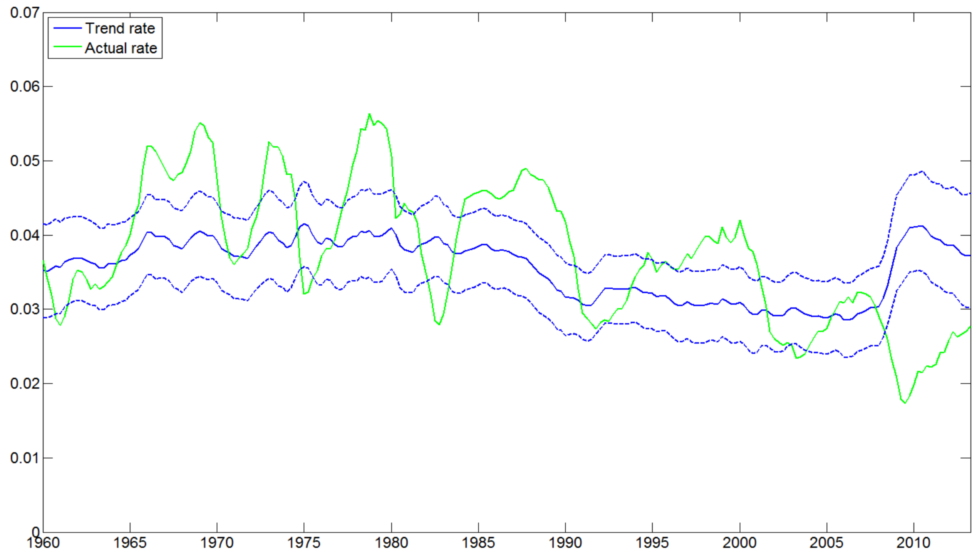
Posterior mean of the trend unemployment rate z_t^u. Dashed lines give the 2.5th and 97.5th posterior percentiles. Source: Author's calculations using state space model.

Figure 8: Posterior trend employment-population ratio $exp(z_t^e)$, 5-sector model



Posterior geometric mean of the trend employment-population ratio $exp(z_t^e)$. Dashed lines give the 2.5th and 97.5th posterior percentiles. Source: Author's calculations using state space model.

Figure 9: Posterior trend vacancy rate z_t^v, 5-sector model



Posterior mean of the trend vacancy rate z_t^v. Dashed lines give the 2.5th and 97.5th posterior percentiles. Source: Author's calculations using state space model.